FOUR GEN AI-ENABLED VALUE LOGICS IN INDUSTRIAL B2B MARKETS

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Generative artificial intelligence (Gen AI) is rapidly transforming industrial B2B markets, yet firms struggle to translate its technological capabilities into realized value. This qualitative multiple-case study examines Gen AI-enabled value logics in six large global industrial B2B firms based on 15 semi-structured interviews. Using an abductive approach, we identify four archetypal value logics: synthesizing, interactional, predictive, and diagnostic. These logics capture distinct ways in which Gen AI structures dispersed data, enhances communication, translates predictive insights into actionable guidance, and supports diagnostic problem resolution. Drawing on a framework integrating AI intelligence types and human–AI interaction modes as an analytical lens, we show that Gen AI value logics in industrial B2B contexts cluster within thinking intelligence and augmentation or automation configurations, reflecting contextual constraints such as safety requirements and relational norms. By shifting attention from technological capabilities to configuration-level value logics, this study advances understanding of how Gen AI reconfigures value creation in industrial B2B markets and offers a typology to guide managerial implementation.

Keywords:
generative artificial intelligence,
value logics,
industrial B2B markets,
human-AI interaction,
value creation

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1 Introduction

Generative artificial intelligence (Gen AI) is rapidly transforming how businesses operate and engage with customers across sectors (Teng et al., 2025; Yuan et al., 2025). In industrial B2B markets, Gen AI reshapes how firms configure and realize value creation through context-sensitive analysis, content generation, and scalable knowledge integration (McKinsey & Company, 2025; Haefner et al., 2023). Yet despite these technological advances, many firms struggle to translate AI investments into sustained competitive advantage (Barney and Reeves, 2024; Kemp, 2024; Yuan et al., 2025).

Existing research on AI and Gen AI has examined capabilities and competencies (Ayala et al., 2025; Li et al., 2024; Sjödin et al., 2021), ecosystems and infrastructures (Burström et al., 2021), adoption drivers and barriers (Chen et al., 2022; Maga and Bodlaj, 2025), and implementation considerations (Grewal et al., 2025; Reim et al., 2020). However, the value logics enabled by Gen AI remain underexplored. In this study, value logics refer to archetypal configurations through which firms structure and realize value creation enabled by Gen AI in industrial B2B contexts. This perspective shifts attention from technological features or articulated market promises to recurring patterns in how value is configured and enacted in practice.

Understanding these logics is critical because Gen AI does not merely enhance analytical processes; it reshapes how knowledge is interpreted, communicated, and operationalized across organizational and relational boundaries (Akter et al., 2023; Jorzik et al., 2024). Moreover, the configuration of human–AI interaction plays a central role in determining how value is enacted in industrial settings (Ayala et al., 2025; Cui et al., 2024; Singh et al., 2024).

In this paper, we aim to deepen the understanding of Gen AI-enabled value logics in industrial B2B markets. We develop a conceptual model integrating two dimensions: AI intelligence types, mechanical, thinking, and feeling (Huang and Rust, 2018), and modes of human–AI interaction, augmentation, automation, and autonomous collaboration (Azer and Alexander, 2025; Davenport and Kirby, 2016). Our research question is: What types of Gen AI-enabled value logics emerge in industrial B2B firms? Drawing on a qualitative multiple-case study of six large industrial firms and 15 interviews, we identify four archetypal value logics: synthesizing, interactional, predictive, and diagnostic.

2 Literature review

2.1 Defining Gen AI

Artificial intelligence can be defined as a system's ability to interpret external data, learn from it, and use these insights to achieve specific goals through adaptive processes (Haenlein and Kaplan, 2019). AI functions as an umbrella term encompassing various algorithmic approaches, including machine learning and deep learning (Strobel et al., 2024). Machine learning enables systems to detect patterns and improve performance over time, while deep learning relies on layered neural networks to learn complex representations from large datasets (Ayala et al., 2025; Naeem et al., 2025).

Generative artificial intelligence is a subset of deep learning distinguished by its ability to produce novel content rather than merely analyze or predict based on existing data (Huang et al., 2024; Singh et al., 2024; Yuan et al., 2025). Compared to conventional AI systems, Gen AI demonstrates stronger adaptability, contextual sensitivity, multimodal data processing capabilities, and the ability to generate human-like outputs (Mariani and Dwivedi, 2024). These capabilities are typically enabled by large-scale generative models trained on extensive datasets and refined through iterative feedback processes (IBM, 2024; Strobel et al., 2024).

