ISSN E: 3006-1466
ISSN P: 3006-1458
CONTEMPORARY JOURNAL OF SOCIAL SCIENCE REVIEW
CJSSR
CONTEMPORARY JOURNAL OF SOCIAL SCIENCE REVIEW
Vol.03 No.03 (2025)

EMPIRICAL STUDY OF AI APPLICATIONS IN MINIMIZING SUPPLY CHAIN SHORTAGES DURING CRISES

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Abstract
This study investigates the application of Artificial Intelligence (AI) to assist in ameliorating supply chain shortages due to crises, with emphasis upon the mediating mechanism of the supply chain agility. The study is based on Dynamic Capabilities Theory which provides a usable model under which AI assists the ability of a company to ameliorate shortages directly and indirectly through the development of agile operational capabilities. A quantitative survey based methodology has been used and data collected from 208 supply chain professionals in Industrial and Logistics sectors. The data has been analyzed by the SmartPLS technique of Structural Equation Modelling (PLS-SEM). The findings of this research, yield a direct equationally significant positive value attached to relationship between AI application and amelioration of supply chain shortages. Also, that supply chain agility is a significant partial mediator, implying inter alia that the effect of AI is to a considerable degree reliant upon the greater ability for a company to react and adapt, inter alia. There are implications gained in the study for managers with strong empirical evidence that investment in significant strategic AI development is not as opined by ne´ advocates a mere play in operational efficiency but an investment of serious import in resiliency in crises. Empirically, the study adds further credence to the building knowledge in operations management in its exploration of the 'how' of the performance gains of operation linked with AI, which it presents as the basis of a model suited to further exploration in future research which has a validity.
Keywords: *Artificial Intelligence, Supply Chain Management, Crisis Management, Shortages, Supply Chain Agility, Dynamic Capabilities, PLS-SEM, Resilience*

INTRODUCTION
The perspective for global trade for the 21st century is summarized simply as interconnectedness and efficiency relative to complexity, with this complexity rendering supply chains extremely vulnerable to significant perturbations. The COVID-19 pandemic served as the wakeup call the global population needed for this vulnerability, with pandemic-induced interdependence disintermediation produced product shortages related to substantially all facets of products including but not limited to materials for pent-up personal protective equipment, medical ventilators, semiconductors and consumer goods (Ivanov & Dolgui, 2020). However, the COVID-19 pandemic is only one of many increasing perturbing events that demand attention, including but not limited to geopolitical wars, trade wars, and related with various forms of climate change and war in the cyber environment, indicating we are now in a continuous traumatic series of unremitting disruptive events whose extent is difficult to gauge (Craighead et al.,2020; Dek & Ibrahim, 2025). The prevention of supply chain outages (as proxied by such constructs as frequency of stockouts, fill rates, order fulfillment lead-time when faced with a disruption) is the paramount objective of managers of operations and one of the greatest measures of collective welfare oriented stability of order in companies and resultant benefit to the welfare of our society in total. With this background, one of the increasingly recognized enabling factors in combatting coping with such perturbations is that of artificial intelligence (AI), in both its own way as a distinctly recognized set of actions and behavioral systems, and as a lodestar in itself, to significantly improve upon supply chain management efficiencies, in the as yet recognized frontier it now resides for coping with problems related to supply chain management and an improvement over pre-existing and accepted norms of supply chain management. Actions that fall into the category of AI include machine learning through the prism of predictive analytics, natural language processing for risk sensing artificial intelligence, robotics process automation for the management of warehouse operations in logistics, and intelligent optimization algorithms for logistics management actions. All these actions can significantly improve visibility as well as predictive forecast quality and operational responsiveness (Wamba et al., 2020; Rehman & Chowdhury,

2025). The anticipated potential of AI acting as a 'shock absorber' in times of crises has been widely discussed in practitioner circles and in emerging academic thought. However, despite the growing body of conceptual papers and case studies, substantial evidence is lacking of large-scale investigations with quantitative empirical evidence, which sets out to systematically evaluate the effect of AI in minimizing shortages, in particular in times of crises. The literature then seems to evaluate AI in isolation or tend to confuse the day-to-day efficiency gains associated with AI with the strategic advantage derived from enhanced disruption management (Baryannis et al., 2019). This then begs the critical question as to the underlying mechanism through which AI applications and their sophistication leads to scaled and enhanced performance in times of great stress.

