Generative AI as a Catalyst for Human-Centric Supply Chains: A Fuzzy-Set Qualitative Comparative Analysis (fsQCA) of Key Adoption Factors

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Abstract

Purpose: Generative Artificial Intelligence (Gen-AI) has been rapidly adopted into organizations; however, the process of how technical implementations match human-driven supply chain dynamics is still understudied. Adoption of technology has previously been viewed as a univariate success–failure metric, failing to account for the underlying configurational complexity of implementation. To address this gap, our research uses configurational theory as a foundation to investigate what set of organizational, technical, human, and external conditions is necessary and sufficient to drive Gen-AI implementation as human-driven supply chain facilitators.

Design/methodology/approach: The research is based on empirical evidence of 137 respondents from manufacturing firms. Utilizing fuzzy-set Qualitative Comparative Analysis (fsQCA), this study finds several equifinal combinations of conditions associated with successful Gen-AI implementation and presents causal asymmetry between high and low implementation conditions.

Findings: The findings identify '*Scalability, Skills and Expertise*, *Collaboration & Communication*, and *Industry Trends*' as necessary conditions for the successful implementation of Gen-AI. Additionally, seven sufficient configurations exhibit extreme equifinality and causal asymmetry in the demonstration of successful implementation, indicating that skills and collaboration were universal core conditions present in each of the seven configurations. Additionally, on the one end of the spectrum, there are solution sets consisting of enabling technology, assuming that "leadership vision, resource availability, innovation infrastructure, and market competition" will complement technological readiness. On the other hand, human factors focus on the change management aspects, like "organisational culture, user acceptance, and scalability". The results from each subsample and holdout analysis add further assurances of the predictive validity of configurational analysis in determining how to implement Gen-AI in human-centric supply chain operations.

Originality: This research contributes to supply chain literature by providing a configurational view of Gen-AI implementation. Instead of continuing the debate of "whether implementation works" by conducting additive analyses, our study unlocks and explains equifinal and asymmetrical causal patterns, thereby offering theory-grounded yet managerially applicable pathways on "how different pathways work" for managers to simultaneously leverage technology acceleration and human empowerment in supply chain ecosystems.

Keywords: Gen-AI technologies; Human-centric; fsQCA; Internal factors; External factors; Necessary and Sufficient conditions

1. Introduction

Technology and innovation are both transforming the globe through new technological opportunities like Generative artificial intelligence (Gen-AI) (Ng et al., 2025), and it is a quickly emerging disruptive phenomenon that is changing how organizations and their supply chains create, exchange, and use knowledge to be competitive and sustainable (Doshi et al., 2025). The fast-paced development of Gen-AI is shifting how organizations and their supply chains manage to innovate, navigate risks, and build resilience (Abbas et al., 2026). Gen-AI is a *"category of AI that can create new content such as text, images, videos, and music"*[1]. Gen-AI can be highly valuable in Supply Chain Management to increase an organization's capability to satisfy the customers' needs through the improvement of decision-making processes by using analytics, predictive analysis, and automating complex business processes (Singh et al., 2025).

Gen-AI can be a force multiplier for human-centric supply chains, which recognises the needs, strengths, and well-being of employees[2], through improved human–machine collaboration, empowering and equipping employees with real-time insights and intelligence, and helping to ensure decisions are faster, more accurate, and ethically grounded, with a focus on human well-being, safety, and stakeholder value (Gstettner et al., 2024). For example, Gen-AI can accelerate the creation of complex applications and supply chain solutions by 30%, increase user adoption and satisfaction by over 60%, reduce administrative and data reconciliation tasks by more than 50%, and improve decision-making speed by over 30%, allowing for faster, more informed decisions (Gstettner et al., 2024). Gen-AI is based on deep neural networks trained on vast corpora of text and operational data. The emergent properties of this data enable outputs that are contextually relevant and helpful and augment human cognitive capacity to understand and analyze complex and massive data sets (Desdevises, 2025).

Machine learning systems and Gen-AI assist enterprises in making sense of vast and complex amounts of data in a shorter time. They help to automatically extract relevant information from unstructured data sources, which can lead to better decisions, enhanced organizational learning, and performance (Just, 2024). This is not just beneficial in sense-making but also powers organizations and their supply chains (i.e., supply chain optimization, market research, consumer behaviour analysis). Advanced capabilities of tools like Google Cloud AutoML (Rosário & Boechat, 2024) and other Gen-AI applications can help organizations reveal hidden patterns, forecast demand patterns,

[1] https://www.oecd.org/en/topics/sub-issues/generative-ai.html (Accessed on 09th December 2025)
[2] https://www.slimstock.com/blog/human-centric-supply-chain/ (Accessed on 07th December 2025)

and generate actionable intelligence to inform strategic decisions. Hence, ML algorithm implementation, including Gen-AI technology, will be a supporting process to set operations. It can become a strategy that changes the analytics mechanism of an organization or its supply chain and achieves competitive advantages (Bornet et al., 2021).

Despite these growing capabilities, the successful implementation of Gen-AI in supply chains depends on the interaction of organizational, technological, human, and external environmental factors that collectively shape human-centric outcomes. Organizational structure and governance determine how AI initiatives are coordinated and managed (Huang & Teo, 2020), while organizational culture and readiness influence employee acceptance and collaboration with AI technologies (Latinovic & Chatterjee, 2022). Technological readiness, data quality, and innovation infrastructure determine the feasibility and scalability of Gen-AI implementation, whereas high implementation costs and complexity often constrain adoption (Ramayah et al., 2016; Chen & Chen, 2020). There are many challenges associated with implementing Gen-AI, given its complexities, but new-era managers continuously pursue the merits of its use and application for their benefit and that of their organization (Yao et al., 2023). Furthermore, external environmental forces such as market competition, customer pressure, regulatory expectations, and technology provider support significantly influence Gen-AI adoption and its human-centric outcomes.

Customers increasingly demand personalized and real-time services, pushing organizations toward digital transformation (Abed, 2020; Sharma et al., 2020), while technology providers and industry ecosystems enable implementation through training, partnerships, and technical support (Maduku et al., 2016). These external, technological, and organizational dynamics collectively determine whether Gen-AI enhances human-centric supply chain operations or remains underutilized. However, existing literature largely examines these factors in isolation, focusing on individual drivers such as technological readiness, user acceptance, or managerial commitment (Abbas et al., 2026; Merhi & Harfouche, 2023; Sharma et al., 2022a). This fragmented approach creates a critical research gap: there is limited understanding of how combinations of organizational, technological, human, and external factors jointly enable Gen-AI implementation for human-centric supply chain operations. In particular, prior studies lack a configurational perspective that explains how multiple interdependent conditions interact to produce successful Gen-AI implementation outcomes.

This gap is significant because human-centric supply chains are inherently complex systems where technology, organizational capabilities, and external pressures interact simultaneously. Without an integrated configurational framework, organizations struggle to identify which combinations of factors lead to successful Gen-AI implementation and human-centric supply chain transformation. To address this gap, this study investigates the following research question (RQ):

RQ: What combinations of organizational, technical, human, and external factors are necessary and sufficient for organizations to implement Gen-AI tools to catalyze human-centric supply chain operations?

To answer this research question, this study adopts a configurational approach using Fuzzy-Set Qualitative Comparative Analysis (fsQCA) and data from industry experts working in manufacturing firms. Drawing on configurational theory (Ragin, 2008a; Fiss, 2011), this study examines how multiple interdependent factors jointly produce successful Gen-AI implementation outcomes rather than relying on single-factor explanations. Importantly, the findings reveal that complex configurations of organizational culture, market competition, technological readiness, data quality, innovation infrastructure, leadership vision and support, and industry trends drive successful Gen-AI implementation for human-centric supply chains. The predictive validity results show high consistency levels and substantial coverage, indicating that multiple configurations of organizational, technological, and external conditions strongly explain Gen-AI implementation success. In particular, configurations combining market competition, industry trends, organizational culture, technological readiness, data quality, and leadership vision demonstrate strong predictive power, covering nearly 49% of implementation outcomes in the holdout sample, thereby validating the robustness of the configurational model.

This way, the study shows that human-centric Gen-AI implementation is not driven by a single dominant factor but by multiple equifinal configurations of organizational, technological, human, and external conditions. This study makes three key contributions. First, it advances Gen-AI and supply chain literature by developing a configurational framework that explains how combinations of organizational, technological, human, and external factors enable human-centric supply chain operations. Second, it extends configurational theory to the emerging domain of Gen-AI by demonstrating how equifinality and conjunctural causation shape technology implementation outcomes. Third, it provides practical insights for managers by identifying specific factor configurations that enhance Gen-AI implementation and human-centric supply chain transformation.

The remainder of this article is structured as follows. Section 2 presents the theoretical background of the study by reviewing the literature on Gen-AI tools in supply chains, human-centric operations, and supply chain, and configurational theory. Section 3 covers the research methodology, followed by Section 4, which offers the results and analysis of this study. Furthermore, Section 5 discusses the findings of the study from the lens of configurational theory, followed by the managerial implications. Section 6 concludes the article by summarizing it and acknowledging the limitations, along with proposing future research directions.

2. Literature review and propositions

2.1. Gen-AI tools and human-centric supply chain operations

Generative artificial intelligence (Gen-AI) is widely implemented by organizations and their supply chains to solve problems by emulating human intelligence (Iansiti & Lakhani, 2020). Gen-AI systems perform a range of activities from data mining to generate new ideas to create different outputs (Johnson et al., 2022). Gen-AI helps businesses improve forecasting and partner collaboration, automate interactions with stakeholders to boost efficiency, eliminate manual tasks to enhance employee performance, and empower data-driven decisions with analytics to optimize their supply chain (Li et al., 2026). Also, armed with Gen-AI, companies can conduct advanced scenario planning (e.g., "What if supplier A goes down? What if demand surges next month?") (Sanchez, 2025). That lets employees better foresee risk and craft contingency plans ahead of crises. Moreover, GenAI is different from traditional AI because it can generate new representations, model future events, and mash up unstructured data to revolutionize how strategy is made in supply chains (Xia et al., 2026).