The content-generative capacity of Gen AI is central to this study. While conventional AI systems primarily produce analytical outputs such as predictions and classifications, Gen AI generates communicable content that reshapes how knowledge is interpreted and how value is articulated and realized in practice (Grewal et al., 2025; Mariani and Dwivedi, 2024; Strobel et al., 2024). Rather than merely enhancing analytical processes, Gen AI transforms the layer through which insights are expressed and operationalized. In the empirical analysis, we use this content-generation criterion to identify what is distinctly generative within each value logic.

2.2 Value Creation and Value Logics in B2B Markets

Building on the definition introduced above, we situate value logics within prior research on value creation and business model design. Prior studies have examined how firms organize and articulate value creation for customers (Payne et al., 2017; Teece, 2010), while service-dominant logic emphasizes that value emerges through interaction and resource integration rather than being embedded solely in outputs (Vargo and Lusch, 2004, 2008; Vargo et al., 2026). Conceptualizations of value have evolved from exchange-oriented, cost-benefit formulations toward multidimensional and use-oriented views that emphasize experience, relationships, and co-creation (Zeithaml et al., 2020; Eggert et al., 2018). In industrial B2B markets, this shift is reflected in a move toward relational and use-based conceptions of buyer–supplier exchange (Eggert et al., 2018). These perspectives suggest that value is enacted through configurations of resources, processes, and relationships.

Gen AI reconfigures both dimensions of this discussion. First, it reshapes how firms articulate and communicate insights, interpretations, and recommendations in customer interactions (Ruokonen and Ritala, 2025; Wessel et al., 2025). Second, it introduces a non-human actor into value co-creation processes, altering how resources are interpreted, combined, and enacted in industrial B2B relationships (Wessel et al., 2025; Wirtz and Stock-Homburg, 2025). Examining Gen AI through a value logic lens, therefore, shifts attention from technological features to how value creation is configured in practice.

2.3 Enhancing B2B Value Logics with Gen AI

To analyze Gen AI-enabled value logics in industrial B2B markets, we employ an analytical framework grounded in two dimensions: AI intelligence types (Huang and Rust, 2018) and modes of human–AI interaction (Azer and Alexander, 2025; Davenport and Kirby, 2016; Raisch and Krakowski, 2021). Together, these dimensions specify both the nature of value generated and how value is configured between human and AI actors.

Huang and Rust (2018) distinguish among mechanical, thinking, and feeling intelligence. Mechanical AI supports routine tasks, thinking AI enables analytical reasoning and decision support, and feeling AI addresses emotional interpretation.

Gen AI is most closely associated with thinking intelligence due to its capacity to generate novel and context-sensitive content (Sedkaoui and Benaichouba, 2024), while also incorporating elements of mechanical automation and emerging affective responsiveness (Huang and Rust, 2024). These intelligence types delineate the qualitative character of value that Gen AI can help configure.

The second dimension concerns how humans and AI collaborate in value creation. Human–AI interaction ranges from augmentation, where AI supports human decision-making, to automation, where AI performs tasks under human supervision, and to autonomous configurations, where AI operates independently within defined boundaries (Davenport and Kirby, 2016; Raisch and Krakowski, 2021). These modes are not strictly sequential; rather, they may coexist and shift depending on contextual and task-specific constraints.

Integrating these dimensions, we develop a conceptual model presented in Table 1. The matrix outlines theoretically possible configurations of Gen AI-enabled value logics across combinations of intelligence types and interaction modes. We use this framework as an analytical lens for interpreting empirical patterns rather than as a rigid classificatory scheme. In industrial B2B contexts, certain configurations may be more feasible than others (Burström et al., 2021).

Table 1: Analytical Framework for Mapping Gen AI-Enabled Value Logics

	Augmentation (Human-led, AI-assisted)	Automation (AI-led, human-supervised)	Autonomous (AI-led, self-supervised)
Mechanical AI	AI supports humans by preparing structured inputs	AI executes routine process steps	AI runs defined workflows independently within specified boundaries
Thinking AI	AI provides insights to support human decisions	AI produces draft decisions or recommendations for human approval	AI optimizes and adapts dynamically within predefined parameters
Feeling AI	AI interprets emotional cues to help humans tailor responses	AI delivers emotionally attuned responses under human oversight	AI adapts communication patterns independently based on detected emotional cues

3 Methods

3.1 Research Approach

To investigate the types of value logics emerging through industrial B2B firms' use of Gen AI, we applied a qualitative multiple-case study approach (Dubois and Gadde, 2002, 2014; Yin, 2018). Given the limited research on Gen AI-enabled value logics in industrial contexts, qualitative methods are appropriate for such discovery-focused research (Eisenhardt and Graebner, 2007; Siggelkow, 2007). A multiple-case study design enabled the generation of holistic insights into how Gen AI-enabled value logics take shape within their real-world contexts (Yin, 2018).

