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Big Data Analytics Powered by AI for Enhancing Supply Chain Agility and Customer Relationship Performance

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ABSTRACT

In today's volatile and complex international organization conditions, B2B manufacturing firms face increasing challenges in managing supply chains that are efficient, responsive and aligned with dynamic customer demands. The rapid changes in the market due to trade wars, pandemics and political instability add more problems to the customer-centric supply chain. This paper examines the function of big data analytics powered by artificial intelligence as a vital facilitator of supply chain agility and customer relationship efficacy in Chinese B2B manufacturing firms. Using the Dynamic Capabilities View, the study presents and experimentally evaluates a model that investigates the impact of big data analytics augmented to artificial intelligence on supply chain agility, both directly and indirectly, through supply chain alignment and Adaptability, while also accounting for market turbulence as a moderating factor between agility and customer outcomes. Data were collected from 434 B2B Chinese manufacturing firms involved in export and import activities through structured questionnaires. Expending Partial Least Squares Structural Equation Modelling, the conclusions confirm that big data analytics and artificial intelligence significantly enhance supply chain agility, supply chain adaptability and supply chain alignment, which in turn positively impact customer relationship performance. The moderating validity of market turbulence signifies that the impact of supply chain agility on customer relationships is particularly significant in conditions of high market volatility. The findings also highlight how critical big data analytics and artificial intelligence has become an essential dynamic capability that converts data into valuable actionable insights and as such, can enable firms align and redesign their supply chain business to achieve higher levels of customer performance. This research also helps digital supply chain literature by connecting advances in technology with the changes in the supply chain and being customer-focused, offering useful information for both theory and practical application in difficult industrial circumstances.

Keywords: *agility, AI, big data analytics, customer relationship performance, market turbulence, supply chain agility, supply chain capabilities,*

1. INTRODUCTION

In the current global business environment characterized by volatility and complexity, supply chains encounter significant challenges due to geopolitical instability, technological disruption, and changing customer expectations (Fan *et al*., 2022; Mishra *et al*., 2024). B2B manufacturing firms, particularly in emerging economies

like China. B2B firms face increasing pressure to address dynamic customer demands while ensuring efficiency, responsiveness, and reliability in their globally dispersed operations (Ivanov & Dolgui, 2020; Zhang & Gao, 2022). The trade conflict between America and China, geopolitical instability, and the Covid-19 pandemic have revealed considerable weaknesses in global supply chains, leading to increased costs, logistical unpredictability, and variable lead times (Fan *et al*., 2022; Fonseca & Azevedo, 2020; Hayat *et al*., 2024; Israfilov *et al*., 2023). Macro-level disruptions have destabilized relationships between manufacturers and their business clients. It is frequently resulting in missed delivery windows, inaccurate demand forecasting, and reduced customer trust (Cui *et al*., 2023; Ivanov & Dolgui, 2025; Xiong *et al*., 2024). In such turbulent conditions, firms can no longer rely on rigid and linear supply chain structures. Instead, they require adaptive, agile, and data-driven capabilities to respond to volatility with speed and strategic foresight (Brunner *et al*., 2024; Wamba *et al*., 2020). To remain competitive and meet escalating service expectations, firms are increasingly turning to new technologies such as the Internet of Things (IoT), artificial intelligence (AI), big data analytics (BDA), and blockchain technologies (Paramesha *et al*., 2024). The big data analytics and twins technologies are enhancing the resilience of supply chain systems. Implementing digital twin technology to predictive maintenance and production in the modern manufacturing facilities increases the responsiveness of the supply chain through the real-time responses to disruptions (Tao *et al*., 2018). Within the global logistics, the implementation of AI-based dynamic routing schemes which utilize real-time maritime data considerably improves the flexibility of the supply chains to changing external factors (Munim *et al*., 2020). A practical example of AI-led systems applied in supply chain agility has been introduced at JD Logistics by using AI to process orders and optimise the routes presented to users, thus demonstrating how such techniques can be used practically in the company (Zhang *et al*., 2024).

The big data analytics powered by artificial intelligence (BDAI) (Dubey *et al*., 2020), is a technology combination of high-volume data processing, machine learning algorithms and predictive insights that can inform real-time decisions across supply chain functions (Fosso Wamba & Akter, 2019; Zamani *et al*., 2023). BDAI offers affordability that traditional tools simply cannot provide, and it allows monitoring of demand patterns and forecasts of disruptions in organizations and helps in coordinating decision-making over global networks with greater efficiency (Rane *et al*., 2024; Zamani *et al*., 2023). However, the strategic benefits of BDAI are not automatic. Their realization is often contingent on complementary supply chain capabilities such as supply chain alignment (SCAl), supply chain adaptability (SCAD), and supply chain agility (SCA) (Iranmanesh *et al*., 2023), dynamic mechanisms that allow firms to sense, interpret, and respond effectively to changes in the external environment (Teece, 2007; Wamba *et al*., 2020). In particular, supply chain agility, the firm's ability to quickly respond to customer and market fluctuations, has been broadly recognised as a serious enabler of customer-focused performance (Gligor *et al*., 2015).

Although the growing concern in BDAI and supply chain digital transformation, several key research gaps remain. First, although BDAI has been shown to enhance operational performance, the mechanisms through which it affects customer outcomes, such as Customer Relationship Performance (CRP) are still underexplored, especially in the B2B manufacturing domain (Cadden *et al*., 2022). Most of the academic research focuses on the efficiency of the upstream supply chain or internal capabilities; however, it rarely addresses the processes through which digital technologies can be transformed into increased customer engagement, responsiveness, and satisfaction (Ardolino *et al*., 2025; Aslam *et al*., 2025; Bejlegaard *et al*., 2021). Second, the intervening roles of supply chain alignment and adaptability as strategic enablers that condition how BDAI is embedded into supply chain processes have not been sufficiently theorized or empirically tested (Cadden *et al*., 2022). Third, while supply chain agility is commonly treated as a performance enhancer, little attention has been paid to contextual variables such as market turbulence (MT) that may moderate its effects. Existing studies tend to assume linear outcomes, overlooking the fact that agility's impact may depend on environmental volatility (Zhu *et al*., 2018; Wamba *et al*., 2020). Fourth, empirical studies focusing specifically on customer relationship performance, verses traditional measures of generalized firm performance, are relatively few in the area of supply chain research, despite its quite relevant relevance in B2B markets where customer retention and customer satisfaction have a direct impact on the flow of revenues and the survival of the business (Lasrado *et al*., 2023; Ruzo-Sanmartín *et al*., 2023).

To bridge these gaps, the study proposes via empirical observation to tests theoretical model that examines how BDAI influences supply chain agility, both directly and indirectly through supply chain alignment and adaptability, and how marketplace turbulence moderates the consequence of agility on customer relationship performance. Drawing on the Dynamic Capabilities View (DVC) (Teece, 2007), the model focuses on the roles of firms in sensing, capture, and reorganizing supply-chain resources in the reaction to environmental transformations. A survey of 434 Chinese B2B manufacturing firms was analyzed using Partial Least Squares Structural Equation Modelling (PLS-SEM). All the expected links were confirmed: BDAI improves supply chain capabilities and these capabilities, in turn, lead to greater agility directly and through other ways. Also, importantly, the analysis shows that agility greatly strengthens relationships with customers and that these benefits are even higher when the market is turbulent. The study presents three main contributions. First, by connecting BDAI capabilities and key dynamic capabilities, the study innovatively adds to digital supply chain literature. It also shows that when supply chains become agile and use data analytics, they create better links between how they work and how customers feel. Third, the study empirically shows that companies benefit the most from being responsive when there is significant environmental unpredictability. By studying these relationships in the area of Chinese B2B manufacturing, where businesses are located where the world connects with their own country, the study brings both theoretical and practical insights up to date.