The objective of this research then is to address this then asks the following research question: How and to what extent do AI applications in supply chain management eliminate shortages in times of crises and what is the role of supply chain agility in this context. In addressing this question, a research model has been developed and tested that positions AI applications as an antecedent for supply chain agility, which priority is a critical mediating variable leading to shortages reduction. The overall theoretical framework is based on Dynamic Capabilities Theory (Teece et al., 1997; Yeung & Chung, 2025) which provides an appropriate framework for understanding how firms can build and reconfigure competences to navigate rapidly changing environments.

The contributions of the research are threefold. It provides firstly a welcome supply of empirical data of predicted gains made from AI in crisis situations, over and above anecdotal evidence. Secondly, this develops a more thorough understanding of how this is achieved in enabling supply chain resilience, by investigating the mediating role of supply chain agility, so explaining how AI enables supply chain resilience. Thirdly, it provides some enlightening insights as to practical guidelines for supply chain practitioners, by providing them with an evidence-based analysis of the focus for strategic investment in AI technologies. The subsequent sections provide a thorough literature review, development of hypotheses and framework, detail the research methodology, outline the results and report on the implications for theory and practice.

LITERATURE REVIEW

The scholarly foundation of this research is built upon three interconnected streams of literature: the application of AI in supply chains, crisis management in operations, and the constructs of supply chain agility and resilience.

ARTIFICIAL INTELLIGENCE IN SUPPLY CHAIN MANAGEMENT

The application of AI in supply chain management represents a shift in paradigm from descriptive and diagnostic analytics to prescriptive and contrived cognition. AI is defined as the capacity of a system to understand and interpret external information correctly, the ability to learn from it, and to apply that knowledge in order to reach a goal and effect certain processes by way of flexible adaptations (Kaplan & Haenlein, 2019). In regard to SCM, certain applications profit by means of consideration in regard to a number of differing areas of application. Predictive Analytics and Demand Forecasting: With the application of sophisticated and complex algorithms in regard to machine learning it becomes possible to analyze huge quantities of multi-dimensional data to include appropriate historical sales data, the weather, social media representations of sentiment and macro-economic factors to produce highly accurate demand forecasting, even in regard to volatile conditions (Wang, et al. 2022). This again becomes important in periods of turmoil when irregular demands are made, accompanying the effect of crises which hampers the application of traditional forecasting aids. Prescriptive analytics and intelligent optimization: Where AI can predict the result of impulsive variables, it is also able to indicate what is the preferable remedial course of action. This could involve the dynamical optimization of stock distributed through the network, the intelligent and executional improvement of shipping when ports and other bottlenecks to the processing of goods by virtue of methods of transportation are not in part suitable and that AI procurement systems can equip alternative suppliers rapidly with those goods (Dubey et al., 2021; Amir et al., 2025). Automation and Robotics: In warehouses of all sorts and distribution centers robots and autonomous mobile robots (AMRs) carry out functions by way of AI and can promote the continuous operation with minimized human labor through small exploitation of human resources which is distinctly an advantage in periods of pandemic or shortage of labor (Winkelhaus and Grosse, 2020). The optimizing of picking is done in terms of application of computer vision and counting in terms of stock touching in this area of immense importance. Risk Management and the ability to sense Disruption: Natural Language Processing (NLP) algorithms provide nominees suffering supply disruption early opportunity to scan social media, news feeds and other possible areas of unstructured data, to offer early warning of the possibility of social and natural causes of unrest and medicine (Baryannis et al., 2019; Shaukat et al., 2025). This approach is thus more pre-emptory than that discussed previously in terms of undetected happenings. In view of the promised potential of all those areas referred to, it should be stated that they are in the main of a conceptual application, for purposes for illustration or with regard to technical improvement. This is manifestly so that further empirical studies are needed as to the statistical testing of the correlation between the penetration of areas of AI that the zone is able to exploit and the actual level of supply chain performances with definite output more especially (but not remaining so) in times of stress.