Gen-AI tools assist with both gaining efficiency in decisions made in design, as well as generating novel opportunities to design the future, like simulating future eco-designs to allow for anticipative action or crafting stakeholder-specific interactive environments (Wamba et al., 2025). Supply chains will also arise from developments within the ownership layer as Gen-AI is designed and integrated into global practices. Gen-AI will not just be another technology layer of the evolving supply chain; it will function, more importantly, as a capacity layer with potential to revolutionize supply chains cognitively, procedurally, and ethically moving forward (Jackson et al., 2024). The popular tools of Gen-AI, such as ChatGPT and Gemini, are conversational agents, which are said to enable decision makers to be more available, sociable, and responsive to the events in the business environment (Huynh, 2024).

Gen-AI tools and agents can reduce human knowledge processing and time constraints, enabling better organizational efficiency and performance (Albishri et al., 2025). Research by Noy & Zhang (2023) found that employee productivity was greatly improved through the use of ChatGPT for intermediate-level professional writing tasks. According to a global survey, nearly 80% of professionals have used ChatGPT at least once for their work (Statista, 2023). Hence, Gen-AI creates new works such as images, videos, documents, and sounds using patterns learned from the data they have been trained on (Peres et al., 2023). This also has strategic implications as it can help in strategic decision-making by being flexible and adaptive to complex environments, optimising operational workflows, and fostering innovation through real-time learning and scenario generation (Sharma et al., 2022b).

Gen-AI may also lead to a different approach in this regard. Instead of simply evaluating provided situations and actions, Gen-AI may also generate creative situations and associated action plans to address disruptions more proactively and adaptively (Zamani et al., 2023). This can also help in enhancing smart planning and intelligent automation. Intelligent automation in smart supply chain management. By replicating a diverse set of supply chain disruptions, such as demand surges, supplier failures, and logistic delays, the scenarios written with the assistance of Gen-AI can help managers make decisions with more anticipation (Abielmona, 2025; Lick et al., 2023). Consequently, Gen-AI can take the human–machine symbiosis paradigm to the next level. As an example, by offering informed suggestions based on historical data, market trends, and external risk factors, Gen-AI might serve as an employee for supply-chain managers (Wang et al., 2024). Furthermore, by combining Gen-AI with enterprise resource planning (ERP) systems (Kunduru, 2023), one could facilitate smoother supplier bargaining, contract verbiage, and real-time risk assessments, as well as ensure greater efficiency in all tactical and operational planning activities.

2.2. Organizational factors and the implementation of Gen-AI tools

Organizational factors, including leadership vision, organizational culture, resource availability, and innovation infrastructure, determine the level of Gen-AI acceptability within a human-centric supply chain. From a traditional perspective, the need for leadership vision is the starting point of any successful technical integration process. Eapen and Finkenstadt (2025) even argue that a management teams clearly stated AI strategy serves as a driver for a shared experimentation purpose. In Alphabet, for instance, Sundar Pichai's "responsibility for sifting through and seizing the commercial opportunities from DeepMind discoveries has produced just the kind of internal tension needed to make significant technical progress" (Ignatius, 2023). Transformational leadership could promote employees' innovative work behaviors greatly (Afsar et al., 2019). Leaders influence employees' innovative work behaviors by establishing the work climate, determining the resources and task characteristics employees will encounter, and impacting employees' behaviors through capitalization of current resources or through creation of new resources (Karimi et al., 2023).

Organizational culture continues to mold employees' attitudes. It engenders trust in both the organization's ethical values and in its management to handle the ethical concerns brought on by adopting AI-based applications at the firm (Callari & Puppione, 2025). Marimon et al. (2025) and Bernstein (2023) posit that cultures celebrating speed and risk-taking increase Gen-AI readiness. Also, having a culture that fosters support for AI as an augmentation tool can increase employee satisfaction and mitigate resistance to adopting new technology (Callari & Puppione, 2025). It also helps promote a growth mindset that furthers both individual and company growth (Callari & Puppione, 2025). Spotify exemplifies this; by fostering an open innovation approach, the company allows for flexible experimentation, launching AI-powered music features organically (Kumar, 2023). This model works for music streaming; supply chains are high-reliability environments. The manner in which Gen-AI was created as well as developed, which is through trial and error (or a fail-fast that Gen-AI relies on for improvement), conflicts with the requirements of supply chain management (Edmondson, 2018). Supply chain management operates in environments where precision is paramount in terms of the execution of work (Weick & Sutcliffe, 2011). If there are any physical mistakes made in supply chain management, there will be delays or potential danger (Weick & Sutcliffe, 2011). Forcing an experimental mode of operation upon logistics workers will inevitably induce stress and anxiety because logistics workers, by design and education, are taught to prevent mistakes, not encourage them (Reason, 2016).

Finally, resource availability, such as financial, human, and technical, serves as a critical enabler. IBM's massive investment in AI research and innovation labs (Goodson, 2023) demonstrates that financial capital sustains long-term competitiveness. Similarly, a robust digital infrastructure facilitates cross-functional collaboration (Sedkaoui & Benaichouba, 2024). However, prioritizing "technical frameworks" over "human-centric design" creates a resource-capability gap (Davenport & Kirby, 2016). If capital is funneled into data architecture, whereas the human skill set remains static, the infrastructure becomes a bottleneck rather than a facilitator (Brynjolfsson & McAfee, 2014). Although these organizational factors are theorized to foster an environment conducive to Gen-AI, the literature remains polarized between technical optimism and human-centric concern. Therefore, an empirical investigation is needed to determine how firms can align leadership vision, culture, resource availability, and infrastructure to leverage Gen-AI without compromising the human agency essential to long-term supply chain resilience.

2.3. Technical factors and the implementation of Gen-AI tools

The successful implementation of Gen-AI tools can be influenced by technical issues. Aspects like data quality and accessibility, technological readiness, cybersecurity, and scalability are crucial for effective Gen-AI utilization (Feuerriegel et al., 2023). High-quality and well-structured data lead to better-trained AI algorithms, contributing to more reliable decision-making (Gangwar et al., 2025). However, out of the 80% of supply chain intelligence that exists in unstructured forms (Gilbert, 2025), much of it must be cleaned before being used to meet the standard for ‘quality’ and create a clean record of the information. This cleaning process causes the loss of rich contextual nuance, which is needed when making complex business decisions and results in an accurate, yet contextually blind machine learning approach (Rahm & Do, 2000).

Accessible and relevant data enable AI to support diverse operational and strategic functions, including product design and service delivery to predictive maintenance and supply chain optimization (Thacharodi et al., 2024). Technological readiness, including the capacity to implement new systems and integrate them with existing software, can expedite deployment and enhance outcomes (Malhotra & Manzoor, 2025; Chergarova et al., 2023). On the other hand, an organization that has invested a great deal of capital in traditional ERP systems will likely have a disadvantage in terms of readiness (Hernandez, n.d.). The effort to integrate Gen-AI into an existing legacy architecture is more frictional than developing a new greenfield solution and, consequently, will often add to pilot failures (Challapally et al., 2025).

Robust cybersecurity measures ensure data integrity, maintaining trust and regulatory compliance, essential in sectors like financial services (Burgers et al., 2024; Shabsigh, 2023). However, such strictness engenders a dichotomy between security and collaboration. Robust “Zero Trust” frameworks, while secure, unintentionally impede the external data sharing essential for Gen-AI’s cross-network learning, rendering the system blind to upstream hazards (Stojanovic, 2025). Scalability, the ability of AI systems to handle increasing data and computational loads without performance loss, is vital for organizations and their supply chains (Moro-Visconti et al., 2023; Emma, 2023). However, the implementation of Gen-AI applications tends to require the use of very expensive GPUs, either on-premises or in the cloud, making it costly to perform large-scale deployments of Gen-AI applications, whereas at the same time, the value gained from such deployments is not commensurate with what has been expended to deploy them (Biswas et al., 2025).

Collectively, these technical factors provide the opportunity for Gen-AI systems to support the human-centric supply chains. But, due to these contradictions, where “best practices” of security or data organization might negatively impact Gen-AI effectiveness, an empirical study is required to identify what technical configurations would effectively balance these contradictions within actual supply chain settings.

2.4. Human factors and the implementation of Gen-AI tools

Human factors encompass employees’ skills, knowledge, attitudes, and involvement in implementing Gen-AI technologies. Skills such as familiarity with AI concepts, programming, and data analysis improve AI system development, deployment, and efficacy (Barcaui & Monat, 2023; Alijoyo et al., 2025). Nonetheless, although foundation skills assist in the adoption of Gen-AI, excessive dependence on Gen-AI may result in deskilling. According to Dell’Acqua et al. (2023), even though Gen-AI enhances the performance of lower-skilled employees, it can also unintentionally erode the capacity for critical judgment of high-skilled professionals who trust the output of AI without verifying it.

Implementation efforts and associated outcomes may be influenced by employee attitudes. For instance, when employees’ positive attitudes are strengthened by training and communication, the likelihood of adoption may increase, potentially leading to favourable organizational outcomes. Healthcare professionals who comprehend the application and usage of AI-based diagnostic tools within their clinical workflow can deliver enhanced patient care and make more accurate decisions (Kim et al., 2024). On the other hand, when it comes to predicting outcomes, people have less sensitivity to the possible errors from algorithms, which leads them to choose riskier methods (and often lower performing), like a human being’s decision-making processes in areas where uncertainty exists. (Dietvorst and Bharti, 2020).

