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Explainable artificial intelligence and agile decision-making in supply chain cyber resilience

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ABSTRACT

Although artificial intelligence can contribute to decision-making processes, many industry players lag behind pioneering companies in utilizing artificial intelligence-driven technologies, which is a significant problem. Explainable artificial intelligence can be a viable solution to mitigate this problem. This paper proposes a research model to address *how explainable artificial intelligence can impact decision-making processes*. Using an experimental design, empirical data is collected to test the research model. This paper is one of the pioneer papers providing empirical evidence about the impact of explainable artificial intelligence on supply chain decision-making processes. We propose a serial mediation path, which includes transparency and agile decision-making. Findings reveal that explainable artificial intelligence enhances transparency, thereby significantly contributing to agile decision-making for improving cyber resilience during supply chain cyberattacks. Moreover, we conduct a post hoc analysis using text analysis to explore the themes present in tweets discussing explainable artificial intelligence in decision support systems. The results indicate a predominantly positive attitude towards explainable artificial intelligence within these systems. Furthermore, the text analysis reveals two main themes that emphasize the importance of transparency, explainability, and interpretability in explainable artificial intelligence.

1. Introduction

Automotive industry leaders, such as Tesla, have made substantial investments in artificial intelligence (AI) to expedite the introduction of self-driving vehicles to the market, enhancing their competitive capabilities. The integration of AI in supply chain operations has played a crucial role in enabling Tesla to optimize its operational costs [64] while simultaneously facilitating the establishment of a Gigafactory in China [78]. We are witnessing a rapid digital transformation driven by the integration of AI in supply chain management. The COVID-19 pandemic forced companies and organizations to expedite the digitalization of their operations [6]. To enhance their competitive edge, prominent companies, including Amazon, Walmart, Alibaba, Siemens, and Toyota have embraced AI-based technologies to automate and digitalize their operations and supply chain activities [1,32]. Digital transformation also introduces new possibilities for potential cyberattacks. However, using AI-based technologies for decision-making during cyberattacks (e.g., American Express monitoring; [75]) offers significant advantages that outweigh the potential losses incurred.

Although AI-based technologies can contribute to decision-making processes in operations and supply chain management, many industry players are lagging behind pioneering companies in utilizing AI-driven technologies, which is a main problem. Therefore, the adoption of AI-based technologies in decision-making processes, particularly during sensitive situations such as cyberattacks, may encounter potential barriers that delay their usage. Due to its vital advantages, AI has received much attention from decision-makers to address resilient case studies [45] and other sensitive problems such as healthcare [69]. The lack of

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explanations of the underlying AI processes leads to the rejection of AI in decision support systems [60]. Leveraging AI-powered decision-making platforms can significantly facilitate and expedite the decision-making process, which results in improved overall performance. For instance, the Colonial Pipeline, a U.S. oil supplier, faced a cyberattack and, after a week of deliberation, opted to pay around $4.4 million to solve the issue [21]. A quick decision on the first day through agile decision-making could have saved them money and enabled the uninterrupted continuation of their operations with stockholders.

Prior work has indicated that explainable artificial intelligence (XAI) can be a viable solution to facilitate AI-based technologies in decision-making platforms in supply chain management [57]. XAI refers to a detailed and illustrative presentation of machine learning algorithms that decision-makers can understand and trust [18,34,51,79]. XAI describes AI models and their anticipated effects and identifies and mitigates potential biases [57]. XAI can significantly contribute to decision-making by mitigating AI-based technology concerns [43]. AI algorithms' results are not understandable, even by engineers who perform the algorithms. In supply chain management, AI algorithms are referred to as "black boxes," which reflects the difficulty in considering them as decision-making tools. XAI adds explainability and interpretability to AI-based technologies, which contribute to implementing AI in critical domains, including supply chain management, insurance, and education [2,18,72]. Due to their simplicity, some machine learning algorithms, such as linear regression and k-means clustering, are widely employed in supply chain management. However, the adoption of deep learning algorithms remains limited due to their black-box nature and despite their better accuracy compared to linear regression algorithms. XAI offers a solution by providing comprehensive explanations in simple language, which results in using deep learning algorithms. Explaining Bayesian networks to non-experts is a classic example of XAI [10,69].

Past review papers have identified the potential role of XAI in business environments (e.g., [2,8,42,46,57]). However, there needs to be more research on the role of XAI in decision-making processes. Thus, the research question is, *How can XAI impact decision-making processes*? This paper addresses this research question by providing a conceptual model, including hypothesized relationships. Empirical data is collected to test the research model. This paper is one of the pioneer papers providing empirical evidence to explain how XAI can impact decision-making frameworks and the consequences of XAI in business environments.