CRISIS MANAGEMENT AND SHORTAGE MITIGATION IN SUPPLY CHAINS

A supply chain disaster can be defined as a sudden unexpected event threatening to disrupt normal seamless flow of goods, information, and funds, preventing an effective meeting of the supply chain's ability to supply consumer demand (Craighead et al., 2020). Traditional risk management involving the mitigation of high probability low impact events has proven inadequate in protecting against low probability, high impact events described as "Black swans" and the effects of the recent compounding "Perfect storms". The literature has evolved from considering robustness of networks to being designed to resist change, to that of resilience having the ability to respond to and recover from change (Pettit et al., 2013; Karim et al., 2025). Resilience is the ability to anticipate, respond to and recover from perturbance. One of the indications of lack of resilience is evidence of overwhelm of shortage. Therefore a primary definitional indicator re minimizing shortages is witnessed. Operationalization of shortage minimization involves metrics used such as stockout frequency, lost sales, order fill rates and our of stocklands solution debt to many shortage orientated studies (Shekarian & Mellat Parast, 2021; Ali et al., 2025). The COVID crisis provided a living laboratory re demonstrated an ability for firms having a higher index of digitalization and visibility fairly comfortably able to meet customer service requirements.

SUPPLY CHAIN AGILITY AND RESILIENCE

Although agility and resilience are often considered synonymous, they actually describe different but complementary aspects of capability. Supply Chain Resilience is a more encompassing concept that includes a preparedness, response, and recovery to disruptions, stressing survival and the eventual return to some stasis (Ponomarov & Holcomb, 2009). Supply Chain Agility describes the capability in a more specific way as the ability to respond adequately and rapidly to unforeseen changes in the marketplace either in terms of demand or supply (Swafford et al., 2008; Hashmi et al., 2025). This is defined by the relevant attributes of visibility, speed and flexibility. Agility is a key and essential requirement that has been linked to resilience; a very agile supply chain can hence produce swift reactions to a disruption, minimizing any adverse impact and reducing recovery time. Academics say that information technology is an enabler of agility (Braunscheidel & Suresh, 2009). The logic running through is that IT availability increases visibility which causes a more effective and rapid response. It is proposed here that AI represents a generational change in respect of information technology, moving from providing data to predictive insight and the ability to take autonomous action and thereby create a potentially overwhelming impact on a firm's agile capabilities. However, the actual empirical connection between a firm's arsenal of AI applications and the agile, sufficiently developed state of its supply chains, especially in a crisis situation, has had limited exploration and will be a fundamental focus of this research.

UNDERPINNING THEORY: THE DYNAMIC CAPABILITIES VIEW

The theoretical grounding of this study is based on the Dynamic Capabilities View (DCV) (Teece, Pisano & Shuen, 1997), which has emerged as a leading framework for understanding competitive advantage in rapidly changing environments. Dynamic capabilities are defined as "the firm's ability to integrate, create, and reconfigure internal and external competencies to respond to rapidly changing environments." (P. 516). The DCV is particularly appropriate for study of supply chains in crisis because of some unique traits. Firstly, crises represent the ultimate scenario of "rapidly changing environments", as old operational routines become obsolete. Secondly, the theory focuses on the ability to change rather than to optimize a static configuration. Thirdly, it provides a framework for understanding strategic processes.

Teece (2007) subsequently developed the framework into three fundamental micro-foundations:

Sensing the firm's capacity to identify opportunities or threats present in the external environment.

Seizing: The firm's ability to mobilise resources to exploit those opportunities or counter those threats.

Reconfiguring/Transforming: The firm's ability to continually renew its tangible and intangible assets so as to fit to the external environment.