Collaboration and communication are also necessary. Well-functioning cross-functional communication will help to translate insights from AI systems into actionable approaches leading to operational alignment (Rojek et al., 2023). Within teamwork frameworks, engineers may collaborate with data scientists and operational staff to generate practical applications using AI technologies, such as predictive maintenance applications in manufacturing. However, Lebovitz et al. (2021) note that domain experts will often disregard valid AI insights that do not align with their own intuition. This results in a “validity gap” in which even technically robust AI tools are squandered at the front line for lack of a shared interpretive scaffolding. Therefore, human factors are required to reach the maximum operational potential of Gen-AI tools. Considering the ambivalent literature, the exact human-dependent conditions under which Gen-AI uplifts the human capacity and, at the same time, does not deplete the indispensable personal judgment required for robust supply chain performance need to be identified.

2.5. External factors and the implementation of Gen-AI tools

External factors are conditions that cannot be controlled at the organizational level that affect Gen-AI implementation. Examples include market competition and industry trends. Awareness of and adapting to the trends within an industry context will allow for more strategic integration of AI, helping to meet the expectations and preferences of a changing market (Wamba et al., 2025). For example, in the automotive industry, the trend towards electric and autonomous vehicles has reinforced the case for AI-powered tools to support actions like predictive maintenance and enhanced driver assistance (Singh, 2023). Market competition provides a rationale for organizations to implement Gen-AI as part of their strategies to maintain advantages in product, service, and operational development. In retail environments, AI-enabled recommendation engines can support the enhancement of personalized experience for consumers, customer loyalty, and product differentiation in competitive markets (Kumar et al., 2025). On the other hand, the findings of Khan et al. (2024) suggest that pressure exerted by market competition is not very important for GenAI adoption, since manufacturing companies are likely to focus on customers' data more than that of competitors. Utilizing external factors provides the foundation for how organisations will implement Gen-AI technology to support their human-centric supply chain operations. However, due to these contradictions of modernisation caused by pressure from outside sources creating urgency, but at times causing organisations to adopt their technology prematurely, empirical research is required to understand how organisations filter external signals and identify what technologies provide true value versus those that are merely market-driven.

2.6. Configurational logic of Gen-AI implementation

The present study is based on Configurational Theory, which posits that organizational outcomes are produced by combinations of conditions working together in mutually dependent ways, not isolated variables (Ragin, 1989). In particular, Configurational Theory's treatment of conjunctural causation, equifinality, causal asymmetry, and contextual embeddedness form the foundation for understanding causally complex processes (Ragin, 2008a). Consequently, the implementation of

Gen-AI in human-centric supply chains is viewed as a multidimensional phenomenon resulting from a confluence of organizational, technical, human, and external factors instead of a simplistic process of linear adoption. Under this framework, there is no single cause that directly leads to success. Instead, success is a consequence of distinct combinations of conditions that reinforce one another. To translate this perspective into operationalization, factors are grouped into four configurational categories including organizational (e.g., leadership vision and support, organizational culture, resource availability, innovation infrastructure), technical (e.g., data quality and accessibility, technological readiness, cybersecurity measures, scalability), human (skills and expertise, user acceptance, collaboration and communication), and external factors (industry trends, market competition). These categories serve as configurational primitives whose conjunctive impact supports Gen-AI implementations in human-centric supply chains. Therefore, we have developed the following propositions for the present research to examine the configurational impact of different factors on Gen-AI implementation for huma-centric supply chain operations:

Proposition 1: Configurations that result in the successful implementation of Gen-AI tools (IGAI) will necessitate the presence of at least one condition from each of the following categories: organizational factors, technical factors, human factors, and external factors.

Proposition 2: Configuration of necessary conditions and a configuration of conditions that are sufficient from a combination of organizational factors, technical factors, human factors, and external factors for the successful implementation of Gen-AI tools.

Proposition 3: There is no one optimal combination of "organisational factors, technical factors, human factors, and external factors". However, there are several equally effective combinations of causative elements that demonstrate equifinality.

Furthermore, based on the propositions, Figure 1 offers the research framework of the present study.

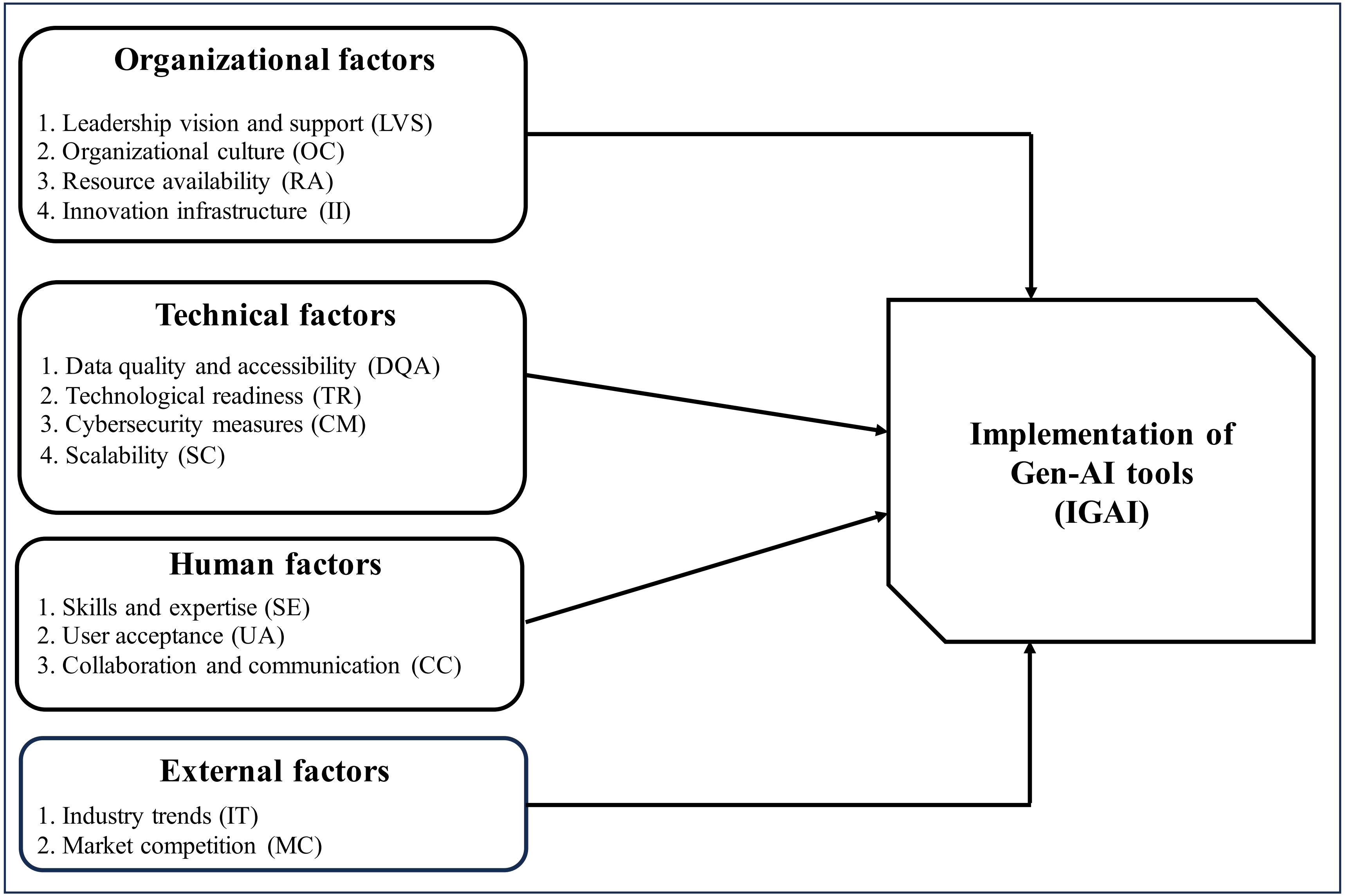

Figure 1: Research framework (Source: Authors own work)

3. Research Methodology

3.1. Sample and demography

We began the process by evaluating the content validity of an initial iteration of the questionnaire with managers from companies of diverse magnitudes. A pretest with 15 respondents was conducted to ensure the questions are readable. The method of translation and back-translation was used to adapt and translate all the scales into English. There were some modifications to the wording of some items to ensure the comprehensibility of the questions. The sampling technique is a purposive (judgmental), and it involves screening-based eligibility criteria so that only project managers who have enough experience with Gen-AI initiatives would participate. The 174 invitees listed were compiled from a large number of sources, such as trade organisations, vendor and industry database listings, and also included “referral” through existing project managers known through the networks. This enabled a diverse set of invitees from various manufacturing sectors to have an equal chance to participate, while maintaining alignment with the objectives of the research, specifically regarding the implementation of Gen-AI systems.

Respondents hail from a variety of industry sectors within manufacturing in India, including automotive, electronics, consumer goods, and industrial machinery. We chose to capture respondents from different industry sectors within manufacturing to observe possible variances in contexts and settings in which Gen-AI solutions are used. They varied in size (small firms had fewer than 100 employees, medium-sized firms between 100–500, and large firms had more than 500 employees) to better understand how Gen-AI was adopted at different organizational levels and how firm size may affect adoption. Once we created our list of invitees, we screened respondents for managerial accountability and involvement in Gen-AI enabled projects. For each stage of project ideation through implementation, we measured the percentage extent to which respondents were actively engaged. Respondents who fell below our cutoff of involvement (> 70% active participation) were screened out of the pool (Balzano & Marzi, 2023). For purposes of questions regarding learning from failure, respondents were directed to reference their most recently completed project on which they were significantly involved (>70%). The demographic of this study consists of Indian manufacturing enterprises, which have shown the highest level of acceptance of AI and machine learning (ML) in the last two years. The manufacturing industry is going through the biggest transformation it’s seen since the first industrial revolution. Artificial Intelligence (AI) and Machine Learning (ML) have shifted from being ‘new and exciting’ technologies to table stakes for businesses. The business functions most likely to prioritize Gen-AI over the next 12 months are Operations (63%), Customer

Service (54%), and Marketing (33%)[3]. 76% of Indian business leaders anticipate a significant business impact from Gen-AI[3]. Zero11 analysis predicts over 85% of mid-to-large manufacturers will have deployed at least one AI-powered solution to production by 2027[4].