Through a serial mediation path, this paper contributes to decision-making models by investigating the relationship between XAI and cyber resilience, which refers to a supply chain's capacity to prevent a cyber-related disruption, continue uninterrupted business operations, or efficiently restore its initial state [55,56]. We introduce the mediating role of agile decision-making and AI transparency in the hypothesized relationships in the research model. Agile decision-making refers to a decision-making capability involving all stakeholders to respond quickly to changes using accumulated information and knowledge [33,81]. Past research has revealed that companies could mitigate supply chain disruptions using agile decision-making, which is critical in building supply chain resilience [15]. Moreover, AI transparency can improve agile decision-making, which refers to the degree to which an AI system discloses information regarding its functions and operations [80].

The rest of this paper is organized as follows: The next section provides theoretical support and presents the research model. Section 3 provides the methodology. Section 4 explains the results. Finally, Section 5 provides a post hoc analysis, and Section 6 discusses the results.

2. Theoretical support and research model

Practice is "a defined activity or set of activities that a variety of firms might execute" ([14], p. 1). There is a high possibility for practice (e.g., XAI) to positively impact firms' performance (e.g., supply chain cyber resilience). This impact can be different for firms based on various enablers and elements (e.g., AI transparency and agile decision-making) applied by firms. The practice-based view (PBV) theory explains and elaborates on this phenomenon [14]. PBV theory is founded on the resource-based view (RBV), which assumes that organizational practices are both rare and difficult to replicate among different organizations [14]. PBV explains the effect of exogenous variables on performance, whereas RBV assesses how these variables influence competitive advantages in buyer-supplier relationships [14]. PBV identifies practices as principal actors that can be adopted and replicated by other firms to enhance performance. Conversely, the RBV focuses on resources that are unique and inimitable by competitors. PBV has received significant attention in past research, aiming to explain phenomena in business environments (e.g., see [41,59,66,67]).

2.1. XAI and supply chain cyber resilience

Innovative solutions through digital technologies offer unparalleled opportunities for organizations and supply chains [48]. Technological innovation plays a crucial role in addressing challenges and changes in business models [22,47]. There is a growing focus on digital innovations to enhance performance [48], and recent technological developments are enhancing buyer-supplier relationships [12]. As a new technological innovation, AI systems make computers intelligent by using prior information. Three main parts create AI systems: input (available data), models (algorithms), and output (decisions or predictions). A fundamental limitation of AI is its inability to describe its decision-making processes or recommendations, which is why it is referred to as a black box [43,50]. Addressing this challenge, XAI can provide valuable insights into the rationale behind AI outcomes. Using XAI techniques, we can provide a deeper understanding of the underlying factors that drive AI recommendations. As previously defined, XAI is an approach that aims to present machine learning algorithms in a manner that is comprehensible and reasonable for decision-makers [34].

An XAI-driven system creates an enhanced level of collaboration between machines and humans. For example, consider an AI system designed for inventory management. The XAI-driven tool not only predicts stock levels with high accuracy but also explains its forecasts in terms understandable to human managers. It is akin to having a perpetual supply chain expert at hand, one who not only provides recommendations on when to reorder stock but also explains the rationale behind these suggestions based on real-time market trends, historical data, and predictive analytics. In supply chain management, segmentation is one of the essential decisions used to group products, customers, and suppliers based on specific criteria such as risk and profit. Using XAI, supply chain managers can analyze the underlying causes behind segmentation (e.g., which factor is the leading player), thereby leveraging their intuition and experience to improve the overall process.

Supply chain cyberattacks occur in environments with massive amounts of data, which can be used in AI-protection systems. Sensitive supply chains such as those in the pharmaceutical, healthcare, and food sectors are highly regulated and entail severe consequences in the event of errors. This renders them well-suited for the adoption of XAI. Intelligence is a principal aspect of resilient supply chains [15]. XAI can contribute to supply chain cyber resilience in three main areas: cyberattack detection, business continuity, and recovery to normal situations.

Limitations hinder AI's effectiveness in fraud detection. Anomaly detection algorithms flag deviations from past patterns, but the inconsistency of human behaviour necessitates additional measures beyond anomaly identification, whereby XAI is helpful. XAI interpretability helps managers assess the reliability and accuracy of the AI system by identifying potential vulnerabilities and making informed decisions regarding cyber threat mitigation strategies. XAI can improve cyber resilience, after which human experts can validate and refine the output of AI models and contribute to their contextual knowledge to improve detection accuracy.