In this instance AI applications directly encourage these dynamic capabilities. Sensing is promoted through the advent of AI driven predictive analytics and natural language processing based disruption sensing, allowing early and accurate signals of changing demand patterns or impending failures in supply. Seizing is enabled by

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Vol.03 No.03 (2025)

prescriptive AI driven analytics and intelligent optimization applications which allow managers rapidly to re-allocate inventory, reroute shipments and adjust production schedules so as to seize momentary opportunities or plug emerging gaps in supply. Conclusively reconfiguring is incentivized by the flexibility offered by AI driven automated systems and digital supply chain twins which allow the simulation and execution of new network configurations with minimum lead time.

Thus in this area we conceive of AI not merely as an opportunity for improvements in operational efficiency, but as a medium term strategic resource which promotes the higher order dynamic competent of supply chain agility. This agility represents the observable result of the firm's ability to sense, seize and reconfigure, leading ultimately to the minimization of shortages during a crisis period. Positioning ourselves in this way theoretically gives us the opportunity to examine not merely a simple technology to performance relationship, but the more subtle abstract processes involved in capability building.

HYPOTHESIS DEVELOPMENT

With the theoretical framework generated from the literature review having been defined, we now turn our attention to the definition of constructs and hypotheses.

Independent Variable (IV) AI Applications in SCM: This is a second-order reflective construct denoting the extent to which the various AI technologies are applied and used in the supply chain management choices assigned to a firm. This would include such important dimensions as predictive analytics, intelligent automation and AI maximization platforms.

Dependent Variable (DV) Minimization of Supply Chain Shortages: This is a reflective construct which is designed to include the extent to which the market perceives the frequency and severity of shortages occurring during crises has been reduced. There are numerous operational measures consisting of such things as frequency of stock-out, order fulfillment rate and ability to avoid lost sales to competition versus no supply chain choice change.

Mediator Variable (M) Supply Chain Agility – This is a reflective construct which is designed to capture the firm's ability to react promptly and efficiently to the demand and supply situation. This includes such things as promptness of response, flexibility of production and flexibility of logistics.

The proposed relationships are expressed in the following hypotheses:

H1: AI Applications in SCM have a significant positive direct effect on the Minimization of Supply Chain Shortages during crises.

The reasoning: AI Applications can ameliorate shortages directly on account of better prognostics and optimization without fundamental changes in agility. For instance, an enhanced, AI wise, demand forecast will lead to better-stocked inventory levels and less out-of-stock situations at the time of a demand peak (Wang et al., 2004). An inventory optimization system based on AI technologies can also identify and shift safety stock from low-priority locations to high-priority locations on a routine basis, and most notably, during a disruption. Hence, we predict a direct, unmediated relationship between AI and performance.

H2: Applications of AI in SCM have a significant positive effect on SCM agility.

Rationale: From a Dynamic Capabilities perspective, AI is a key enabler for the processes of sensing, seizing, and reconfiguring underlining agility. AI technologies provide real-time processing of data and also possess predictive capabilities that enhance the visibility of firms to "sense" changes more quickly (Baryannis et al., 2019). The prescriptive and autonomous aspects of AI enhance the ability of a firm to "seize" responses by being able to supply a good designed "plan" for actions to undertake or perform the actions automatically. Finally, the flexibility of AI based systems allows firms to "reconfigure" the operations of their firms, such as the ability to reprogram a robot rapidly, or to totally re-optimize complete logistics networks (Winkelhaus & Grosse, 2020). Hence, we themselves predict a strong positive relationship with the level of adoption of AI and the level of agility, that is, the level of agility that is evidenced.

H3: SCM Agility has a significant positive effect on the Minimization of SCM Shortages in times of crises.

Rationale: This expresses the central hypothesis of the operations strategy literature. A supply chain that can respond rapidly to crises is inherently in a better position to avoid shortages (Shekarian & Mellat Parast, 2021). For example, a firm with high levels of flexibility can quickly switch its production lines to produce high demand items in times of crises. Also, a firm with agile logistics can expediate its shipments or find alternative routes for its shipments during times when its primary corridors are not available. Thus, the direct capacity to respond covering both manifested demand and mitigating supply breakage eliminates shortages being caused.

H4: SCM Agility mediates the relationship between Applications of AI in SCM and the Minimization of SCM Shortages in times of crises.