3.2 Data Collection

Table 2: Overview of Firms and Respondents

Firm	Industry	Workforce	Identified Gen AI Value Logics	Interviewees
A	Elevators and escalators	60,000-65,000	Synthesizing, interactional, predictive, diagnostic	Senior Gen AI Strategic Designer; Product Manager (2)
B	Chemicals	≤ 1,000	Synthesizing	Development Manager; CIO
C	Welding	≤ 1,000	Synthesizing	Service Manager
D	Electrification and automation	≥ 100,000	Synthesizing, interactional, predictive, diagnostic	SVP Service; Head of Sales; Director Digital Ecosystems
E	Mining and metals	15,000-20,000	Synthesizing, diagnostic	SVP Services; Lead Service Designer; Director Data & AI; Design Manager
F	Marine and energy	15,000-20,000	Synthesizing, predictive, diagnostic	Lead Business Innovation Manager; Head of Lifecycle Data Operations

We employed purposive sampling (Patton, 2015) to identify six industrial B2B firms operating in different markets that had begun leveraging Gen AI in concrete initiatives relevant to value creation. The empirical data were collected through semi-structured interviews with informants responsible for developing Gen AI customer interactions and related value creation practices within their organizations. We employed snowball sampling, in which key informants recommended additional experts from their firms for further interviews (Miles *et al.,* 2014). An open-ended thematic interview guide was used to focus on the key objectives, requirements, and challenges of leveraging Gen AI to create customer value. We conducted 15 interviews with the six case firms, each transcribed verbatim. An overview of the firms, interviewees, and identified value logics is provided in Table 2.

3.3 Data Analysis

We used an abductive analysis approach, iteratively moving between empirical data and theoretical literature to conceptualize Gen AI-enabled value logics (Dubois and Gadde, 2002, 2014). The analysis proceeded in three stages consistent with Yin's (2018) multiple-case study techniques. First, we conducted within-case analysis to develop detailed descriptions of Gen AI-enabled value creation and modes of human-AI interaction within each firm. Second, we conducted a cross-case synthesis to compare cases and identify recurring patterns. Third, we used these cross-case findings to support analytic generalization toward higher-level theoretical insights about Gen AI-enabled value logics. These generalizations were elaborated abductively through iterative movement between data and theory (Dubois and Gadde, 2002, 2014).

4 Findings

Based on the data analysis, we identified four archetypal Gen AI-enabled value logics enacted by industrial B2B firms: synthesizing, interactional, predictive, and diagnostic. Firms frequently enacted multiple value logics at once rather than relying on a single dominant configuration. Table 3 summarizes the core characteristics of each value logic, including their primary intelligence type, interaction mode, generative mechanism, commercialization pattern, and key challenges.

Table 3: Gen AI-enabled Value Logics

	Synthesizing Value	Interactional Value	Predictive Value	Diagnostic Value
Mechanical and Thinking AI	Mechanical AI	Thinking AI	Thinking AI	Thinking AI
Human-AI Interaction	Augmentation & Automation	Augmentation & Automation	Augmentation & Automation	Augmentation & Automation
Overall Goal	Process and structure large volumes of data	Enhance communication and information accessibility	Analyze data to forecast and make recommendations	Identify root causes and help with problem resolution
Distinct Generative Mechanism	Generates structured documents	Generates conversational, context-sensitive responses	Generates narrative explanations and optimization strategies	Generates step-by-step troubleshooting guidance and resolution pathways
Key Customer Benefit	Faster, more comprehensive service	Enhanced access to relevant information	Improved operational efficiency	Self-service problem solving; faster service
Commer-cialization Pattern	Enhances existing services	Embedded or subscription add-ons	New service modules or add-ons	Enhances existing service contracts
Key Challenge	Siloed data	Human preference for personal interaction	Data acquisition and accuracy	Product/process complexity

4.1 Synthesizing Value

The synthesizing value logic focused on structuring large volumes of dispersed data to improve efficiency and accessibility across internal and customer-facing processes. It combined mechanical and thinking intelligence within configurations of augmentation and automation.

Its distinct generative mechanism lies in Gen AI's ability to compose structured documents from unstructured inputs. Rather than merely retrieving or classifying information, Gen AI generated integrated outputs such as draft tenders, sales proposals, and part-identification reports that combined multiple data sources into coherent, human-readable formats. For example, one firm used Gen AI to identify damaged spare parts from photographs to ensure accurate replacements, while another applied it to extract tender requirements and suggest compatible products. As one informant explained:

"Gen AI has been utilized in the sales proposal creation process, especially in simple, high-volume product areas. It enables making customer proposals faster and more easily" (Director, Firm D).