A total of 174 individuals were contacted and invited to respond to the survey. All respondents were project managers who were involved in Gen-AI initiatives in manufacturing firms. Respondents were screened to ensure they had managerial responsibilities and were involved with projects that leveraged Gen-AI technology in some capacity. Some surveys were removed during the data collection process because they were incomplete, irrelevant, or invalid. The sample for analysis consisted of 137 valid responses. A review of the sample suggests it is a reliable set of observations for understanding the experience of respondents and drawing inferences related to the research questions and managerially relevant propositions.

The sample consists of well-educated and experienced project managers, with 62.04% holding undergraduate degrees and 37.96% possessing postgraduate qualifications, indicating strong academic exposure to technology-driven initiatives. In terms of industry experience, 41.61% of respondents have 1–5 years of experience, 45.25% have 6–10 years, and 13.14% have more than 10 years of experience, suggesting a predominantly mid-career managerial workforce with substantial practical exposure to Gen-AI-enabled projects. Regarding AI engagement, 67.88% of respondents have been involved with AI initiatives for less than one year, while 32.12% have more than one year of experience, reflecting the emerging nature of Gen-AI adoption in manufacturing supply chains. The majority of respondents fall within the 31–45 years age group (59.85%), followed by 20–30 years (26.28%) and above 45 years (13.87%), indicating active involvement in digital transformation initiatives. The gender distribution shows 70.80% male and 29.20% female respondents, broadly reflecting the current composition of the manufacturing sector in India. Overall, the demographic characteristics confirm that the sample represents experienced and relevant managerial professionals, strengthening the reliability and validity of the empirical findings.

3.2. Bias control

To reduce the potential for bias associated with collecting information from one source, we sampled multiple firms (Bianchi et al., 2019). The framework was excluded to prevent any potential bias in the attention of respondents to the relationships under study in this research (Groves et al., 2011). To reduce the social desirability bias, we attempted to ensure confidentiality and asked open-ended questions about the organization and behaviour of its employees. In addition, institutional items

[3] https://www.ey.com/en_in/newsroom/2025/11/india-s-ai-shift-from-pilots-to-performance-47-percent-of-enterprises-have-multiple-ai-use-cases-live-in-production-ey-cii-report (Accessed on 08th December 2025)
[4] https://www.zero11.it/en/magazine/artificial-Intelligence-in-manufacturing-the-industry-revolution-in-progress#:~:text=Copied%20to%20Clipboard-,Report%20%2D%20AI%20Industrial%20Market%20Analysis%202025,the%20European%20and%20global%20markets. (Accessed on 05th December 2025)

were less likely to cause social desirability bias because they are not tied to specific individuals' behavior (Groves et al., 2011). We also conducted independent sample t-tests to test for response bias to assess the potential impact of response bias on the accuracy of our data. No significant differences were observed between early and late respondents or the randomly assigned respondent groups. Lastly, we conducted a full collinearity assessment recommended by Kock (2015). The full collinearity test showed that all values for the variance inflation factor (VIF) were below 5.00, which meant that common method bias was not present in the collected dataset.

3.3. Measurement reliability and validity

Cohen (1992) suggests that researchers may examine power tables or perform power analyses using software such as GPower (Faul et al., 2009) to determine the sample size required to achieve a desired level of statistical power. With a total sample of 137 responses, the data in this study are well within the limits for performing Structural Equation Modelling (PLS-SEM) since there are 14 independent factors and the models contain 47 aggregate indicator items. An a priori power analysis using GPower calculated that 55 completed responses would provide 80% power at an alpha level of 0.05. Hair et al. (2021) have shown that PLS-SEM-derived estimates can be trusted even with small samples, do not suffer from identification issues, and can result in very high levels of statistical power. The sample size of 137 should therefore provide acceptable estimates and valid inferences.

To guarantee the constructs' validity, we used scales that have been verified in prior published research in this study. Constructs were assessed on a five-point Likert scale, with certain adjustments made to align with the Gen-AI setting in terms of their impact on the human-centric supply chain operations. Table A (online supplementary file) lists the scales that were used to quantify and characterise the independent and dependent factors. After undergoing the Kaiser-Meyer-Olkin (KMO) and Bartlett's tests, the sample adequacy measure was determined to be 0.788. A result over 0.60 is deemed excellent and acceptable (Kaiser, 1974). Statistical significance is defined as a value below 0.001, and Bartlett's test of sphericity yielded a value of 0.000. All the factors in the study had correlations less than 0.8, which could be an indicator that the factors are not the same but somehow connected (Table 1). The conclusion that can be drawn from this is that the collected data set is suitable for further multivariate testing. As shown in Table A (online supplementary file), all the items have loadings above the accepted threshold of 0.7 (Hair et al., 2021), which is an indicator that the level of indicator reliability is at an acceptable level. The Average Variance Extracted (AVE) for all constructs is above the 0.5 level, which shows that convergent validity is adequate, and all the inter-factor correlations are positive (Hair et al., 2021). Also, the Composite Reliability (CRs) for all constructs are above the recommended threshold of 0.7 (Hair et al., 2021), which indicates the reliability of the measurement scales.

Table 1: Descriptive statistics (Source: Authors own work)

	Correlations														Mean	S.D.
	LVS	OC	RA	II	DQA	TR	CM	SC	SE	UA	CC	IT	MC	IGAI		
LVS	1														3.72	0.93
OC	.137	1													3.49	0.92
RA	.734	.169	1												3.59	1.02
II	.075	.284	.243	1											3.80	0.96
DQA	.592	.227	.615	.282	1										3.66	1.11
TR	.613	.221	.612	.277	.757	1									3.55	1.06
CM	.625	.275	.609	.278	.742	.727	1								3.48	1.01
SC	.079	-.216	-.002	-.160	-.024	-.010	.026	1							4.03	0.88
SE	.187	.098	.134	-.077	.074	.127	.162	.390	1						3.96	0.91
UA	-.005	.056	.044	.036	-.008	-.083	-.006	.062	-.035	1					3.93	0.97
CC	.085	.146	.094	-.048	.139	.119	.199	.310	.638	-.129	1				3.87	0.90
IT	-.047	.093	.096	.034	.128	.115	.156	.351	.611	-.055	.619	1			3.91	1.00
MC	-.010	.186	.131	.678	.257	.252	.272	-.189	-.158	.033	-.124	-.098	1		3.88	0.83
IGAI	-.060	.146	.062	.056	.041	.067	.089	.292	.572	-.110	.571	.558	-.032	1	3.91	1.00

3.4. Fuzzy-set qualitative comparative analysis

The present research uses fuzzy-set qualitative comparative analysis (fsQCA) to conduct the analysis and drive the findings from it. fsQCA calculates the extent to which a case belongs to a particular set, thereby establishing a connection between qualitative and quantitative approaches (Rihoux and Ragin, 2008). fsQCA serves the purpose of aiding qualitative researchers in understanding both significant and irrelevant variations, as well as assisting quantitative researchers in accurately positioning examples about each other (Vis, 2012). In addition, fsQCA specifically investigates the intricate and asymmetrical relationships between the result of interest and its antecedents. Also, fsQCA may be used for a wide range of sample sizes, from very small (fewer than 50 instances) to extremely large (thousands of cases). When using fsQCA for data analysis, the resulting combinations of independent factors may contain additional factors that are not discovered by traditional variance-based techniques, which only capture major effects (Woodside, 2014). Also, in fsQCA, the sample's representativeness does not impact all solutions (Liu et al., 2017), making it more resilient than variance-based approaches as it is not influenced by outliers.

3.5. Calibration of items and truth table

When utilising fsQCA, it is preferable to employ a fuzzy scale (continuous) for both result and predictor factors instead of a binary scale (discrete). fsQCA encompasses two distinct kinds of conditions: necessary and sufficient. These configurations may exist or not exist, or there may be a circumstance where they are not important. In order to do fsQCA, it is necessary to identify both the dependent and the independent measures. Subsequently, we standardised all measurements by converting them into fuzzy sets, where the values spanned from 0, representing complete non-membership to the set, to 1, indicating complete membership to the set. In accordance with the detailed method described by Pappas and Woodside (2021), the factors were calibrated using fsQCA version 4.1. We adhered strictly to the authors' detailed protocol for doing fsQCA. During the calibration procedure, three important thresholds were established: a whole set membership threshold of 0.95, a full set non-membership threshold of 0.05, and a cross-over point threshold of 0.5.

We computed the 95th, 50th, and 5th percentiles of our measurements using percentiles so that we could find the data values that corresponded to the three criteria. The three criteria used for factor calibration in the fsQCA 4.1 software were these percentile values. The thresholds determined for the 95th, 50th, and 5th percentiles had an average value of 4, 3, and 2, respectively. Assessing the requirements that fall precisely on 0.5 (i.e., intermediate-set membership) using fsQCA is challenging since situations that are perfectly on 0.5 are eliminated (Ragin, 2008a). To address this issue, Fiss (2011) suggests that a constant of 0.001 should be applied to all the causative factors when the whole membership scores are equal to 1. Subsequently, the truth table was constructed (see Table 2). The truth table consists of 2^k rows, where 'k' indicates the number of potential combinations of result predictors.