We have organised our paper as follows. Section 2 examines the significant literature and develops the theoretical base and hypotheses founded on the Dynamic

Capabilities View. Section 3 describes the study methodology, involving data gathering, sample, and measurement instruments. Section 4 presents the data analysis and conclusions covering measurement model assessment and hypotheses testing. In Section 5, we discuss the discussion, implications for theory and practice, the limitations and future research directions of our study before the conclusion section of the paper.

2. THEORETICAL FRAMEWORK AND HYPOTHESES DEVELOPMENT

This study employs the dynamic capabilities view as a strategic framework to elucidate how businesses adapt and evolve in constantly changing environments (Teece, 2007). The Dynamic Capabilities View (DCV), as initially expressed by (Teece *et al*., 1997), has been proposed to describe the capacity of any firm to acquire, improve, and restructure internal and external competitive capabilities, so as to effectively accommodate volatile and fast-changing market conditions. Unlike the traditional resource-based perspective, which prescribes the consumption of resources that are already present in the organisation in order to gain a competitive advantage, the DCV focuses on how organisations build capacity that will maintain agility, fit, and responsiveness in the long term. In supply chain contexts, dynamic capabilities are exemplified by an organisation's capacity to reorganize its logistics, supplier relationships, manufacturing systems, and customer strategies in response to disturbances or emerging possibilities (Eisenhardt & Martin, 2000). This paper explores three key dynamic supply chain capabilities, which include alignment, flexibility, and agility. These competencies are dynamic processes that allow organisations to be aware and react to ecological changes, including those caused by the disruption of global trade or demand movements (Kalubanga & Gudergan, 2022). BDAI is a technological enabler of dynamic capabilities that are defined in this study. BDAI is an improvement in a company's capability to formulate and use predictive and prescriptive analytics to make supply chain-related decisions, perform market trend analysis, and simulate reactions to supply chain disruptions (Riipa *et al*., 2025). BDAI, in line with DCV, enhances the power of the organization to recognize the exogenous change (i.e., through real-time demand perception), to exploit the new opportunity (i.e., through rapid rearrangement of available resources) and to re-create the processes (i.e., through re-modeling of the supply networks).

SCAl as a dynamic capability facilitates setting a unified objective, key performance indicators (KPI), and activities between functional and inter-organizational boundaries (Junaid *et al*., 2023). The alignment of the supply chain makes sure that the information provided by BDAI is converted into a synchronized action between suppliers, internal teams, and distributors in an effective way (Liao *et al*., 2023). The articles prove that alignment increases the supply chain's visibility and trust, thereby simplifying and speeding decision-making and increasing consistency (Baah *et al*., 2022; Christopher & Holweg, 2011). The SCAD enables businesses to respond to structural changes in progress, which may be the emergence of new trade rules, technological upheavals, or fluctuations in consumer demands. The BDAI enables flexibility by pinpointing the strategic restructuring of supplier networks and consumer interaction approaches with the aid of scenario-based analytics and forecasting features (Mikalef *et al*., 2021; Wang *et al*., 2024). Flexibility therefore gives the firm the ability to become competitive in the long term despite changes in the environment. SCA the capability to act promptly and adaptively in response to the temporary disturbances is theorized as the product of alignment and adaptability. Although alignment offers the coordination necessary to use agile implementation, adaptability guarantees that agile feedback is encouraged by adaptable infrastructure and systems. When utilized together with these capabilities, BDAI helps to make decisions faster and enhance responsiveness particularly in dynamic settings (Sheel & Nath, 2019; Sullivan *et al*., 2023).

Finally, the study incorporates market turbulence as a moderating variable. DCV acknowledges that ecological situations can structure the importance of dynamical potential. In highly turbulent markets, such as those affected by global trade wars, customer preferences shift rapidly, and firms face higher uncertainty and risk (Cui *et al*., 2023; Jaworski & Kohli, 1993). Agility, in this context, has become an important element in the sustenance of CRP, a mixture of satisfaction, loyalty, trust, and continuity of a relationship. Nevertheless, in low-turbulence conditions, the minor advantages of agility on CRP can be reduced (Zhou *et al*., 2019). Using DCV in this case, the study effectively describes BDAI not a mere digital tool, but a key facilitator of dynamic supply chain capabilities. The design framework also describes how such capabilities are translated into performance outcomes, such as CRP, in the workplace environment where there is uncertainty. This theoretical perspective justifies the multi-layered nature of the proposed model where BDAI has a direct and indirect influence upon agility via alignment and adaptability and the alignment and CRP relationship are mediated by external turbulence. The Figure 1 shows theoretical framework and hypotheses.

2.1 Big Data Analytics Powered by AI to Effect Customer Relationship Performance

In the modern B2B production marketplace, it has been observed that the development of strong relationships with clients has proved to be another critical consideration in the realization of robust competitive advantages (Wirtz & Kowalkowski, 2023). Good customer relationship, with its emphasis on trust, being happy, responsiveness and loyal support, plays a vital role in sensitive areas in a business (Morgan & Hunt, 1994; Palmatier *et al*., 2006). As international supply chains become progressively complicated and consumer expectations fluctuate frequently, organisations must continually refine their relational strategies (Adeniran *et al*., 2024; Bag *et al*., 2021). Recent digital technology, particularly through the assistance of BDAI has significantly influenced enterprises' customer management strategies, as shown by (Cui *et al*., 2023; Wamba-Taguimdje *et al*., 2020). BDAI applies algorithms and data analysis to get, arrange, and analyse a great amount of data, some of which comes from social media platforms

and transactions (Song *et al*., 2022). BDAI enables the organization to understand the customer requirements as well as the proactive market dynamics, thus helping them to identify strategies that would satisfy their customers in time. The latest empirical research proves that BDAI can significantly enhance CRP by permitting the utter engagement of clients and the ability to take proactive steps. The research conducted by (Bahrami & Shokouhyar, 2022) demonstrates that enterprises utilising insights from AI and big data may more effectively predict customer requirements and respond swiftly, hence enhancing customer loyalty. Similarly, (Wang *et al*., 2024) found that digital analytics enable manufacturers to adapt their product and facility contributions in response to rapidly changing market conditions, hence improving customer relationships. From the perspective of dynamic competencies, BDAI is a dynamic capability that transcends operational efficiency and includes relational excellence (Sullivan *et al*., 2023).

The conventional IT solutions are mainly automated. BDAI, on the contrary, can help organizations to identify the changes in the preferences of consumers consistently and jointly create value to consumers with individualized offerings (Van Rijmenam, 2019). The possibility to integrate the customer information in the operational and strategy levels contributes to the CRP more than efficiency in the reduced form of transactional satisfaction to trust, reliability, and proportional growth (Ma & Chang, 2024; Osakwe *et al*., 2023). The relationship between BDAI and CRP is contingent upon organisational readiness and the ability to translate data insights into actionable, customer-centric initiatives (Song *et al*., 2022). Factors such as digital maturity, interdepartmental alignment, and a customer-centric culture are crucial in shaping this connection (Lemola, 2024). In fragile circumstances like the Chinese manufacturing industry, firms that adeptly integrate Big Data and Artificial Intelligence into customer-focused operations are more inclined to sustain and expand their consumer base (Abbas Khan *et al*., 2024; Es-satty *et al*., 2025; Mutiarachim, 2025). The study posits the following hypothesis to enhance the current model based on these theoretical and practical insights:

H1: *BDAI has a positive effect on customer relationship performance*.