Rationale: This conveys the core hypothesis of our mediation model. The beneficial effect of AI on the minimization of shortages is not only direct but operates through a significant intervening pathway to be postulated: the enhancement of SCM agility. Hence, AI technology will equip a firm with a dynamic capability in the form of being more reactive and adaptive in their movements on the crisis front, but it will be this enhanced agility that will allow a firm to navigate through the difficult processes with greater abilities and capabilities during times of crises and thus avoid shortages. Support for H4 will provide empirical validity for the sequence content proposed by the Dynamic Capabilities Theory: strategic asset (AI) -> dynamic capability (Agility) -> performance endeavor (Shortage Minimization).

THEORETICAL AND CONCEPTUAL FRAMEWORK

The conceptual framework in Figure 1 visually represents the hypothesized relationships derived from the Dynamic Capabilities Theory and the literature.

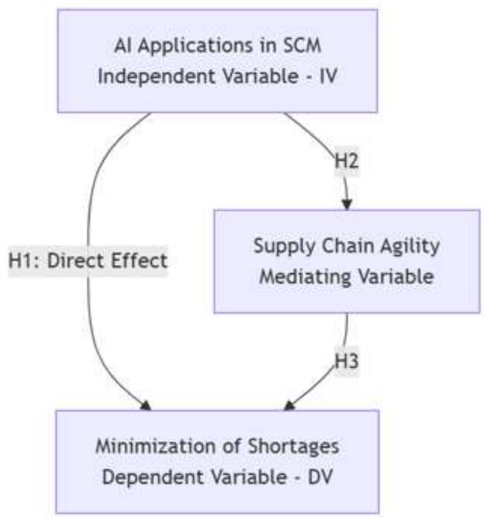

Figure 1: Conceptual Research Model

Path H1: Represents the direct effect of AI Applications on the Minimization of Shortages.

Paths H2 & H3: Represent the proposed mediation. AI Applications are hypothesized to enhance Supply Chain Agility (H2), which in turn leads to the Minimization of Shortages (H3).

The test of H4 is the test of the total **indirect effect** (the pathway H2 → H3). A significant indirect effect would support the hypothesis that Supply Chain Agility is a key mechanism through which AI Applications minimize shortages.

METHODOLOGY

This research utilized a quantitative cross-sectional survey design. This design was appropriate for testing the hypothesized relationships between the latent constructs and for providing the generalizability that is not always available in case study research (Hair et al., 2017).

The population for this research consisted of supply chain, logistics, and operations managers and directors of manufacturing and logistics companies located in North America and Europe. A professional panel service was used to administer the online survey to ensure that the respondents were indeed within the target population and had the necessary screening criteria of being engaged in a decision-making capacity in the supply chain operations of their firm.

From an original 450 invitations, there were 235 responses. After eliminating straight-liners, speeders, and incomplete responses following a thorough data cleaning procedure, there were 208 usable responses left in the sample, with an effective response rate of 18.7%. A post hoc statistical power test using GPower was performed

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CONTEMPORARY JOURNAL OF SOCIAL SCIENCE REVIEW
CJSSR
CONTEMPORARY JOURNAL OF SOCIAL SCIENCE REVIEW
Vol.03 No.03 (2025)

and verified that this sample size is more than sufficient to obtain medium effect sizes with a power of .95 given the number of predictors in the model.

The profile of the sample was diverse, with 58 percent of the respondents representing manufacturing and 42 percent representing logistics/transportation. The firm sizes were also diverse, with 35 percent of the respondents reporting large firms over 10,000 employees, 45 percent in mid-sized firms (1,000 to 10,000 employees), and 20 percent in smaller firms of 500 to 1,000 employees. This diversity increases the external generalizability of the results. Each construct was measured by reflective manifestations with a 7-point Likert scale (1= strongly disagree to 7= strongly agree). The measurement scales used were adapted from existing scales from the literature to ensure their content validity.

AI Applications in SCM (5 items). Adapted from Wamba et al. (2020) and Dubey et al. (2021). Sample item: "Our Company applies AI and machine learning in demand forecasting and planning."