The truth table was arranged in order of frequency by sorting the 'number' column (Ragin, 2008a). Given that our sample size was 137, we established a frequency threshold of 2 (Fiss, 2011; Ragin, 2008a). Consequently, all combinations with frequencies below 2 were excluded from further analysis. The truth table was first sorted based on frequency and then further sorted based on "raw consistency" using a frequency threshold of 0.75 (Rihoux and Ragin, 2008). In addition, the Proportional Reduction in Inconsistency (PRI consistency) ratings were taken into account, with scores below 0.5 indicating significant inconsistency (Greckhamer et al., 2018). Finally, SYM consistency (i.e., Symmetric Consistency) was also taken into account. This was initially developed for fuzzy-sets but can be used when we want to evaluate both the presence and the negation of the outcome and use the same consistency standard for both the presence and its negation analyses (i.e., both presences and absences are assessed by the same consistency standards) (Dul, 2016).

Therefore, after giving priority to frequency, next to raw consistency, and finally to PRI consistency, the final solution sets were assigned numbers 0 or 1. The selection of either 0 or 1 determined if a combination accurately accounted for the result, with '1' being assigned to combinations that met the specified criteria and '0' assigned otherwise. The distribution of solution scores '0' and '1' is shown and clarified using the truth table presented in Table 2. When examining the 'raw consistency' column in Table 2, it is evident that the raw consistency scores are initially high and then gradually decrease. The values are as follows: 0.997245, 0.997028, 0.996979, 0.990926, 0.973134, 0.95, 0.936873, 0.910648. After these values, there is a clear breakpoint, with the subsequent score being 0.8625. As all scores above the consistency criterion of 0.75, we identified the value with a "breakpoint" as the one displaying severe inconsistency (Pappas and Woodside, 2021). Consequently, we assigned a solution score of '0' to this value, whereas all other values received a score of '1'. The "Standard Analysis" technique was used to create solution sets that include "complex, parsimonious, and intermediate."

Table 2: Truth table (Source: Authors own work)

MC	IT	CC	UA	SE	SC	CM	TR	DQA	II	RA	OC	LVS	number	IGAI	raw consist.	PRI consist.	SYM consist
1	1	1	0	1	0	1	1	1	1	1	1	1	3	1	1	1	1
0	1	1	1	1	1	0	0	0	0	0	1	0	3	1	0.997245	0.995781	0.995781
1	1	1	1	1	1	0	0	0	1	0	1	0	5	1	0.997028	0.996071	0.996071
1	1	1	1	1	0	1	1	1	1	1	1	1	4	1	0.996979	0.995681	0.99568
1	1	1	0	1	1	1	1	1	1	1	1	1	7	1	0.990926	0.988877	0.988877
1	0	1	1	1	1	1	1	1	1	1	1	1	4	1	0.973134	0.961039	0.961039
1	1	1	1	1	1	1	1	1	1	1	0	1	4	1	0.951000	0.938363	0.938363
1	1	1	1	1	1	1	0	1	1	1	1	1	2	1	0.936873	0.913216	0.913215
1	1	1	1	1	1	1	1	1	1	1	1	1	48	1	0.910648	0.904361	0.908864
0	1	1	1	1	1	1	1	1	0	1	1	1	3	0	0.862510	0.793566	0.824513
1	0	0	1	0	0	0	0	0	1	0	1	0	2	0	0.433898	0.0722222	0.0722222
1	0	0	1	0	0	1	1	1	1	1	1	1	4	0	0.363825	0.0783131	0.0797544

Note: PRI consist.: - Proportional Reduction in Inconsistency; SYM consist.:- Symmetric Consistency

4. Results and analysis

4.1. Necessary and sufficient conditions

The strategy for configurations, as described by Kosmidou and Ahuja (2019), acknowledges the challenge of establishing cause-and-effect relationships due to the presence of several interdependent factors that contribute to outcomes. fsQCA considers the interconnectedness among elements when generating the output. If particular conditions are required for an outcome to happen, those conditions are deemed necessary. On the other hand, if the existence or happening of a condition always results in an outcome, that condition is considered sufficient. However, the same outcome can be achieved through other conditions as well (Beynon et al., 2016). Further, the research illustrates both the necessary and sufficient conditions for the outcome to occur. Table B (online supplementary file) offers the analysis conducted to test the necessary conditions for the outcome. The analysis (see Table B, online supplementary file) revealed that the factors scalability (SC), skills and expertise (SE), collaboration and communication (CC), and industry trends (IT) are considered necessary conditions for the effective implementation of Gen-AI tools (IGAI) for human-centric supply chain operations since they have consistency scores over 0.9 (Ragin, 2008b).

The fsQCA software consistently offers all three alternatives on every occasion. The researcher computes both “complex and parsimonious” solutions, independent of any simplifying assumptions used. However, the “intermediate solution” is dependent on these assumptions. Although the intermediate solution encompasses both core and peripheral circumstances, it is necessary to provide a clear method for distinguishing between them to enhance our understanding and presentation of the responses. Merging the “parsimonious and intermediate” solutions may provide a more comprehensive and consolidated perspective of the results (Fiss, 2011). In order to do this, the researcher may discern and annotate the conditions of the parsimonious answer that are also present in the intermediate solution. This will result in an intermediate solution that emphasises the fundamental conditions, clearly displaying both essential and secondary circumstances, enabling a more accurate evaluation of the data. Often, we encounter scenarios in which many fundamental conditions coincide within a particular instance.

To understand the fsQCA findings, the final solution sets were determined by considering the proposed intermediate solutions (Ragin, 2008b). Put simply, sufficient solutions are self-sufficient in achieving the desired end, and hence, do not need any other essential circumstances. The fsQCA analysis yielded three distinct combinations of causative factors that resulted in the effective implementation of Gen-AI tools (IGAI) for the human-centric supply chain operations. The outcomes for sufficient conditions are given in Table 3.

Table 3: Sufficient conditions configurations to determine the outcome and subsample solutions (Source: Authors own work)

Configurations		Solutions 1	2	3	4	5	6	7
	Leadership vision and support	●	●	●	●	⊗	⊗	●
Organizationa	Organizational culture	●			●	●	●	●
l factors	Resource availability	●	●	●	●	⊗	⊗	●
	Innovation infrastructure	●	●	●	●	⊗	●	⊗
	Data quality and accessibility	●	●	●	●	⊗	⊗	●
Technical	Technological readiness	●	●	●	●	⊗	⊗	●
factors	Cybersecurity measures	●	●		●	⊗	⊗	●
	Scalability		●	●	●	●	●	●
	Skills and expertise	●	●	●	●	●	●	●
Human	User acceptance		●	●	●	●	●	●
factors	Collaboration and communication	●	●	●	●	●	●	●
External	Industry trends	●	●	●		●	●	●
factors	Market competition	●	●	●	●	⊗	●	⊗
Raw coverage		0.467	0.397	0.372	0.381	0.032	0.060	0.043
Unique coverage		0.114	0.044	0.018	0.027	0.019	0.043	0.024
Consistency		0.930	0.919	0.914	0.916	0.997	0.997	0.862
Overall solution coverage		0.647						
Overall solution consistency		0.941						

Subsample solutions

Subsample models	**Raw coverage**	**Unique coverage**	**Consistency**
MC*IT*CC*UA*SE*SC*CM*TR*DQA*II*RA*LVS	0.435	0.073	0.998
MC*IT*CC*UA*SE*SC*CM*DQA*II*RA*OC*LVS	0.400	0.037	0.999
MC*IT*CC*SE*SC*CM*TR*DQA*II*RA*OC*LVS	0.438	0.077	0.999
~MC*IT*CC*UA*SE*SC*~CM*~TR*~DQA*~II*~RA*OC*~LVS1	0.039	0.025	1
MC*IT*CC*UA*SE*SC*~CM*~TR*~DQA*II*~RA*OC*~LVS	0.063	0.045	0.997
Overall solution consistency	*0.999*		
Overall solution coverage	*0.622*		

*Note: *: Conjunction (AND), ~: Negation (NOT).*

The black circles (●) represent the existence of a condition, crossed-out circles (⊗) signify the nonexistence of a condition, and blank spaces show a circumstance where the result is unaffected by the presence or absence of the causative conditions (Mikalef and Krogstie, 2020). Skills and expertise (SE) and collaboration and communication (CC) are universally essential in all situations. This result demonstrates that the successful implementation of Gen-AI tools (IGAI) for the innovativeness of organizations and their supply chains is closely linked to skills and expertise (SE), and collaboration and communication (CC). Furthermore, these factors are necessary conditions for achieving this outcome, which supports the findings presented earlier (for necessary conditions).

Solution 1 is specifically suitable for manufacturing businesses that can accomplish effective implementation of Gen-AI tools (IGAI) for human-centric supply chain operations, considering all the relevant factors, including organisational, technical, human, and external aspects, excluding scalability (SC) and user acceptance (UA). Solution 2 applies to manufacturing organisations that can reach their desired end without the need for organizational culture (OC). The third solution pertains to organisations that hold the belief that the cybersecurity measures (CM) and organizational culture (OC) have no significant impact on their operations, acknowledging that the existence of all other factors is still necessary.

Solution 4 applies to manufacturing enterprises that believe industry trends (IT) will not impact the efficiency of the implementation of Gen-AI tools (IGAI). However, the existence of other factors is necessary for this to occur. In addition, solution 5 is specifically designed for manufacturing firms that prioritise the presence of organizational culture (OC), scalability (SC), skills and expertise (SE), user acceptance (UA), collaboration and communication (CC), and industry trends (IT) as crucial factors for achieving successful implementation of Gen-AI tools (IGAI) inside their organisation. Similarly, solution 6 is exclusively designed for manufacturing organisations that recognise the essential role of organizational culture (OC), innovation infrastructure (II), scalability (SC), skills and expertise (SE), user acceptance (UA), collaboration and communication (CC), industry trends (IT), and market competition (MC) in achieving successful implementation of Gen-AI tools (IGAI) in firms. Finally, solution 7 is suitable for manufacturing businesses that may accomplish efficient implementation of Gen-AI tools (IGAI) without the need for innovation infrastructure (II) and market competition (MC).