2.2 Big Data Analytics Powered by AI to Effect Supply Chain Agility

In today's fast-paced industrial landscape, agility has emerged as one of the most critical capabilities for supply chains facing volatile customer demands and environmental uncertainties. Supply chain agility indicates a company's capacity to perceive alterations in the external environment and respond swiftly and effectively through adaptable operations, decision-making, and resource allocation (Christopher & Towill, 2001; Gligor & Holcomb, 2012). In the case of B2B manufacturing companies, especially those that operate in the global marketplace, such as China, flexibility is the only way to maintain the reliability of the service, the flow of the production, and the satisfaction of the customers in the cases of unceasing disruptions, such as trade tensions, fluctuating demand, and so on.

The recent theoretical knowledge is gaining growing acceptance of BDAI as a key facilitator of SCA. BDAI can be described as the ability to gather, process, and analyze large amounts of data that are high volume, high velocity and high variety with the help of an AI-driven tool, such as machine learning, natural language processing, and cognitive computing (Wamba *et al*., 2017). BDAI enables real-time information on customer demand patterns, inventory levels, supplier availability and logistics performance, making firms proactively change their supply chain functions (Dubey *et al*., 2019; Mikalef *et al*., 2021). According to (Teece, 2007; Teece *et al*., 1997) the DCV agility is a process-oriented capability adequately than a stable resource, founded on the principles of sensing, seizing, and changing. BDAI uplifts such dimensions allowing enterprises to see the first signs of change, come up with fast resolutions, and continually learn with the changing trends of data. In the B2B manufacturing setting, BDAI implementation allows businesses to predict customer reorder schedules, predict supply disruptions, as well as launch dynamic manufacturing, and as a direct result of agility provision services.

This relationship is being progressively supported with the help of empirical research. For example, (Wamba *et al*., 2020) found that BDA capabilities significantly enhance supply chain responsiveness by improving demand visibility and operational synchronization. Similarly, (Dubey *et al*., 2019) demonstrated that firms using BDA tools were better able to adapt logistics and procurement in response to geopolitical breakdowns. According to (Liu *et al*., 2013) based on the Chinese manufacturing plants where AI-based analytics have been implemented, lead times have been reduced, and order precision has improved, both of which are critical metrics of operational slickness. The nature of BDAI with SCA is determined by such variables as preparedness of the organization and supply chain design. BDAI, in other words, cannot cause agility on its own, as it needs to be incorporated into the mechanisms that ensure rapid implementation and the cross-disciplinary teamwork (Gunasekaran, Papadopoulos, *et al*., 2017). This is an indication of the importance of integration of data, analytical skills and of digital culture within the organization. BDAI also operates as the interface between information collection and actionable intelligence in manufacturing environments marked by geographically dispersed and informative supply chains that had been disrupted and were also characterized by technologically fine grain information. It enables faster planning processes, universal procurement, and improved cooperation between suppliers. Such abilities are essential especially when there is a fluctuation in the market as they allow firms to react faster and, in a cost efficient and coordinated way. As a result, there is theoretical and empirical evidence that supports the following hypothesis.

H2: *BDAI has a positive effect on supply chain agility*.

2.3 Big Data Analytics Powered by AI Relationship with Supply Chain Alignment

In a global networked industrial environment, especially in B2B environment, the SCAl is a key component in realizing harmonized operations and strategic regulation through the alignment of the states of the supply chain to the point that the supply chain partners, often referred to as suppliers, manufacturers, and distributors, coordinate their

goals, information exchange, decision-making process, and operations such that uniform performance results are achieved (Cui *et al*., 2023; Wu *et al*., 2024) . During situations like trade wars and changes in overall demand disruptions can further cause delivery delays, miscommunication and poor reactions which confirms the value of having better integration and visibility. By using BDAI supply chain actors can enjoy more transparency, knowledge of future events and greater teamwork (Bahrami & Shokouhyar, 2022; Wamba *et al*., 2020). Through external interference like trade wars and demand changes across the globe, misalignment exacerbates delays, production variances, as well as inefficient responsiveness and integration and visibility become imperative. BDAI adds value to SCAl through provision of real-time visibility, predictive understanding as well as coordinated action among chain players (Bahrami & Shokouhyar, 2022; Wamba *et al*., 2020). AI-augmented analytics process large-scale data from varied sources and enable the identification of process bottlenecks, demand shifts, and procurement issues, which, in turn, guide shared decision-making across B2B supply networks (Wang *et al*., 2024). BDAI serves as the analytical foundation for SCAl's collaborative forecasting, scenario planning, and KPI harmonization. The DCV states that being able to align helps companies act by altering their setup within the firm and their relationships with outside forces as things change (Belhadi *et al*., 2022).

By having one management style, it smooths out the ways different departments function and ensure better performance. (Wamba *et al*., 2020; Wu *et al*., 2024) assert that employing BDA to integrate the supply chain enhances functioning effectiveness and aligns KPI. (Mikalef *et al*., 2021) indicate that AI functions enable teamwork in the organization by boosting shared education and digital maturity. The Chinese B2B industrial setting is complex and large-scale, thus the use of BDAI would aid in uniting the data flow consistency among the departments and companies, thus creating coordinated workflows. AI-driven insights enable departments to harmonize procurement, inventories, production, and logistics with consumer demand signals, leading to coordinated and agile operations (Chin *et al*., 2021). This facilitates both vertical (intra-firm) and horizontal (inter-firm) alignment. Consequently, the capacity of BDAI to enable SCAl is crucial for B2B enterprises functioning in volatile and time-critical marketplaces. As alignment is a necessary condition for resilience and agility in complex B2B supply chains, it is hypothesized that:

H3: *BDAI has a positive effect on supply chain alignment.*

2.4 Big Data Analytics Powered by AI Relationship with Supply Chain Adpatability

BDAI also plays a conclusive role in empowering SCAD particularly where industries in the world face dynamic global shifts. SCAD can be described as the ability of a firm to reincarnate its supply chain design, policies, and relationships as a result of structural adjustment of that firm due to changes in customer demand, regulatory forces, and technological anomaly (Dubey *et al*., 2021; Ivanov & Dolgui, 2020). For Chinese B2B manufacturing firms, the ability to swiftly adjust sourcing strategies, production locations, or customer service models is fundamental to resilience and long-term competitiveness (Tian *et al*., 2024). Based on the DCV, adaptability is the ability of firms to feel and capture opportunities and reconfigure the resources with alterations in the structure. This process is supported by BDAI by intensifying data-driven sensing and predictive analysis of scenarios as well as perpetual organizational learning (Bahrami & Shokouhyar, 2022; Wamba-Taguimdje *et al*., 2020). For instance, (Dubey *et al*., 2018) show that BDAI-enabled firms demonstrate superior responsiveness to trade policy volatility through scenario-based simulation and real-time adjustments. Machine learning devices within BDAI take a shorter time to identify any changes in the environment enabling companies to restructure their supply chains ahead of time through capacity redistribution, supplier diversification or a shift in logistics strategies (Gunasekaran, Papadopoulos, *et al*., 2017).