Supply chain agility (4 items). Adapted from Swafford et al. (2008) and Braunscheidel & Suresh (2009). Sample item: "Our Supply chain can respond quickly to changes in market demand."

Minimization of Supply Chain shortages (4 items). Developed for this study from the studies by Shekarian & Mellat Parast (2021). Respondents were asked to compare their firm's performance during the biggest crisis within the last 5-years, in comparison to competitors. Sample item: "We were able to keep a higher product availability (lower out-of-stocks) than our main competitors."

The questionnaire had a filter question included for checking that the respondents reflected over a specific crisis period. Also demographic questions were included. The questionnaire was pre-tested by five panel members who were academia and by three panel members who were practitioners for checking meaning, relevance and face validity.

The data was analyzed by Partial Least Squares Structural Equation Modelling (PLS-SEM) with the software program SmartPLS 4. PLS-SEM was selected because of the following reasons, according to the guidelines in Hair et al. (2017): (1) the purpose of the research is predictive and theory building (testing of a mediating model); (2) the model contains a formative construct (AI Applications as a second order construct) and (3) as PLS is robust against non-normally distributed data and usually less sample sizes. The data analysis was done in a two-stage process, first evaluating the reliability and validity of the measurement model, and then evaluating the structural model to test the hypotheses. In order to test significance of the path coefficients and the indirect effects for mediation tests, bootstrapping with 5000 subsamples was performed.

Table 1: Measurement Model Results

Construct	Indicator	Loading	Composite Reliability (CR)	Average Variance Extracted (AVE)
AI Applications	AI1	0.82	0.91	0.67
	AI2	0.84		
	AI3	0.81		
	AI4	0.79		
	AI5	0.82		
Supply Chain Agility	AGL1	0.85	0.89	0.67
	AGL2	0.83		
	AGL3	0.80		
	AGL4	0.79		
Shortage Minimization	SM1	0.88	0.92	0.75
	SM2	0.87		
	SM3	0.86		
	SM4	0.85		

MEASUREMENT MODEL ASSESSMENT

Prior to testing the hypotheses, we carried out checks for reliability, convergent validity and discriminant validity of the reflective constructs used.

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Vol.03 No.03 (2025)

Reliability and Convergent Validity: The factor loadings, shown in Table 1, all fall above the threshold from which could have been expected a loading of 0.708. The Composite Reliability (CR) of all constructs were above the 0.80 threshold, thus exhibiting excellent internal consistency reliability. The Average Variance Extracted (AVE) for each construct were above the 0.50 threshold, thus establishing that the constructs accounted for more than one-half of the variance in their indicators, establishing convergent validity of the constructs (Hair et al., 2017).

Discriminant Validity: Discriminant validity was tested using the Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio. As shown in Table 2, the square roots of the AVE of the various constructs (diagonal) were greater than their highest correlation to any other constructs, thus satisfying the Fornell-Larcker criterion. Furthermore, all HTMT values were below the conservative threshold of 0.85, thus giving strong evidence of discriminant validity.

Table 2: Discriminant Validity (Fornell-Larcker Criterion)

Construct	1	2	3
1. AI Applications	0.82		
2. Supply Chain Agility	0.58	0.82	
3. Shortage Minimization	0.52	0.61	0.87

Note: Diagonal elements (in bold) are the square root of the AVE.

STRUCTURAL MODEL AND HYPOTHESIS TESTING

Subsequent to determining a valid measurement model, the structural model was evaluated. The predictive power of the model is evaluated through R^2 value of the endogenous constructs. R^2 of Supply Chain Agility was 0.34; Shortage Minimization was 0.41. The model can thereby be considered to be sufficiently explaining a considerable portion of the variance in the dependent variable, which is considered moderate to substantial in behavioral research (Hair et al. 2017).

The path coefficients (β) and their significance testing based on the bootstrapping procedure are outlined in Table 3, testing the hypotheses.