The implementation of Gen-AI tools (IGAI) has a solution coverage of 0.647. This relates to the solution's explanatory power, which is the extent to which every configuration has been represented (Rihoux and Ragin, 2008). The results presented in Table 3 demonstrate that different configuration paths of conditions can lead to the same outcome with equal effectiveness. These routes deal with the three main characteristics of causal complexity, namely "asymmetry, equifinality, and conjunction" (Schneider and Wagemann, 2012). Unlike the approach of analysing individual attributes in isolation, fsQCA allows for a comprehensive understanding of how these attributes interact and mix. This enables the identification of equifinality, which refers to the idea that multiple configurations of circumstances may lead to the same result with equal effectiveness (Gonçalves et al., 2016).

4.2. Specific propositions

Following the acquisition of all solution sets derived from fsQCA, we conducted a test to ascertain the number of instances in the sample where a certain proposition is valid (Pappas et al., 2020). This was accomplished by conducting a test on our previously stated proposition 1, which states that "Configurations that result in the successful implementation of Gen-AI tools (IGAI) will necessitate the presence of at least one condition from each of the following categories: organizational factors, technical factors, human factors, and external factors". The process included constructing a model in fsQCA by calculating the necessary particular configuration and graphing it against the outcome factor, which is the implementation of Gen-AI tools (IGAI) for the organizations and their supply chains. As other solution routes provide diverse explanations for the result, in our specific example, we focus on the supporting sufficient conditions of solution 5, since it has the highest solution consistency of 0.997. This restates our proposition 1 as follows: "Configurations in which manufacturing firms consider organisational culture (OC), scalability (SC), skills and expertise (SE), user acceptance (UA), collaboration and communication (CC), and industry trends (IT) will result in the successful implementation of Gen-AI tools (IGAI)". Ultimately, we generated a graphical representation of the new model by using the "XY plot" feature inside the fsQCA 4.1 programme. The results (Figure 2) indicated that the proposition was only partly supported. The factor Y represents our outcome, whereas X represents proposition 1.

The data shown in Figure 2 indicates that the observations plotted strongly support the relationship $X \leq Y$, meaning that X is a subset of Y, with a consistency level of 0.91. The level of consistency between the displayed observations when X is at least as large as Y ($X \geq Y$), i.e., Y is a subset of X, is 0.52. If one of these two readings indicates a high level of consistency, the other may be regarded as a measure of coverage (Pappas and Woodside, 2021). Given that the value for $X \leq Y$ is 0.91 and the value for $X \geq Y$ is 0.52, the calculations indicate that our sample supports the notion that X is a subset of Y with a 91% inclusion rate, and it covers 52% of Y. This implies that X represents 52% of the total memberships in Y. Further, Models that have a consistency level over 0.80 are valuable and may contribute to the improvement of theory. In this case, the consistency level is 0.91, which indicates that the present model is valuable and can contribute to theory improvement (Woodside, 2017). Overall, findings show 23 persons are in the favour that manufacturing firms should consider organisational culture (OC), scalability (SC), skills and expertise (SE), user acceptance (UA), collaboration and communication (CC), and industry trends (IT) for successful implementation of Gen-AI tools (IGAI) (scores over 0.7), out of which only 17 are in strong favour of this (scores over 0.80). Thus, proposition 1 includes only 23 cases, but 17 out of 23 will have strong favour in this direction (upper right corner in the plot). These configurations are not attached to a particular solution found by fsQCA. On the other hand, they allow us to identify specific cases (which and how many) within the sample that will have highly successful implementation of Gen-AI, depending on particular antecedent conditions (whether they are high or low/medium) (Pappas, 2018). Indeed, the asymmetric analysis showed that high scores on a configuration usually occur for high scores on the outcome condition, making the configuration useful for researchers. Configurations with consistency larger than 0.80 are useful and could be used for theory building (Woodside, 2017).

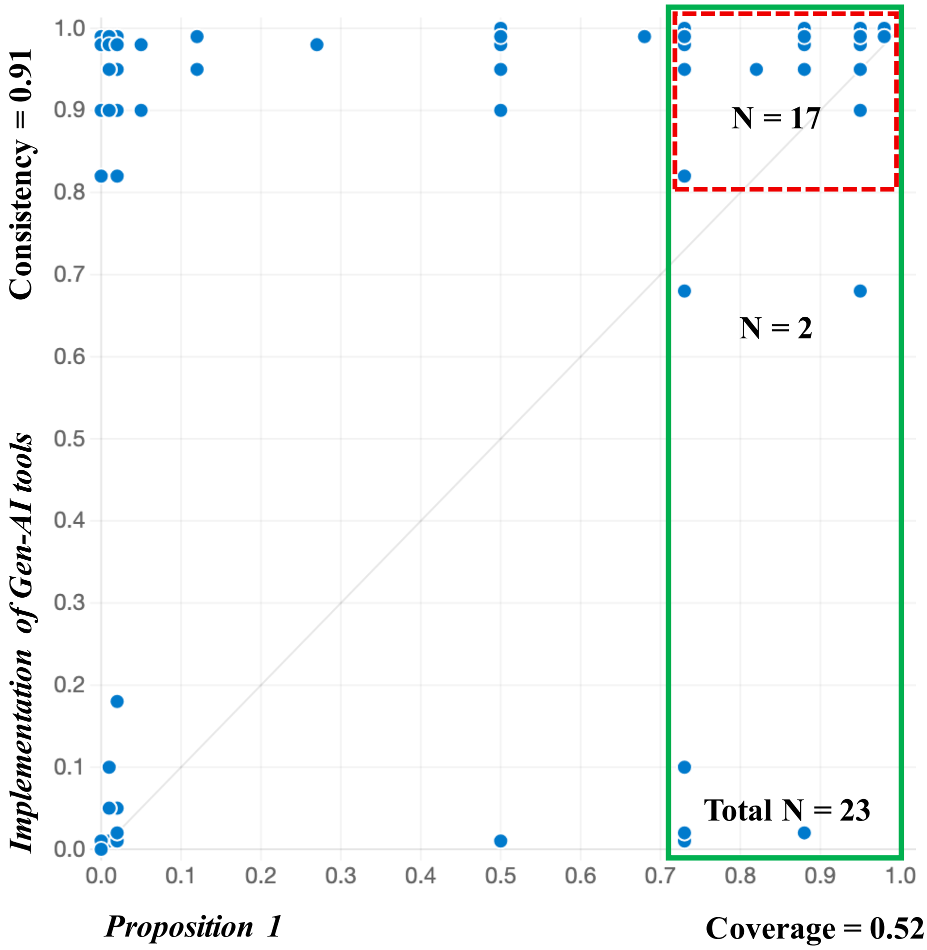

Figure 2: Proposition 1 Fuzzy XY plots for testing. *[Green rectangles indicate cases for which values of the propositions are over 0.7, but Gen-AI tool use can be high (over 0.8) or low, and this is true for different persons in the sample]* (Source: Authors own work)

4.3. Predictive validity testing

Evaluating the predictive validity of our solutions (models) is crucial. Predictive validity measures the accuracy with which the model forecasts the dependent factor in new samples (Woodside, 2014). The importance of predictive validity lies in the fact that a model's strong fit does not guarantee accurate predictions. To assess predictive validity, we first partition the data into two groups: a subsample and a holdout sample. We next perform identical analyses on both groups, as explained in the preceding sections. In addition, we conducted fsQCA analysis on the subsample and then validated the acquired results using the holdout sample. It is always feasible to test for predictive validity by using hold-out samples. Doing so significantly enhances the usefulness of both quantitative positivistic and interpretive case studies (Woodside, 2013).

The data shown in Table 4 consistently demonstrate that firms with complicated circumstances tend to get high scores in the successful implementation of Gen-AI tools (IGAI), as seen in the subsample. Ultimately, the model 1 (derived from subsample 1) is plotted against the desired result using the holdout sample (Figure 3). Here, the value of 0.82 represents a high level of consistency, whilst the value of 0.49 represents the extent of coverage. These calculations suggest that the data strongly support the notion that Model 1 is a subset of the implementation of Gen-AI tools (IGAI). The data also show that Model 1 covers 49.2% of the implementation of Gen-AI tools (IGAI). Model 1 represents 49.2% of the total membership in the implementation of Gen-AI tools (IGAI). In this way, predictive tests for the models indicate that the very robust models for the subsample have a high predictive power for the holdout sample and vice versa, for highly successful implementation of Gen-AI.

Table 4: Subsample solutions (Source: Authors own work)

Subsample models	Raw coverage	Unique coverage	Consistency
MC*IT*CC*UA*SE*SC*CM*TR*DQA*II*RA*LVS	0.435	0.073	0.998
MC*IT*CC*UA*SE*SC*CM*DQA*II*RA*OC*LVS	0.400	0.037	0.999
MC*IT*CC*SE*SC*CM*TR*DQA*II*RA*OC*LVS	0.438	0.077	0.999
~MC*IT*CC*UA*SE*SC*~CM*~TR*~DQA*~II*~RA*OC*~LVS1	0.039	0.025	1
MC*IT*CC*UA*SE*SC*~CM*~TR*~DQA*II*~RA*OC*~LVS	0.063	0.0450	0.997
Overall solution consistency	*0.999*		
Overall solution coverage	*0.622*		

Note: *: Conjuction (AND), ~: Negation (NOT).