They follow the DCV's (Teece, 2007) base of sensing, seizing and transforming so that BDAI continuously contributes to long-term transformation of supply chains. On top of this, adaptable businesses are helped by AI-powered feedback systems that improve organizational learning. (Mikalef *et al*., 2020) state that with BDAI, organizations can learn permanently, adjust their algorithms and keep decisions updated using new information in real time. Because learning is institutionalized, society can handle uncertainty in ways that are efficient, sustainable and can be scaled up. Organizations that have effective BDA abilities are likely to model risks proactively and adapt their supply networks in uncertain times (Bahrami & Shokouhyar, 2022). In highly turbulent conditions, such capabilities are not just advantageous but essential for sustained performance. Because of such capabilities, firms in China can now shift from making emergency changes to preparing for long-term transformation. Being able to adapt is what allows B2B manufacturers to use data-driven sensing to address unexpected disruptions, minimize the difficult aspects of change and better meet customer expectations (Bahrami & Shokouhyar, 2022; Ivanov & Dolgui, 2020). Therefore, we propose.

H4: *BDAI has a positive effect on supply chain adaptability.*

2.5 Supply Chain Alignment and Adaptability Enhance Supply Chain Agility

With the increasing turbulence in the global marketplaces, firms have realized that agility is not a sufficient tool to ensure competitive advantage, but agility should be complemented with such vital attributes as alignment and adaptability. These two equivalents though conceptually different have complementary roles in enhancing the ability of the organization to respond effectively and promptly as market volatility strikes, particularly B2B manufacturing supply chains where customer-selection is tricky and service cycles are dogmatic. SCAl evaluates the degree of adherence of personnel on different sources to the same goals, rules and procedures (Aslam *et al*., 2020). SCAl allows different actions in big Chinese manufacturing networks to work together instead of conflicting, so the response to changes is more efficient. Having a clear line up among teams means making quick choices, as people stay on the same page and save time

communicating important things. This makes work processes uniform, so it's easier to fix problems as they appear (Sheel & Nath, 2019). Besides, SCAl aids data exchange, clear real-time views and collective forecasts for all involved in the supply chain, making pre-agility arrangements and execution better. Therefore, BDAI becomes vital because it delivers critical market signals rapidly, allowing members to respond collectively to changes within the chain. When firms mean adaptability in the supply chain, they are really referring to a firm's capability to keep changing its supply configuration, approaches and relationships in reaction to macro-level changes (Eckstein *et al*., 2015).

In such challenging B2B markets, businesses must often update their sourcing practices, upgrade their technology and change how they deliver their goods to remain ahead. Through adaptation, an organization can adjust and respond due to learning, adjusting plans and staying ahead of changes (Gligor *et al*., 2019). The ability to sense the environment continuously and to learning loop in order to build institutional memory helps organizations to react quicker and more efficiently to future events an example of organizational agility. Investments in flexible infrastructure, multifunctional teams, and modular production systems are often associated with high SCAD and lead directly to enhanced SCA (Swafford *et al*., 2008). These relationships supported by empirical findings. For example, (Gligor *et al*., 2015) showed that adaptable organizations exhibit greater agility in dynamic demand settings. Similarly, (Aslam *et al*., 2020) confirmed that SCAl is a significant antecedent of agility by ensuring process consistency and unified execution during change. The use of SCAl and SCAD in the Chinese B2B manufacturers context allows translating insights produced by BDAI into coherent and scalable operation mechanisms. Without alignment, organizational agility can be threatened with being disenfranchised, and without the presence of adaptability, the agility can simply be at a surface level, and unsustainable. Hence, we proposed the following hypotheses.

H5: *Supply Chain Alignment has a positive impact on Supply Chain Agility*.

H6: *Supply Chain Adaptability has a positive impact on Supply chain Agility*.

2.6 Supply Chain Agility Enhance Customer Relationship Performance

Consumer interactions provide a clear advantage in completing well within the competitive and fast-changing B2B manufacturing sector. CRP measures how well a company can keep satisfying customers with trust, happiness, fast answers and ongoing loyalty (Iranmanesh *et al.*, 2023). In manufacturing firms, particularly those bound by long-term contracts and extensive delivery mechanisms, any lapse in responsiveness or service reliability quickly results in loss of customer retention and damages strategic reputation (Li *et al.*, 2021; Wamba *et al.*, 2020). SCA the capability of a firm to quickly detect and react to supply or demand changes is widely regarded as a core enabler of responsiveness (Ashrafi *et al.*, 2019; Iranmanesh *et al.*, 2023). It enables firms to adjust production, reallocate inventory, and respond flexibly to customer needs, especially in B2B settings where expectations are complex and responsiveness is paramount (Aslam *et al.*, 2020; Iranmanesh *et al.*, 2023). In the DCV agility is define as a mechanism for continuous transformation to meet rapid shifts in external conditions (Bag *et al.*, 2021; Teece, 2007). Many studies have found that this linkage exists. Gligor *et al.* discovered that supply chains based on agile methods lead to higher responsiveness to customers and increase the value of the relationships involved. Just as well, (Riipa *et al.*, 2025) concluded that those businesses reacting more quickly to the COVID-19 crisis delivered better to their B2B clients and were rewarded with loyalty and trust. Despite this, some new research suggests that agility might not be enough.

According to (Iranmanesh *et al.*, 2023), direct efforts to enhance agility did not significantly influence CRP. Thus, it appears agility needs SCAl and SCAD as supplementary factors to improve customer results. In their book, (Brusset & Teller, 2017) believe that failing to ensure alignment within agility may cause different areas of the company to respond without direction, resulting in inconsistency for customers. In addition, (Wu *et al.*, 2024) pointed out that agility can only work if the infrastructure is flexible and all parties are in agreement to avoid making unrealistic plans that disrupt service. In other words, the success of agility rests on having certain supporting factors. Because things are so complicated, it highlights the need for proper capability integration. Respond quickly as you may, but your actions need to be planned and practical to matter in the long term (El Baz & Ruel, 2021). This supports the main point of this study: to effectively handle customer contacts in unstable B2B supply environments, we must understand how agility interacts with alignment, adaptability and turbulence. Therefore, we proposed the hypothesis.

H7: *Supply Chain Agility has a positive impact on Customer Relationship Performance*.

2.7 Mediating Role of Supply Chain Alignment and Supply Chain Adaptability Between Big Data Analytics Powered by AI and Supply Chain Agility

BDAI is transforming supply chains by enhancing organizations' capability to detect, respond and change to environmental changes. BDAI systems handle large amounts of both unstructured and structured data on the fly, and therefore enable accurate forecasting, optimal resource distribution and efficient management of disruptions, which form the basis of greater supply chain responsiveness (Belhadi *et al.*, 2024; Wamba *et al.*, 2020). Nevertheless, this influence is hardly linear. It has been proposed that there are structural mechanisms and interactive mechanisms between the BDAI and SCA, with the most prominent being SCAl and SCAD. Supply chain alignment is used to describe the level at which internal units and external suppliers are operationally and strategically aligned where they exchange data, objectives and decision-making models. Alignment will make sure that various stakeholders operate under one plan and can thus plan and work in concert (Chen *et al.*, 2022; Gunasekaran, Subramanian, *et al.*, 2017). AI-powered analytics enhance SCAl by enabling real-time sharing of actionable insights, harmonizing demand planning, production scheduling, and logistics execution across the chain (Toorajipour *et al.*, 2021). Chinese B2B manufacturing companies use alignment to address the delivery challenges

such as regulatory uncertainty and fragmented market of suppliers by standardizing the understanding of the BDAI insights (Tian *et al.*, 2024). SCAl acts as a channel for turning BDAI into coordinated agility (Riipa *et al.*, 2025) demonstrate that companies utilizing big data analytics technologies experience enhanced planning consensus and operational coherence, which are critical for effective execution.