Unlike the other value logics, synthesizing value was predominantly internally oriented. Customer benefits were realized indirectly through faster responses, improved documentation accuracy, and greater service consistency. These capabilities were embedded within existing operational processes rather than introduced as separate commercial initiatives. A key challenge concerned siloed data across legacy systems and organizational units, which constrained effective Gen AI deployment:

"Customer sentiment data has traditionally been owned by marketing and sales. Technical data is owned elsewhere, and combining these two data areas brings many discussions" (Head of Lifecycle Data Operations, Firm F).

Addressing these silos required both technical integration and cross-functional coordination.

4.2 Interactional Value

The interactional value logic centered on enhancing customer communication and improving access to relevant information. It was primarily grounded in thinking intelligence and enacted through augmentation and automation.

Its distinct generative mechanism was Gen AI's ability to produce conversational, context-sensitive responses tailored to specific customer queries. Unlike conventional AI-based search systems that retrieve pre-authored content, Gen AI generated novel responses by integrating multiple knowledge sources and adapting outputs to the framing of each request. For instance, one firm implemented a Gen AI-driven chatbot within its customer support portal, while another used Gen AI to assist call center agents by suggesting context-specific responses. As one informant noted:

"Based on a customer inquiry [to the call center], the [Gen AI-based] tool already provides potential responses, and they [the agents] then choose the one that is most applicable, or they may make some changes. ... We have not made the step yet to automate customer interaction completely. This is due

to the safety requirements of our industry, where we do not want to risk giving customers incorrect advice" (Strategic Designer, Firm A).

Interactional value increased accessibility and responsiveness by enabling customers to obtain relevant information more quickly and with less effort. In most cases, Gen AI operated as an assistant to customer-facing personnel, scaling expertise and promoting consistency across interactions. Even when embedded behind human agents, the value logic remained directly customer-facing. Commercialization typically involved embedding AI capabilities within existing services or offering premium features as add-ons. A key challenge concerned established customer preferences for direct human interaction and strong personal relationships:

"As the customer base is limited, our interaction with customers tends to be very personal. These interactions tend to be personified to our account managers [rather than mediated by technology]" (Director, Firm E).

This preference for human contact required firms to balance AI-enabled efficiency gains with maintaining the relational quality valued by customers.

4.3 Predictive Value

The predictive value logic focused on analyzing operational data to support forward-looking decision-making, particularly in predictive maintenance and resource optimization. It was grounded in thinking intelligence and enacted through augmentation and automation.

While predictive analytics has long been present in industrial B2B markets, the generative contribution of Gen AI did not primarily concern improved forecasting accuracy. Instead, Gen AI transformed how predictive insights were communicated and operationalized. By generating narrative explanations, scenario-based reasoning, and natural-language recommendations, Gen AI enabled customers to understand not only what was predicted, but why it mattered and how different courses of action might unfold. This communicative layer bridged quantitative model outputs and situated decision-making. For example, one firm used Gen AI to analyze weather and energy market data to optimize energy consumption strategies. Another enhanced predictive maintenance services by refining forecasts and contextualizing recommendations:

"Instead of just telling the customer they need a service, and maybe explaining why, we can now also estimate what would happen if they do not have that service" (Product Manager, Firm A).

The predictive value logic emphasized foresight. Customers could anticipate operational risks, evaluate the consequences of inaction, and make more informed decisions about maintenance and resource allocation. For firms, these capabilities enabled scalable service extensions across installed bases. A key challenge concerned the availability and reliability of operational data:

"We know what the configuration of the asset is. But the challenge [for predictive accuracy] is that while we know the asset and its surroundings well, the actual process or the operational purpose of the asset varies widely" (Director, Firm E).

Such data limitations constrained the reliability and applicability of predictive Gen AI solutions and required firms to invest in improved data integration and governance practices.

4.4 Diagnostic Value

The diagnostic value logic centered on identifying the root causes of operational problems and supporting their resolution. It was grounded in thinking intelligence and enacted through augmentation and automation.

Although diagnostic systems have long relied on conventional AI techniques such as anomaly detection and fault classification, Gen AI added a generative layer by producing step-by-step troubleshooting guidance tailored to specific operational contexts. Rather than simply detecting and classifying malfunctions, Gen AI generated contextual natural-language advice that guided technicians or customers through resolution processes in real time, explaining both how and why particular actions were appropriate. For example, one firm integrated Gen AI into its remote services to support troubleshooting, while another piloted diagnostic tools providing real-time guidance to field technicians:

"The fact that our field service technicians can now get real-time help and advice for their problem-solving when there is an issue at the customer site, that is something we have piloted now with Gen AI" (Strategic Designer, Firm A).