In addition, XAI can offer decision-makers clear and comprehensible alternatives during cyberattacks, thereby expediting the decision-making process. A recent missed XAI opportunity is the cyberattack targeting the Colonial Pipeline, a major oil supplier in the United States. After a week of deliberation, the company paid approximately $4.4 million to resolve the issue [21]. Last but not least, XAI plays a vital role in the recovery stage by offering comprehensive scenarios of available business continuity plans and their anticipated outcomes, thereby aiding in effective decision-making and facilitating the restoration process. XAI is a practice in every company. The theory of PBV defines a practice as "a defined activity or set of activities that a variety of firms might execute," which is "publicly known, imitable, and amenable to transfer across firms" ([14], p. 1). Therefore, the hypothesized relationship is as follows:

H1. Explainable artificial intelligence correlates positively with supply chain cyber resilience.

2.2. XAI and AI transparency

Machine learning algorithm outcomes are more understandable and transparent using XAI techniques such as LIME (local interpretable model-agnostic explanations; [43]), RETAIN (reversed time attention; [16]), and LRP (layer-wise relevance propagation; [9]). LIME is a post hoc model of prediction accuracy techniques, which operates as a technique providing explanations and transparency after a decision-making process. A notable advantage of LIME is its model-agnostic nature, enabling its application across various model types. The methodology of LIME entails perturbing or subtly modifying the model's inputs to examine the resulting changes in outputs. This facilitates the identification of inputs that exert the most influence on the outputs, thereby offering valuable insights into the model's decision-making process [43]. RETAIN is an XAI technique focused on healthcare applications to provide transparency, for example in heart failure diagnoses [44]. By achieving comparable predictive accuracy to other models, RETAIN provides valuable insights into the influential factors within the clinical data that contribute to the occurrence of heart failure [16]. LRP operates reversely within a neural network, identifying the input values that hold the maximum weight in determining the corresponding output [9].

Using traceability techniques such as *DeepLIFT* (deep learning important features; [61]), XAI can mitigate concerns about a lack of transparency in AI systems, which is a significant drawback [43]. AI transparency is the extent to which AI information is disclosed, encompassing positive and negative aspects (S. [37]). XAI is the main contributor to visibility in AI systems [2]. XAI enables non-experts to comprehend and articulate the underlying rationale of AI systems, which provides a deeper understanding of their decision-making processes. This empowers individuals without specialized expertise to effectively explain and interpret the functioning of AI systems [74]. XAI can create transparency in AI systems by making information available regarding AI functions and operations (B. [36,80]). Based on the PBV theory, within companies, XAI techniques are activities that are replicable, widely known, and can be imitated, thereby enhancing organizational processes [14]. Thus, we can hypothesize the following:

H2. Explainable artificial intelligence correlates positively with artificial intelligence transparency.

2.3. AI transparency and agile decision-making

In competitive environments, quick and collaborative decisions are essential for promptly addressing business needs [49]. Decision support systems have recently been used to employ agile decision-making to sustain their competitive advantage. In agile decision-making, the best information should be available for stakeholders to quickly address changes [33,81]. Therefore, agile decision-making requires collaborative and transparent processes.

Technology is essential to developing agile decision-making [19]. For instance, AI systems can significantly influence agile decision-making [17,20]. To make well-informed decisions, decision-makers utilize a combination of assessments, which can be improved by a comprehensive understanding of decision processes and outcomes [70]. In other words, clear and understandable information can improve agile decision-making [73]. AI techniques are highly recommended in decision support systems [68] because their transparent processes help decision-makers respond quickly to a change. When AI systems are transparent, their processes, algorithms, and decision-making criteria are clear and understandable to all stakeholders. For example, consider a decision tree algorithm, which is often used in machine learning for classification problems. The decision tree algorithm is transparent in the sense that it provides clear and interpretable rules that lead to a decision. Each node in the tree represents a decision point, and the path from the root to a leaf node illustrates the reasoning process of the algorithm. Stakeholders can follow these paths to understand the criteria used at each stage of the decision-making process. This transparency allows stakeholders, even those with limited technical expertise, to comprehend how the AI system arrives at its conclusions, fostering trust and facilitating more informed decision-making across the organization. AI transparency improves decision-making criteria and the performance of AI algorithms. Therefore, an agile decision-making system with transparent AI techniques can make AI-based decisions clear and understandable for all stakeholders by creating a collaborative environment where a change is quickly addressed. A report from IBM indicates that a majority of Europeans and Americans have called for transparency in AI, especially when such systems are utilized in decision-making [27]. The theory of PBV explains the significant impacts of facilitators within companies, which result in different outcomes depending on various organizational mechanisms, such as transparency [14]. Thus, we can hypothesize that,

H3. Artificial intelligence transparency correlates positively with agile decision-making.