Organizational alignment in dynamic operation environment leads to trust, consistency of key performance measures, and streamlines decision-making process, thus agile strategies, i.e., dynamic routing, delay planning, and adjusting production it has. As a result, SCAl is a central mediating concept, which connects BDAI and organizational agility thanks to the implementation of a digital supply chain bundle that has been operationalized continuously. Adaptability means the ability of the supply chain to change its architecture, its operational patterns and its inter-organizational relationship based on enduring changes on the market or on the environment. These types of responsiveness include a changing customer expectation, regulatory changes and political instability. BDAI enhances SCAD through advanced sensing, scenario planning, and data-driven learning (Belhadi *et al.*, 2024; Wamba *et al.*, 2020; Wang *et al.*, 2024). AI abilities allowed the businesses to track weak indications such as early changes in customer choices or upstream disruptions and reconfigure operations before risks materialize. According to dynamic capability theory, adaptability is the firm's skill in recognizing chances and changing what is available to it. To assist in this, companies can use BDAI to make informed design changes to their networks, product portfolios and supply processes (Bahrami & Shokouhyar, 2022). In China's manufacturing sectors under pressure from higher trade restrictions and technology changes, those companies that adapt well, thanks to BDAI have managed to stay strong by designing in modules and sourcing from various places (Chen *et al.*, 2022). According to research, BDAI can be transformed into agility through people's adaptability. The (Wu *et al.*, 2024) documented that firms need flexible organizations and an ability to learn fast to be agile. In addition, being adaptable helps organizations become agile by focusing on learning, adding feedback to their plans and supporting important changes. Machine learning methods support this by repeatedly improving predictions and choices which allows an enterprise to become more flexible with time (Dennehy *et al.*, 2021). All in all, although BDAI delivers the technology for agility, how agile this relies to a large extent on SCAl and SCAD. Operational alignment is provided by SCAl and SCAD ensures structural flexibility in using BDAI's potential for fast progress. Because Chinese B2B manufacturing is unpredictable, these mediators turn information into practical action. Therefore, we proposed the following hypotheses.

H8: *Supply Chain Alignment mediated the link between BDAI and Supply Chain Agility*.

H9: *Supply Chain Adaptability mediated the link between BDAI and Supply Chain Agility*.

2.8 The Moderator Role of Market Turbulence Between Supply Chain Agility and Customer Relationship Performance

The dynamics of the global manufacturing landscape have triggered a heightened level of market volatility, which has happened in the form of unpredictable changes on consumer preferences, sudden fluctuations in demand, accelerated technological advancements, and heightened competition (Wamba *et al.*, 2020). MT has brought about sudden, ambiguous shifts in customer demography and tastes, thus changing the way businesses operated with a basic albeit paradigm shift in the supply chain management of customers and the business management as such (Gu *et al.*, 2021; Yu *et al.*, 2021). When markets are volatile, it can change things for B2B manufacturing firms linked to global supply networks. These issues include wrong demand forecasts, problems with supplier relationships, slow procurement and differences between production and what the market demands (Belhadi *et al.*, 2024). Challenging settings often cause companies to disappoint their clients since they don't change, move too slowly or blend their forces properly (Wu *et al.*, 2024). Organizations consider SCA a key strategic tool to react quickly to disruptions by changing operations according to trends in the marketplace (Ivanov, 2022). Even so, agility does not guarantee complete success in enhancing CRP, because various external aspects remain important. When the market is dependable, companies generally do not need to adjust operations and being agile might be seen as redundant or expensive with little use in terms of relationships (Wamba *et al.*, 2020). Meanwhile, when markets are highly unpredictable, being agile makes it easier for companies to meet customers' expectations, ensure all orders are right and let customers know about important changes promptly, thus raising both trust and satisfaction (Bahrami & Shokouhyar, 2022). In the study according to (Chin *et al.*, 2021) when faced with a lot of uncertainty, buying experience could be greatly improved simply through agile strategies.

Furthermore, (Sullivan *et al.*, 2023) state that flexibility with operations and schedules is especially important for firms in dynamic business settings which raises the relational value of agility. On theoretical level, the moderate effect being seen is in line with contingency theory that argues that the usefulness of any organizational capability will vary according to the external environment (Tian *et al.*, 2024; Yuan *et al.*, 2023). Agility provides better customer experience through preventing volatility in unstable environments without compromising the quality of provided services. This is an opinion that is supported by the dynamic capabilities model, where agility, market sensing, and speedy response is critical to coping with uncertainty (Teece, 2007). Moreover, when market volatility is high, customer loyalty decreases, and switching costs are lower. Firms that maintain responsiveness in such contexts can sustain trust, extend contract renewals, and earn reputational advantages (Bahrami & Shokouhyar, 2022; Belhadi *et al.*, 2024). The study theorizes that market instability enhances the favorable impact of SCA on customer relationship performance. One of the major areas of relevance of this effect is the histories of Chinese manufacturing firms facing the current trends in global trade policies, geopolitics, and fluctuating customer

demand. Experimental data showed that organisational agility significantly boosts CRP in a high-MT environment, thereby supporting the conditionally significant value of dynamic talent capabilities.

H10: *MT moderated the relationships between supply agility and customer relationship performance*.

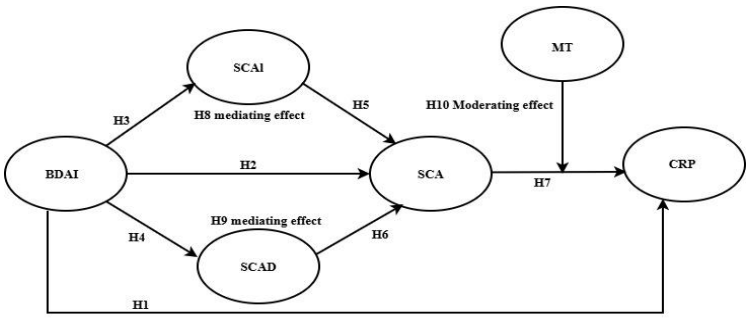

Figure 1 Theoretical Framework

3. METHODOLOGY

3.1 Sampling and Data Collection

The research investigates Chinese B2B manufacturing firms, focusing on the effect of AI-enabled BDA on supply chain capabilities and CRP. The scientific rigor and reduction of potential biases were accomplished by using multi-phase data collection process. During the first stage, a complete sampling frame was developed based on the consolidation of firm-level information in the official registries and it included the State Administration of Market Regulation (SAMR) and provincial governments directories in Shandong, Guangdong, Hubei, Liaoning provinces, and the province of Shaanxi. Eight hundred manufacturing companies out of 800 were chosen which represented almost all industries such as textiles, automotive, electronics, building materials, machinery, food and beverages and pharmaceuticals. Out of 800 contacted firms, 500 agreed to participate in the survey. The questionnaires, initially developed in English using validated scales from the literature, was subjected to a comprehensive translation and back-translation process (Brislin, 1970). The Mandarin translation was done by two linguistic scholars and highly qualified graduate students and semantic and cultural equivalence checked by bilingual scholars. The Mandarin translation was done by two bilingual academic supervisors and trained graduate students and then confirmed to be semantically and culturally equivalent by bilingual authorities. A back-translation was done by an independent translator into the English language and discrepancies were solved by the members of the study team through an iterative process.