This value logic emphasized faster and more accurate problem resolution. Customers could address certain issues independently and accelerate service encounters requiring on-site intervention. For firms, diagnostic capabilities also generated insights into usage patterns and recurring failure points, improving reliability and reducing troubleshooting costs. These capabilities were typically embedded within existing service contracts rather than introduced as standalone offerings. A key challenge stemmed from product and process complexity:
"In industrial markets, it is rarely the case that you just download something from the internet and start using it. Instead, there is much configuration required to have exactly the right approach and data sources" (Director, Firm D).

The bespoke nature of industrial equipment required significant contextual adaptation of Gen AI systems, limiting the scalability of standardized diagnostic solutions across diverse installed bases.

5 Discussion and Conclusions

5.1 Theoretical Contributions

Drawing on a qualitative multiple-case study, this research makes two contributions. First, we develop a conceptual model for understanding Gen AI-enabled value logics in industrial B2B markets by integrating AI intelligence types (Huang and Rust, 2018) with modes of human–AI interaction (Azer and Alexander, 2025; Davenport and Kirby, 2016; Raisch and Krakowski, 2021). While prior research has examined these constructs separately, we connect them through a value logic lens and apply the framework empirically.

Second, we identify four archetypal Gen AI-enabled value logics: synthesizing, interactional, predictive, and diagnostic. We respond to calls for research that clarifies how AI reshapes value creation and that develops typological understandings of AI-driven configurations (Bahoo et al., 2023; Jorzik et al., 2024). Our findings offer context-specific insight into industrial B2B markets, where technological capabilities, organizational conditions, and relational norms appear to jointly shape how Gen AI is enacted. A central empirical pattern across our cases is that all four value logics cluster within thinking intelligence and augmentation or automation configurations. Autonomous and feeling-oriented configurations remained largely unoccupied in our data. These patterns suggest that technological capability alone does not determine enacted value logics. In the industrial B2B contexts we studied, factors such as safety requirements, siloed data, product complexity, and customization demands shape how Gen AI is configured in practice, constraining enactment to modes that preserve human oversight and relational trust.

From an organizational perspective, augmentation and automation did not emerge as sequential stages but rather appeared as coexisting configurations within a single value logic. This is consistent with the view that human–AI interaction is dynamically balanced rather than linearly progressing toward autonomy (Raisch and Krakowski, 2021). From a relational perspective, Gen AI introduces a non-human actor into buyer–supplier interactions (Wessel et al., 2025), potentially enabling greater responsiveness and foresight while simultaneously requiring careful preservation of trust-based norms (Kamalaldin et al., 2020). The unoccupied cells in the analytical framework may thus be read as theoretically possible but contextually constrained configurations rather than as inevitable developmental trajectories.

5.2 Managerial Implications

For managers, the typology of Gen AI-enabled value logics offers a structured lens for evaluating AI initiatives. Rather than focusing on technological capabilities, firms can assess how Gen AI is configured in relation to value creation objectives and organizational readiness. The predominance of augmentation and automation suggests that near-term gains are most effectively realized through human–AI collaboration. At the same time, firms should evaluate where greater autonomy is contextually appropriate, particularly in predictive and diagnostic applications where outputs can be validated against measurable operational outcomes. Interactional value logics, which depend on relational trust and contextual judgment, are likely to remain human-centered. For customers, the typology offers distinctions obscured by generic claims about AI-enabled value. Customers may use it to articulate the value they are seeking and to negotiate the degree of human involvement that aligns with their safety, confidentiality, and relational preferences.

5.3 Limitations and Future Research Areas

This study has several limitations that point to avenues for further research. First, our empirical base of six large industrial firms and 15 interviews is modest, and may explain the limited variation observed across intelligence types and interaction modes. Future research should examine smaller firms and alternative contexts to assess the generalizability of the identified value logics. Second, the cross-sectional design limits insight into how value logics evolve over time. Longitudinal studies could explore how configurations shift as technological capabilities and organizational readiness develop. Third, the distinction between mechanical, thinking, and feeling intelligence warrants reassessment as AI technologies mature. Finally, ethical considerations, including accountability, bias, and trust in AI-mediated interactions, merit investigation, particularly regarding how governance practices shape the legitimacy and development of Gen AI-enabled value logics.

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