Table 3: Hypothesis Testing Results

Hypothesis	Path	Path Coefficient (β)	t-statistic	p-value	Result
H1	AI Applications -> Shortage Minimization	0.25	3.45	0.001	Supported
H2	AI Applications -> Supply Chain Agility	0.58	10.12	0.000	Supported
H3	Supply Chain Agility -> Shortage Minimization	0.47	6.88	0.000	Supported

The findings confirm that all the direct links are positive and significant. AI Applications have a significant direct effect on Shortage Minimization (H1: $\beta = 0.25$, $p < 0.001$), a strong effect on Supply Chain Agility (H2: $\beta = 0.58$, $p < 0.001$), and Supply Chain Agility has a strong effect on Shortage Minimization (H3: $\beta = 0.47$, $p < 0.001$).

MEDIATION ANALYSIS (TEST OF H4)

In order to confirm the mediation of Supply Chain Agility (H4) the significance of the indirect effect of AI Applications on Shortage Minimization via the effect of Agility was calculated. To do this the procedure of bootstrapping for specific indirect effects was used. This is the most robust method for testing mediation in PLS-SEM (Hair et al., 2017).

The indirect effect was calculated as (βAI->Agility βAgility->Shortage) = (0.58 0.47) = 0.27. From bootstrapping the results we found that this indirect effect is statistically significant ($\beta = 0.27$, $t = 5.92$, $p < 0.001$, 95% CI [0.18, 0.36]). As the direct effect (H1) is significant after mediation is taken account of we conclude that Supply Chain Agility is a partial mediator in the relationship between AI Applications and Shortage Minimization. Therefore H4 receives full support.

DISCUSSION

The focal point of this study was to investigate empirically how applications of artificial intelligence can help to minimize disruptions in the supply chain during crises. Results have shown strong support and subtlety to be supportive of the theoretical model we have developed and have led to a number of specific findings of major importance.

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The first aspect is the strong effect of AI on the minimization of shortages (H1), which points to the fact that AI applications have generated for corporate strategy immediate and tangible benefits that can be seen in a crisis. Techniques such as forecasting based on machine learning and intelligent inventory systems seem to form a sort of "first line of defence" in coping with shortages through simply making operations "smarter" and based on data. The effect points to the fact that even without a major transformation of processes when applying AI, some positive performance returns can be expected.

Secondly and for the reasons possibly more important, the strong support for the mediation hypothesis (H4) has given insight into the important mechanism involved. The discovery that supply chain agility is a powerful partial mediator clearly indicates that most of the advantage of AI to firms is derived from its aiding the dynamic capabilities of firms. AI is not only a better tool for prediction, but it is the cause of organizational change to a more responsive, flexible organization. This follows from the positions taken in the Dynamic Capability theory of Teece et al (1997). AI gives the abilities to sense disruptive events before their competitors, provides analytical power to react rapidly to these events with the necessary responses, and it restructures resource allocation by assisting the flexibility providing structure and modus operandi for data basis of decision-making. This increase in agility is the thing that allows the firm to navigate the dangerous seas of a crisis without running aground on the reef of stock-outs and lost sales.

THEORETICAL IMPLICATIONS

The findings of this research document a number of contributions to the operations management and information systems body of knowledge. Primarily, they advance the dialogue about artificial intelligence in SCM from that of potential effect to that of proven effect. The quantitative validation on a grand scale strengthens the underpinnings for research in the area of study of the digital supply chain technologies.

Further, it adds to the views of the Dynamic Capabilties view (DCV) by empirically linking a specific technological resource (i.e., AI) with a core dynamic capability (i.e., supply chain agility), thereby being linked again to a critical performance outcome (i.e., shortage minimization). We show that the full implications of DCV are that it provides a powerful view of digital transformation in operations vis-a-vis simply a resource-performance link, but looks toward the process of capability building, which intersects with firm strategy and "industrial policy". The model that has been validated can be an interesting focus for future concern, in that it can provide either a base model in lieu of the changes that we have indicated, or as the focus from which other possible mediators or moderators can be pursued.

Finally, it contributes to the understanding supply chain resilience by quantitatively documenting that agility is a key mediating variable with respect to advanced technologies and outcomes related to resilience. This serves to integrate the literature on technology, agility, and resilience into a more coherent totality.