Multi-wave, multi-respondent approach was applied to address issues that are related to common method bias (CMB). In the first stage (Time 1), 1000 questionnaires were sent to 500 organizations and it is expected that two main participants in the respective firms who happen to be supply chain and customer relation managers would respond. The Time 1 survey included demographic information gathered by respondents, including age, gender, education, and experience, and organisational data including global orientation, size, sector, and years of operation, of which 480 out of 240 companies were surveyed, and therefore, yielded a response rate of 48%. Eight weeks later, the second wave was conducted with firms that had completed the initial survey Table 1 represent the demographic factors. The Time 2 questionnaire included additional constructs aligned with the conceptual framework. A overall of 445 finalized responses were collected from 223 firms in this round. The final paired dataset which was obtained after eliminating non-matched and incomplete answers consisted of 434 valid responses of 217 firms. The design of the study, which is systematic, time delayed, and multi-source, contributes to authenticity and strength to the data and places with longstanding valid processes in research of a supply chain and organizational behavioral studies.

3.2 Measurement

The constructs of the study were measured and adopted from the published literature. The components of BDAI were obtained from (Chen *et al*., 2015; Dubey *et al*., 2020). SCA, SCAD and SCAl is adopted from (Iranmanesh *et al*., 2023). The assessment of market turbulence was adopted from (Ashrafi *et al*., 2019; Iranmanesh *et al*., 2023). Customer relationship performance was derived from (Hallikainen *et al*., 2020; Homburg *et al*., 2015). The variables were assessed, utilising 7-point Likert scale, ranging from "1 = Strongly Disagree" to "7 = Strongly Agree." The study entailed the adaption and modification of validated items from existing literature to align with its context. Thereafter, the content validity and face validity of the metrics were assessed via a pretest involving two technological specialists and five academics. The goods were changed according to their input. The modified survey was evaluated by 20 senior managers and academic professionals to determine the reliability of the constructs and to verify the clarity of the items (Maroufkhani *et al*., 2020). The Cronbach's alpha values for all adopted variables exceeded the recommended 0.7 threshold by (Hair *et al*., 2019), indicating reliable measurements. Appendix A represent a details measurement item.

3.3 Data Analysis

The Partial Least Squares Structural Equation Modelling (PLS-SEM) technique was utilised to examine the hypothesised linkages inside the study model. Due to the study's emphasis on prediction and its intricate framework, PLS-SEM was considered suitable, particularly for research related to theory development and exploratory analysis. The evaluation approach consisted of two phases: initially, the measurement model was assessed to determine the reliability

and validity of the constructs; then, the structural model was examined utilising a bootstrapping procedure, as recommended in prior methodological literature (Hair *et al.*, 2019).

Table 1 Demographic factor.

Demographic Factors	Category	Frequency	percentage
Global Orientation	Domestic only	57	13.13%
	Export only	188	43.32%
	Export and Import	167	38.48%
	Import only	22	5.07%
	Total	**434**	**100.00%**
Number of Employees	Below 50	55	12.67%
	51-100	134	30.88%
	101+	245	56.45%
	Total	**434**	**100%**
Operation years	Below 5 years	103	23.73%
	6 to 15 years	135	31.11%
	16+	196	45.16%
	Total	**434**	**100%**
Gender	Males	297	68.43%
	Females	137	31.57%
	Total	**434**	**100%**
Education Level	High School	56	12.90%
	Bachelor's	261	60.14%
	Master's and above	117	26.96%
	Total	**434**	**100%**
Manufacturing Type	Textile	67	15.44%
	Automotive	57	13.13%
	Electronics	97	22.35%
	Food and Beverages	56	12.90%
	Pharmaceutical	45	10.37%
	Plastic and Rubber	23	5.30%
	Others	89	20.51%
	Total	**434**	**100%**

4. RESULTS

4.1 Measurement Model Assessment

In line with the methodological guidance provided by (Hair *et al.*, 2019), The measurement model's reliability and validity were evaluated using four key indicators: factor loadings, composite reliability (CR), average variance extracted (AVE), and the Heterotrait–Monotrait ratio (HTMT). All item loadings exceeded the threshold of 0.70, confirming satisfactory indicator reliability presented in **Error! Reference source not found.**. The AVE values for all constructs surpassed 0.50, while CR values exceeded the 0.70 threshold, demonstrating robust convergent validity and internal consistency (Hair *et al.*, 2019). The HTMT criterion was employed to establish discriminant validity, as all inter-construct HTMT ratios remained below the advised threshold of 0.85. HTMT and fornell-larcker criterion, **Error! Reference source not found.** and **Error! Reference source not found.**, thus demonstrating the empirical distinctiveness of the constructs (Henseler *et al.*, 2015).

4.2 Measurement of Structural Model

The anticipated model clarified 42.37%, 23.12%, 72.17% and 21.07% of the variance (R^2) SCAl, SCAD, SCA and CRP. The Stone-Geisser (Q^2) values for all endogenous constructs were greater than zero, demonstrating the model's predictive capability. This study employed the bootstrapping approach to test the hypotheses. The Bias-Corrected and Accelerated (BCa) bootstrap technique was employed, and the significance level of two-tail test is 0.05, utilising 5000 resamples (Preacher & Hayes, 2008). The PLS path coefficients and their corresponding values of "p" have been reported in **Error! Reference source not found.**. According to the results BDAI significantly influences CRP (β = 0.149; p 0.042), agility (β = 0.45; p 0.00) and SCAl (β = 0.447; p 0.00), and SCAD (β = 0.292; p 0.00). supply chain alignment and adaptability significantly influence SCA (β = 0.169; p 0.001), (β = 0.134; p 0.007). The relationship among supply chain agility and customer relationship performance was supported (β = 0.264; p 0.038).

We performed a mediating analysis to examine the mediating role of supply chain alignment and adaptability between BDAI and supply chain agility, based on the concepts of (Henseler & Chin, 2010). **Error! Reference source not found.** presents the coefficients of the mediation paths along with their respective "p" values. Both the mediations path was partially mediated, through adaptability (β 0.039; p <0.015), through both placements (β 0.076; p

<0.03), BDAI effect through agility (β 0.119; p <0.045) was also significant. Hence, we supported H7, H8 and H9. Next, our hypotheses were tested for the moderation effect of MT. The moderation path (β 0.057; p <0.041) was significant but partial. Hence, we supported moderation.

Table 2 Measurement model assessment.