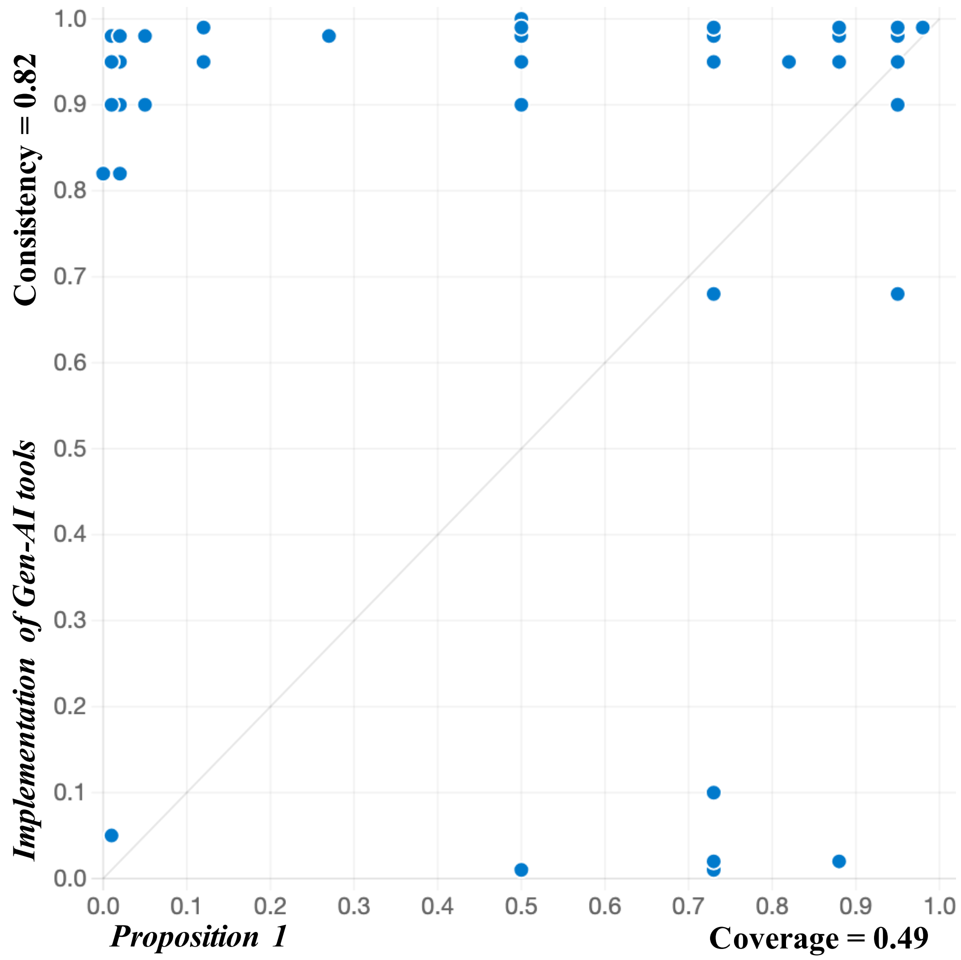

Figure 3: Model 1 plotting using holdout sample data (Source: Authors own work)

5. Discussion and implications

The present research addresses the *"RQ: What combinations of organizational, technical, human, and external factors are necessary and sufficient for organizations to implement Gen-AI tools to catalyze human-centric supply chain operations?"* first by developing three propositions and second by testing those propositions through the fsQCA approach. Consistent with the lens of configurational theory, the results reported here suggest that outcomes in organizations are influenced by configurations of conditions that combine together to create effectiveness, not by isolated independent variables acting independently of each other. Instead of positing linear additive models of causality, this research takes a set-theoretic approach to causation that is grounded in equifinality, conjunctural causation, and causal asymmetry.

Importantly, this configurational perspective also opens a debate between human-centric and purely technology-supported supply chains, as some configurations demonstrate that technical efficiency can be achieved even with limited human-centric elements, raising questions about the extent to which human-centricity is always necessary for Gen-AI-enabled supply chain success. The implementation of the fsQCA method led to seven different configurational solutions for the effective implementation of Gen-AI for human-centric supply chain operations. The solutions suggest that various mixes of technical, organizational, human, and external factors may exist that are equally effective. Consequently, this study contributes to previous research by moving away from generalized "best practices" and toward adoption patterns specific to each configuration that are contingent on the context. The interpretation below describes each solution in terms of practical settings found in industry and discusses how the findings relate to and expand upon past research. This also introduces a critical discussion point: while human-centric supply chains emphasize employee well-being, collaboration, and empowerment, some configurations highlight the efficiency and scalability of technically supported supply chains, creating a constructive tension between socio-technical balance and technology-driven optimization.

Solution 1: This solution reflects a manufacturing setup with an installed Gen-AI capability, where neither Scalability (SC) nor User Acceptance (UA) was an objective of the design. The literature emphasized that 29% of work hours can, in theory, be automated using Gen-AI, and simply deploying the technology does not guarantee a successful outcome (Marston & Lagunas, 2024). The design omits User Acceptance, which suggests a top-down mandate that doesn't align with Bililies & Pak (2025), who emphasized that even advanced models would not work without genuine engagement and trust. This setup subverts the "copilot" paradigm (Wang et al., 2024) by eliminating the human empowerment element, likely resulting in a "compliance-driven" adoption culture, where the tool is used due to policy, rather than perceived utility. This insight enriches the literature by evidencing that a technically functional implementation can occur in the absence of the "emotional intelligence" and "clarity" (Bililies & Pak, 2025) necessary for a truly resilient, human-centric workforce, possibly culminating in the pushback. This solution subtly raises a counter-argument to human-centric supply chains by showing that technically functional systems may still operate under compliance-driven environments, suggesting that efficiency and automation can sometimes overshadow human empowerment, thereby questioning whether human-centricity is always a prerequisite for operational success.

Solution 2: This solution is a scenario in which Gen-AI is implemented without involving organizational culture (OC), instead using other factors. This addresses the "technical frameworks" versus "human-centric design" tension described by Davenport & Kirby (2016). In literature, this issue is solved by cross-functional communications, needed to operationalize the AI-generated insights (Rojek et al., 2023). Eliminating culture for this solution creates a transactional environment, where the "validity gap" (Lebovitz et al., 2021) may become even more prominent; domain experts may dismiss AI insights, because there is no shared interpretive scaffolding between the algorithmic output and their intuition. This research contributes to the extant literature by providing evidence that “siloed efficiency” is a viable, if not ideal, mode of operation. It shows that Gen-AI can be used as an isolated instrument for particular tasks, but the absence of a unifying culture means that the social part of the sociable decision-makers (Huynh, 2024) is foregone, leaving the system as a mere mechanical tool rather than a partner to work with. From a debate perspective, this solution supports the argument that technically supported supply chains can achieve operational efficiency even in the absence of strong human-centric cultural foundations, although such efficiency may come at the cost of long-term trust, collaboration, and knowledge integration.

Solution 3: The implementation of this solution does not incorporate Cybersecurity Measures (CM) and Organizational Culture (OC) is contrary to many requirements for supply chain management, which is often considered “highly reliable” (Weick & Sutcliffe, 2011). The literature indicates that precision and the prevention of errors are critical to the success of supply chain management (Reason, 2016), whereas Gen-AI typically relies on “fail-fast” trial-and-error methods to improve its capabilities (Edmondson, 2018). This solution removes the level of protection offered by cybersecurity and organizational culture. By doing so, it sends employees into a high-pressure situation requiring them to play the role of maverick, balancing between two contrasting elements: the “Zero Trust” required for cybersecurity (Stojanovic, 2025) and the required level of transparency for the advancement of Gen-AI learning. This finding builds on previous knowledge to include the introduction of a highly exploratory innovation mode of operation, and presents an empirical manifestation of the fear alluded to by Stojanovic (2025), that in the absence of systemic protections, the entire weight of security will lie on the shoulders of humans, thereby increasing their cognitive load and risk of committing catastrophic errors in the name of speed. This solution further intensifies the debate by illustrating that excessive reliance on technical experimentation without human-centric safeguards may increase cognitive burden and operational risk, reinforcing the argument that purely technology-driven supply chains may create vulnerabilities in high-reliability environments.

Solution 4: This solution works despite the lack of consideration of Industry Trends (IT), and it is instead driven by the internal operational requirements. This finding is in strong concurrence with the study of Khan et al. (2024), who posit that the pressure from market competition is often overshadowed by the need for customer data management. In this case, the employees are not driven by the “hype” from the outside (Wamba et al., 2025) but rather by the need to use Gen-AI to address certain local challenges, such as bottlenecks or inventory reallocation (Vallabhu, 2025). This study contributes to the literature through the validation of a pragmatic adoption model. Moreover, our results highlight that human-centric organizations may benefit by reducing the number of contradictions associated with modernization, enabling their employees to utilize tools that allow them to achieve real value (such as the specific scenario planning for supplier disruptions noted by Sanchez, 2025), rather than tools that are simply influenced by the market signals. Here, a counterargument emerges that human-centric supply chains may benefit from selective technological adoption rather than blindly following industry trends, suggesting that technical sophistication should be guided by human and operational needs rather than market hype.

Solution 5: This solution is an example of the human-machine collaboration paradigm (Wang et al., 2024) as it prioritizes Skills and Expertise, User Acceptance, Collaboration and Communication, and Organizational Culture as the four pillars of the solution. The solution also directly addresses the potential for deskilling (Dell'Acqua et al., 2023) by allowing humans to remain as the ultimate judges of all AI-generated outputs, as stated in the literature that Gen-AI should allow managers to focus their time on high-value, strategic work (Marston & Lagunas, 2024), and this solution provides the necessary environment for this to take place. In its focus on collaboration, the research affirms that the “validity gap” (Lebovitz et al., 2021) can be closed only by combining expertise. This is a significant finding that contributes to the body of literature by, in essence, proving the copilot concept (Marston & Lagunas, 2024) to be true. The most effective, human-centered operations are those that treat Gen-AI as a colleague with a skilled, culture-aligned, and communication-transparent workforce that can help to unlock the sociable (Huynh, 2024) potential of conversational agents. This solution strongly supports the human-centric supply chain argument by demonstrating that collaborative human–AI integration produces more sustainable and resilient outcomes compared to purely technical implementations, reinforcing the socio-technical balance advocated in recent Gen-AI literature.