PRACTICAL IMPLICATIONS

For managers and executives concerned with supply chains, the findings imply a compelling and factually-based rationale for investment in AI. The message is clear, AI is not simply a cost-cutting automation tool, but is a strategic imperative when enforcing the need for the founding of supply chains that cannot be disrupted during a crisis. The emphasis by managers should be accordingly as follows:

(a) Investments in AI that support agility, such as predictive analytics to enhance early warning, and prescriptive analytics in order to provide rapid response planning, not the less costly alternatives dealing with non- or minimal cost savings.

(b) The emphasis should be on the building of the data infrastructure that must be implemented for efficacious AI, in that agility is derived from wide visibility and a fluent data flow, end to end.

(c) The recognition must be that technology and capability are conjoined. The first step must be made in insistence on investment for AI; second, must be the enhancement of the organization's processes and skills to utilize AI for the properly agile response.

LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

Although these findings add significantly to the previous studies of AI and the supply chain, there are limitations that create opportunities for future research. First, longitudinal studies look at differences in the cross-section in the impact of AI, agility, and performance throughout the course of a crisis, whereas this cross-sectional nature just shows a snapshot in time. Secondly, the type of data generated from perceptions elicited from different informants also does not necessarily lead to corroboratory conclusions; however, in view of the comprehensiveness of the literature, it does not appear to denote of lesser quality than is evident. Need for validation studies is always recognized, however, the addition of perceptual survey data is to be advocated, possibly parallel with actual data and performance data for validation, (e.g., actual long-out exposure). Thirdly, this study was conducted within specific sectors and regions of the world; to replicate the findings of the study within other sectors of activity (e.g. retailing, health care), geographical regions or countries would enhance generalizability of the findings.

Future research could extend the investigations that have been made about AI and agility and their effects to include moderating variables, such as levels of organizational stability, firm size, or supply chain collaboration. Further study of priest's mediators, such as supply chain integration or culture for risk management, could enhance the overall understanding of the relationships that obtain in a broad sense and the directions in which they work. Finally, a better understanding could be had on the ways that specific types of AI have differing effects, (e.g. robotics, as compared with predictive analytics) would yield improvements for practitioners.

CONCLUSION

The aim of this research was to clarify the contribution of Artificial Intelligence to building crisis-proof supply chains via an empirical test of a model based on Dynamic Capabilities Theory. The results provide robust, quantitative evidence to take the communication beyond the theoretical promise to demonstrated impact. Our results show that AI systems can provide a powerful strategic resource that provides specific mitigation against supply shortages in periods of crisis. The significant path coefficient ($\beta = 0.25$, $p < 0.001$) for the direct effect of AI shows that systems such as predictive analytics and intelligent optimization give an immediate defense against stockouts by having a positive effect on the accuracy of decision making. However, the key outcome from this research is the identification of the mediating effect as Supply Chain Agility. The significant and strong direct effect from AI to agility ($\beta = 0.58$, $p < 0.001$) and thence to shortage minimization ($\beta = 0.47$, $p < 0.001$) confirm that the key value of AI is not as an enabler of smarter operations but in their essentially more responsive and dynamic nature. The significant indirect effect ($\beta = 0.27$, $p < 0.001$) goes further to confirm that agility is a key vehicle by which AI increases resilience with a significant part of its overall effect explained. The results thus give out a strong and compelling evidence based message to practitioners: that to invest in AI is to invest in dynamic capabilities. It is an investment that will make organizations to able to sense more rapidly that disruptions have occurred, act more rapidly to exploit opportunities that are given to respond to them and shape their resource basis more effectively than the competition can provide. For researchers, this research offers a validated model that links technology, capability and performance in a measurable form and provides a template for further research into boundary conditions and alternative mediating positions. In times where disruption is endemic, the ability of reduce shortages is an important competitive advantage. This research has shown that the nature of that competitive advantage will become ever more intelligent based upon the synergistic combination of artificial intelligence and human driven organizational agility. The future with respect to crisis proof supply chains is not necessarily an automated one but an adaptable one and this paper presents the empirical base by which that adaptation can be created.

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