Construct	Items	F. loadings	α	CR	AVE
Big data analytics powered by AI	BDAI1	0.744	0.911	0.927	0.58
	BDAI2	0.759			
	BDAI3	0.706			
	BDAI4	0.775			
	BDAI5	0.772			
	BDAI6	0.800			
	BDAI7	0.778			
	BDAI8	0.775			
	BDAI9	0.766			
Market turbulence	MT1	0.833	0.734	0.0834	0.63
	MT2	0.683			
	MT3	0.851			
Supply chain agility	SCA1	0.794	0.911	0.927	0.613
	SCA2	0.845			
	SCA3	0.797			
	SCA4	0.754			
	SCA5	0.790			
	SCA6	0.755			
	SCA7	0.770			
	SCA8	0.766			
Supply chain adaptability	SCAD1	0.861	0.808	0.886	0.72
	SCAD2	0.853			
	SCAD3	0.834			
Supply chain alignment	SCAI1	0.821	0.804	0.872	0.63
	SCAI2	0.817			
	SCAI3	0.749			
	SCAI4	0.786			
Customer relationship performance	CRP1	0.834	0.844	0.889	0.67
	CRP2	0.747			
	CRP3	0.823			
	CRP4	0.861			

*Factor Loading > 0.7, Cronbach'salpha >0.7 *Average variance extracted >0.5

Table 3 Discriminant validity-Heterotrait–Monotrait ratio (HTMT).

	BDAI	CRP	MT	SCA	SCAD	SCAI	MT x SCA
BDAI	1						
CRP	0.076	1					
MT	0.068	0.083	1				
SCA	0.579	0.084	0.056	1			
SCAD	0.444	0.285	0.088	0.503	1		
SCAI	0.299	0.236	0.071	0.423	0.757	1	
MT x SCA	0.03	0.099	0.036	0.023	0.043	0.045	1

Note: HTMT ratios (best if < 0.85, good if < 0.90)

Table 4 Fornell-Larcker criterion.

	BDAI	CRP	MT	SCA	SCAD	SCAI
BDAI	0.764					
CRP	0.04	0.806				
MT	-0.047	-0.069	0.808			
SCA	0.54	0.021	-0.016	0.783		
SCAD	0.384	0.229	-0.068	0.446	0.85	
SCAI	0.256	0.181	-0.038	0.379	0.607	0.794

Table 5 Direct Hypotheses results**.**

Hypotheses	β	S. D	T-stat	P-val	LLCI	ULCI	Decision
H1. BDAI → CRP	0.149	0.073	2.036	0.042	0.009	0.292	Yes
H2. BDAI → SCA	0.45	0.05	9.077	0.000	0.354	0.548	Yes
H3. BDAI → SCAI	0.447	0.054	8.327	0.000	0.342	0.552	Yes
H4. SCAI → SCA	0.169	0.052	3.281	0.001	0.069	0.272	Yes
H5. BDAI → SCAD	0.292	0.053	5.521	0.000	0.187	0.396	Yes
H6. SCAD → SCA	0.134	0.05	2.693	0.007	0.038	0.232	Yes
H7. SCA → CRP	0.264	0.127	2.075	0.038	0.016	0.508	Yes

Table 6 Mediation and Moderation hypotheses results

Hypotheses	β	S. D	T-stat	P-val	LLCI	ULCI	Decision
H8. BDAI → SCAI → SCA	0.076	0.025	2.997	0.003	0.03	0.127	Yes
H9. BDAI → SCAD → SCA	0.039	0.016	2.425	0.015	0.011	0.073	Yes
H10. MT*SCA → CRP	0.057	0.028	2.044	0.041	-0.111	-0.003	Yes

5. DISCUSSION

The study explores the multifaceted relationships among BDAI, supply chain dynamic capabilities, SCA and CRP. Supply chain capabilities: adaptability and alignment in the supply chain are investigated, as well as how MT moderated the relationship between SCA and CRP. Results from our study support recent findings that BDAI makes it easier for firms to adjust to changes in the industry (Gunasekaran *et al*., 2019; Song *et al*., 2022; Wamba *et al*., 2020). Within the competitive landscape of Chinese B2B manufacturing, utilizing AI-driven data analytics enables prompt adaptations to fluctuations in supply and demand, hence improving firms' ability to retain uniformity in service and response from consumers. Importantly, we found that SCAl plays a significant role in linking BDAI to SCA. While BDAI technologies offer the technical framework of the insight and forecasts, its effectiveness is conditional on the ability of firms to reconcile strategic and operational goals at the internal level and external relations (Brusset, 2016; Lu & Ramamurthy, 2011). Misaligned objectives and inconsistent planning can impede the translation of analytics into synchronized action (Dennehy *et al*., 2021; Gunasekaran *et al*., 2019). Based on the latest studies, the adoption of SCAl can assist different supply chain partners to achieve a compromise concerning data and promote AI-based approaches in speeding up supply chains. Concisely, a robust SCAl assists businesses to collaborate to execute analysis-driven processes that reduce the amount of time to make decisions. As we continue to work, we also demonstrate that SCAD is also a significant factor in the process of BDAI attachment to SCA. Firms that use SCAD in complex and world-spanning B2B manufacturing networks can adapt to continuous external changes, whereas the addition of machine learning in BDAI enhances predictive capabilities of firms and gives them opportunities to make numerous modifications such as switching suppliers and changing production lines (Queiroz *et al*., 2022). Recent research reveals that when applying the BDAI system to SCAD, firms are able to use modular approaches and shift resources as needed to keep going during disruptions (Tian *et al*., 2024).

While the direct impact of SCA on CRP appears modest, the relationship is nuanced. Agility alone may not suffice for superior customer relationships (Pavlou & El Sawy, 2010), it must be complemented by consistent alignment and adaptability. Recent research indicates that customer agility which can be defined as the sense ability coupled with quick response to customer demands improves customer satisfaction and retention which improves performance (Pertusa-Ortega *et al*., 2025). Therefore, SCA in combination with SCAl and SCAD is the answer to the improvement of CRP. Agility must be embedded into an organisational structure that enables an organisation to co-exist between customer orientation and operational quickness. Agility used excessively without it being

structured and flexible may be a problem because it may result in the loss of service delivery or a mix of expectations (Patrucco *et al*., 2025). The custom nature of the solutions and their dependability on performance in the competitive B2B setting in China creates the need to implement a prudent combination of SCA, SCAl, and SCAD as a more sustainable approach to the improvement of CRP (Chen *et al*., 2022). They also discovered that environmental dynamism is a moderator, and agility becomes more significant not only to customer satisfaction and loyalty but also to the customer (Singh & Power, 2014). In large fluctuations in regulations and trading transitions, SCA increases the perception of valuable relationships in an organisation. In our study, we discovered that the improved SCA of enterprises allowed them to address the needs of the customers sooner, control their production cycles and lead the consumers through the transparency and flexibility (Ashrafi *et al*., 2019; Cui *et al*., 2023). The study results confirm with the DCV, highlighting that the significance of agility depends on environmental complexity and market volatility (Teece, 2007; Toorajipour *et al*., 2021).