Solution 6: This solution expands the original model to include Innovation Infrastructure (II) and Market Competition (MC). It is in line with the current dominant view that financial capital and strong digital infrastructure (Goodson, 2023; Sedkaoui & Benaichouba, 2024) are important enablers for longer-term competitiveness. At the same time, it directly tackles the “resource-capability gap” (Davenport & Kirby, 2016) by tying such infrastructure to human skills and expertise (SE) as well as Organizational culture (OC). According to the literature, using Gen-AI with old software has been described as creating a lot of “friction” (Challapally et al., 2025); however, having complete support reduces friction between that technology and institutions. This research presents a new way to integrate Gen-AI that supports the creation of a mature ecosystem, which is a significant advance in the literature. This research indicates that a complete or holistic approach can be considered the most effective way to avoid the “pilot failures” referenced by Challapally et al. (2025) when combined with “leadership vision” (Eapen & Finkenstadt, 2025) and appropriate support systems to protect employees from the stress of insufficient tools and still satisfy a highly competitive marketplace. At the same time, this solution highlights the complementary perspective that advanced technical infrastructure and market-driven pressures remain essential, indicating that human-centric supply chains cannot function effectively without strong technological foundations and resource support.

Solution 7: This scenario is a grassroots solution with the supply chain implementing Gen-AI without costly Innovation Infrastructure (II) and Market Competition (MC) pressures. It is, in short, the interpretative perspective on human-driven patterns. Employees are not waiting for their company to purchase high-priced servers or customized software packages (which Biswas et al., 2025, find can be prohibitively expensive), but are solving their day-to-day problems with standard tools such as basic ChatGPT (Korzynski et al., 2023). This also fits with the theme of not needing to make a huge IBM-style investment to start with (Goodson, 2023). The "human-centric" value is resilience; the workforce did not depend on a captive IT department to carry them by the hand. They were applying their own baseline skills to make the technology work for their needs. This solution contributes to the debate by showing that grassroots, human-driven Gen-AI adoption can succeed even without heavy technical investments, supporting the argument that human adaptability and creativity can sometimes substitute for expensive technological systems.

Collectively, the set of seven solutions further emphasizes a core belief of configurational theory: that there does not exist a singular requisite that can assure successful implementation of Gen-AI across all contexts. Rather, Organizational Culture (OC), Innovation Infrastructure (II), and Market Competition (MC) only appear in some pathways leading to successful outcomes, while missing from others. This suggests equifinality; multiple combinations of conditions will produce the same result of effective Gen-AI implementation. Additionally, the study results demonstrate conjunctural cause-and-effect relationships, where outcomes from any given condition only occur when that condition is joined with other complementary conditions. As an example, for Innovation Infrastructure (II) to be effective, it must be aligned with both Skills and Expertise (SE) and Organizational Culture (OC) [Solution 6]; furthermore, User Acceptance (UA) only becomes a major contributor when part of a collaborative structure [Solution 5]. Thus, taken in isolation, these factors aren't going to produce the desired results; however, by linking them together, they become strong enablers.

The results also show causal asymmetry, another signature of configurational thinking. Failure is not automatic if some condition is absent (Industry Trends, in Solution 4 or Innovation Infrastructure, in Solution 7). Its absence might well be "made up" through other facilitating configurations. Such findings contradict variance-based reasoning, which relies on effects being symmetrical (present versus absent). Importantly, these findings highlight an ongoing debate in supply chain research: whether human-centric supply chains should be prioritized over technically supported supply chains or whether both should coexist in a balanced socio-technical framework. While some configurations demonstrate that strong technological infrastructure and market-driven pressures can independently drive Gen-AI implementation, others emphasize the central role of human skills, collaboration, and organizational culture. This suggests that human-centric and technically supported supply chains should not be viewed as competing paradigms but as complementary approaches that must be aligned depending on contextual and strategic requirements.

The contribution of this paper to the literature is threefold. First, by inducively extending configurational theory to Gen-AI implementation within manufacturing supply chains, this research steers away from deterministic narratives of “technology success factors” and toward a systemic, socio-technical perspective. Second, it connects descriptive adoption studies with prescriptive implementation logic by describing how and under what combinations of conditions Gen-AI works, rather than simply whether it works. Third, it offers a diagnostic tool practitioners can use, knowing that you don't have to score highly on all factors, but should score consistently within a configuration. Overall, this research not only affirms that anthropocentric supply chain transformation results from coherent configurations of organizational, technical, human, and external factors but also acknowledges the counter-argument that technical efficiency and automation may sometimes dominate operational priorities, thereby reinforcing the need for a balanced and context-sensitive approach to human-centric Gen-AI supply chains.

5.1. Managerial implications

This article provides managers with different solution-oriented implications for supply chain leaders as follows:

Prioritize Cultural Alignment Over Technical Perfection: We believe that brittleness is less likely to occur because an organization chose a sub-optimal Gen-AI solution and more likely to happen when organizations mandate compliance-based approaches to how people should use Gen-AI tools. Leaders could do well to focus on the soft aspects of implementation. According to Ignatius (2023), productive “internal contradictions” exist in firms focused on innovation; therefore, leaders need to find a balance between their goals of generating revenue and exploring technology. The successful implementation of Gen-AI, on the other hand, is more dependent upon the social and organizational alignment than on its technological superiority.

Balance Experimentation with High-Reliability Requirements: Although many digitally native organizations have a culture of experimentation (Kumar, 2023), supply chains are high-reliability organizations where errors can cause large-scale disruptions to operations and reputation (Weick & Sutcliffe, 2011). Managers can create psychological safety and organizational “safe sandbox” spaces to experiment with Gen-AI while ensuring key logistics metrics are not affected. Mechanisms like learning systems (Edmondson, 2018) can encourage experimentation without hurting accuracy.

Close the Resource–Capability Gap Through Strategic Upskilling: This study raises concerns around a "resource–capability gap", in which organizations heavily invest in hardware such as GPUs but fail to invest similarly in skills (Biswas et al., 2025). Managers could not make investment decisions based solely on technological capabilities developed in silos. Investments into technology infrastructure could be paired with specific AI training, cross-training, and other exercises that grow human capabilities in tandem with technology.

Adopt a "Copilot Model" for Human–AI Collaboration: Instead of aiming for automation, managers could aim to utilize Gen-AI via what Marston and Lagunas (2024) call a "copilot model." With this model, AI is used to handle structured tasks that can easily be automated (cleaning data, running simulations/scenarios) and leave humans in control of the relational and highly judgmental tasks (supplier negotiation, coordination) (Marston & Lagunas, 2024). Copilot models allow for human-centered supply chains by enhancing managers' decision-making rather than replacing them.

Combine Innovation with Robust Governance Mechanisms: Frugal innovation with off-the-shelf tools may allow experimentation with AI more cheaply than otherwise (Stojanovic, 2025). This is especially true for smaller organizations that may not have extensive resources. However, security concerns should not be neglected. Managers could deploy "Zero Trust" architectures and other methods of securing corporate data. Governance could allow for external connectivity and learning from AIs without sacrificing cybersecurity.

Resist Market Hype and Focus on Context-Specific Utility: Resistance could also come from managers based on adoption caused by "market hype" (Wamba et al., 2025). Instead of mindlessly following their peers, organizations can assess Gen-AI tools for their operational usefulness and contextual applicability (Vallabhu, 2025).

6. Conclusion

This study examines the importance of aligning the organizational, technical, human, and external aspects to effectively implement Gen-AI tools for human-centric supply chain operations. Specifically, the study's focus is on understanding how these four elements work together and create innovative opportunities. To date, this study represents the first nationwide empirical effort to create a socio-technical map of the Gen-AI landscape within the manufacturing supply chain. Arguably, the most important contribution of this research is the departure from a "one-size-fits-all" paradigm. The empirical results provide a rich data set that confirms that there are many paths to configuration success, and that all practitioners who operate in comparable economies can use this information as a powerful platform to diagnose technology adoption and to help strike a balance between their organization's human and technical assets.

Despite aiming to provide a first socio-technical map of Gen-AI implementation in manufacturing supply chains in India, this study has certain limitations. Due to non-stratified national sampling, our sample is not nationally representative and may limit the generalizability of findings despite being diverse in firm size, sector, and context. All measures were self-reported, cross-sectional data, limiting causal conclusions. Moreover, while the fsQCA-based map of configurations presented here offers an exploratory view of the domain, it does not represent a national map either. Future studies might leverage stratified, representative samples and longitudinal datasets to examine overall population trends and investigate temporal shifts over time. Even with these limitations, we present useful information regarding configurations of organizational, human, and technical configurations affecting Gen-AI implementation. Furthermore, we have developed a few future open research questions (ORQs) for future researchers to explore this topic in other dimensions to strengthen and contribute to this area as follows:

ORQ1: How does the implementation of Gen-AI influence human–AI collaboration, employee well-being, and job satisfaction in human-centric supply chains?

ORQ2: What roles do leadership styles and ethical governance mechanisms play in shaping human-centric generative AI adoption in supply chains?

ORQ3: How does generative AI reshape organizational culture and employee adaptability in human-centric supply chain ecosystems over time?

ORQ4: How do external stakeholders (customers, regulators, technology providers, and communities) influence the development of human-centric Gen-AI supply chains?

ORQ5: How do institutional environments and regulatory frameworks shape the configurations of Gen-AI implementation for human-centric supply chains across countries?

ORQ6: What are the short-term and long-term performance outcomes of Gen-AI-enabled human-centric supply chains in terms of resilience, sustainability, and employee productivity?

ORQ7: How do configurations of organizational, technological, human, and external factors evolve in shaping human-centric Gen-AI supply chains?

ORQ8: What new skill sets and training mechanisms are required to support human-centric generative AI supply chains?

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