The study emphasizes the significance of integrating digital transformation initiatives with relational and structural capabilities. Although BDAI tools like predictive analytics and real-time data visualization have been widely adopted among Chinese manufacturers (Tian *et al*., 2024), yet their effectiveness is profoundly influenced by organizational preparedness and cross-functional collaboration (Gregory *et al*., 2015; Song *et al*., 2022). Firms that combined the introduction of BDAI with strategic investment in the culture of sharing data, modular architecture, and the formation of partner trust reached their objectives of better relational performance and competitive advantage (Bag *et al*., 2021; Bahrami & Shokouhyar, 2022). In the study, the basic mechanisms of BDAI to improve SCA and consequently CRP under unstable conditions have been confirmed. It was discovered that the technological characteristics of BDAI should be employed in combination with the approach that promotes alignment, flexibility and environmental awareness. This perspective is associated with recent studies suggesting that it is necessary to consider digital technologies primarily as customer success drivers rather than more effective business processes (Cui *et al*., 2023; Wamba *et al*., 2020). The manufacturing industry of China is a good example of how both BDAI and digital revolution can be integrated into the supply chain (Ma & Chang, 2024). The Made in China 2025 initiative has also addressed the development of AI, robotics and automation, resulting in more resilient and efficient supply chains (Norman, 2024). JD Logistics have implemented AI-powered systems for order processing and route optimization, demonstrating the practical application of these technologies in developing SCA (Zhang *et al*., 2024). Moreover, the application of blockchain and IoT technologies contributed to making the supply chains more transparent and connected, which can make real-time decisions and mitigate risks. BDAI investments in B2B manufacturing management do not need to be much weight especially when combined with structures that ensure sound alignment and flexibility particularly in periods of uncertainty in the market. Agility and consistency have to be incorporated in order to guarantee boosted consumer trust and loyalty in the process of digital transformation works.

5.1 Theoretical Implication

This study validates DCV as a critical theoretical background for understanding how BDAI might enhance customer relationship performance through SCA, with SCAl and SCAD acting as vital mediators. This study when considered through the prism of DCV shows that BDAI does not simply act as an operational enabler but is a strategic resource reconfiguration process that enables firms to recognize, leverage and reorganize resources in accordance to the external volatility (Bahrami & Shokouhyar, 2022; Swafford *et al*., 2008; Teece, 2007). We added to the DCV by proving that digital transformation, powered by BDAI, enhance firm's capacity to adjust and respond fast in B2B industrial supply chains, a key aspect for staying ahead of competitors (Bahrami & Shokouhyar, 2022; Sullivan *et al*., 2023). It also shows that SCAl and SCAD are important for developing BDAI's skills into important strategic strengths. They illustrate just how much the tools an organization uses contribute to its functionality. Both BDAI and SCAl provide rapid data processing and decision-making, but BDAI concentrates on personal growth, whereas SCAl ensures the supply chain partners work together using the available knowledge (Brusset & Teller, 2017; Wamba *et al*., 2017). In addition, SCAD proves that businesses are able to keep adjusting to new developments in the market (Ivanov, 2020) . The (Gregory *et al*., 2021; Tian *et al*., 2024) agree that, in DCV frameworks, extra resources and business processes are necessary to link DCV enterprises with outside partners and help them handle their business operations. Adding market turbulence to the study enhances the usefulness of the DCV in the digital era. In times of great uncertainty, dynamic global firms tend to play a bigger and more important role in the company's strategy (Sullivan *et al*., 2023; Wamba *et al*., 2020). This emphasizes that the special value of agility is linked to changes happening outside the business (Dennehy *et al*., 2021; Waller & Fawcett, 2013). Consequently, this research contributes to the growing interpretation of how DCV can lead firms in harnessing BDAI capabilities for relational and competitive resilience, particularly in complex B2B manufacturing contexts.

5.2 Limitation and Future Direction

Even though the study was conducted carefully and the findings are supported by facts, some limits deserve closer consideration. The data gathered by the research was mainly from surveys and this approach can lead to distorted results because of bias and mental errors in reporting. These issues were minimized by employing statistical equipment but the work of future research could be based on obvious performance indicators or view the data in a different perspective. The research only concerned Chinese B2B manufacturing firms which restricted the usefulness of the findings for places or businesses outside this category. Later studies could explore data from various organizations or cultures to improve the study and confirm the framework. Apart from alignment and adaptability, using agile supply chain practices and working together on new ideas can help companies achieve success through BDAI. Subsequent research should investigate these additional mediators and their interaction effects to offer a more comprehensive

understanding of the relationship between BDAI and performance, big data analytics and customer relationship performance relations with supply chain alignment.

6. CONCLUSION

In conclusion, BDAI, as an emerging digital tool, enhances the effectiveness of customer relationship management in B2B manufacturing supply chains by improving agility. Cooperation among supply chain partners enables flexible operations, and dynamic capabilities play a crucial role in the business's digitalisation. Given the moderating role of market volatility, the contingency perspective becomes more powerful, showing that being agile is beneficial for retaining customers and meeting their needs, primarily in high-volatility markets. This research underscores the importance of companies adopting BDAI technologies and ensuring their internal teams and systems are flexible enough to support digital intelligence effectively. Monitoring market volatility helps organizations modify their agility strategies, so their technology boosts customer loyalty and keeps them ahead of the competition. This study fills gaps in academic literature on BDAI, dynamic capabilities, and customer relationship management by focusing on how organizations can manage complexity and avoid risks within today's B2B ecosystems. More research is needed to examine how these insights apply across different settings and to identify how these factors relate to digital transformation in the supply chain.

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CONFLICT OF INTEREST

The authors declare that they have no conflicts of interest.

DATA AVAILABILITY STATEMENTS

Data will be made available on formal request.

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Appendix A. Measurement Items

Construct	Measurement Items	Adopted from
Big data analytics powered by artificial intelligence	1. Suppliers analysis 2. Customer behavior analysis 3. Inventory planning 4. Transportation planning 5. Process and equipment monitoring 6. Warehouse operations improvements 7. Demand forecasting 8. Human resource management 9. Costing	(Chen *et al.*, 2015; Dubey *et al.*, 2020)
Customer relationship performance	1. The customer satisfaction is an achievement. 2. Present customers retention. 3. Quality of the products and services (e.g. greater customer benefit) 4. Customer structure (e.g. stable customer relationships).	(Hallikainen *et al.*, 2020; Homburg *et al.*, 2015)
Supply chain alignment	1. Our company's ability for process integration will be increased through the utilisation of Big Data Analytics, Artificial Intelligence, Internet of Things, and blockchain technology. 2. The functioning of blockchain will boost our firm's ability to connect sourcing, service processes, transportation, and other internal domains. 3. Our company's competence to link sourcing, transportation, examine processes, and other outer domains with suppliers will be enhanced through the utilization of Big Data Analytics, Internet of Things, Artificial Intelligence, and blockchain technology. 4. The amalgamation of sourcing, service methods, transportation, and other areas with customers will be enhanced through the utilization of blockchain technology.	(Iranmanesh *et al.*, 2023)
Supply chain adaptability	1. Our firm can swiftly alter the design in response to market demands by leveraging BDAI and blockchain technology. 2. Our firm can rapidly modify the production mix utilizing BDAI and blockchain technology. 3. Our organization can modify the quantity and quality composition of purchases through the utilization of BDAI and blockchain technology.	(Iranmanesh *et al.*, 2023)
Market turbulence	1. In the industry, consumer product preferences fluctuate significantly steadily. 2. Promotion methods within our product domain are always evolving. 3. The introduction of new products occurs with great frequency in this industry.	(Ashrafi *et al.*, 2019; Iranmanesh *et al.*, 2023)
Supply chain agility	1. Blockchain facilitates the reduction of production lead time. 2. Blockchain increases the rate of new product launches. 3. Blockchain helps improve the progress cycle time. 4. Blockchain enables improved product customization and customer service. 5. Blockchain improves delivery capabilities. 6. Blockchain and data-driven technologies facilitate adaptation to evolving market demands. 7. Blockchain improves delivery dependability. 8. Blockchain helps adjust to shifting market wants.	(Iranmanesh *et al.*, 2023)

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