2.4. Agile decision-making and supply chain cyber resilience

Agility can contribute to supply chain management by allowing for rapid responses to unexpected changes [35]. An agile decision-making system includes high-quality data, which is available to all stakeholders to make decisions quickly [81]. Information flow is one of the critical flows in supply chain management. Agile decision-making can facilitate and expedite decision-making processes by providing on-time information in a collaborative environment [77]. Cyberattack techniques change quickly due to the dynamic nature of technology. Agile decision-making properly addresses dynamic changes in organizations [70]. Agile decision-making helps competitive businesses respond quickly to uncertainty [49]. Using agile decision-making, companies can react quickly in disruptive environments [5]. Moreover, agile decision-making is essential to mitigating high-velocity environments [81]. In business continuity planning, agile decision-making can quickly provide multiple scenarios, which improves resilient systems [15]. Companies can collaborate with suppliers and customers in an agile decision-making system [11]. Thus, agile decision-making creates a collaborative environment for all stakeholders to address possible supply chain disruptions, such as data breaches and cyberattacks.

Cyber resilience heavily relies on decision support systems in terms of access to information for identifying potential cyberattacks and providing business continuity plans [55]. Agile decision-making includes four significant principles, information, collaboration, quick change, and business continuity plans, which can significantly contribute to supply chain cyber resilience [4,33,81]. Information availability helps decision-makers identify potential cyber threats and create and develop multiple applied alternatives during cyberattacks. This attribute would have helped the Colonial Pipeline, a U.S. oil supplier, to save $4.4 million when it experienced a cyberattack [21]. Collaborative engagement due to an agile decision-making system considerably supports cyber resilience by presenting applicable and acceptable continuities and recovery plans that work for all supply chain members. Last but not least, quick reaction is a required practice in supply chain cyber resilience, as it can improve the quick-change capability of agile decision-making systems. According to the PBV theory, practices are not influenced by individual decisions but by a group of decision-makers. They require collective knowledge and social interactions within an organization. Agile decision-making is an ongoing interaction and learning process, which can contribute to effective practices [14]. Thus, we can hypothesize that,

H4. Agile decision-making correlates positively with supply chain cyber resilience.

Fig. 1 shows the research model, including hypothesized relationships.

3. Methodology

We employed an experiment using a vignette-based design to test the hypothesized relationships. The experiment included three main phases: company and role scenarios, manipulated variables scenarios, and measuring variables [54]. We followed the recent suggestions to create scenarios and experiments such as news-based scenarios and the less-personal approach [3,23,54]. For instance, we mitigate possible demand effects using a between-subjects design, while research questions were not identified by design.

3.1. Data and sample

We targeted a specific population of individuals with AI and risk management experience in operations, logistics, and supply chain management. To gather a representative sample from this population, we used Amazon Mechanical Turk (M-Turk). M-Turk's database includes around 500,000 participants across 200 countries, which improves generalizability [29]. M-Turk has received considerable attention from scholars publishing in journals in the business, management, and engineering fields due to the reach of its database, including the *European Journal of Operational Research* [58], *Industrial Marketing Management* [71], and *Decision Support Systems* [30]. Subject recruitment and experiment design can considerably impact the quality of data [76]. We improved the quality of data collection on M-Turk by following the steps suggested by Brazhkin [13] and Wessling et al. [76].

Following the Institutional Review Board and Amazon's privacy policy, researchers cannot identify participants. However, considering that a significant proportion of survey respondents demonstrated a high level of precision in past studies [52], a pre-screened pool can help ensure the validity of the participants' responses (interested readers can see [53]). We used a pre-screened pool of 140 individuals who work in risk and supply chain management. Participants were asked the following pre-screening questions in this pool: *Do you have risk management experience in operations, logistics, and supply chain management*? *Have you used any AI systems or machine learning algorithms*?

Based on nine video calls, experts assessed the clarity and simplicity of the design. Based on their suggestions, we simplified the scenarios and revised specific wording in the questions. Using Qualtrics software, we posted the designed experiment link and a consent letter on the M-Turk platform. The resulting sample contained 140 participants (including 43 women) aged 24 to 73 years old, with an average age of 37 and a standard deviation of 10. Table 1 shows more details about the participants.

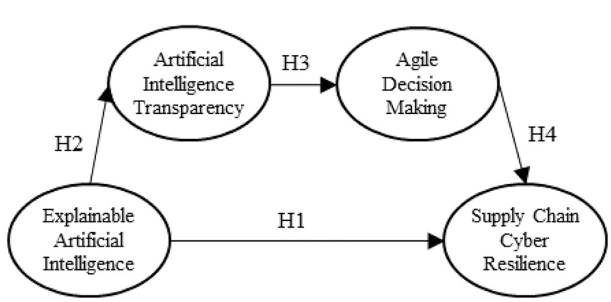

Fig. 1. Research model.

3.2. Experiment design

The experiment design included three main phases: scenarios of the supply chain role and the company, the manipulated variables, and the measurement. Participants became familiar with the role of a supply chain manager at a hypothetical company in the first phase. Note that participants' learning was measured with questions. Next, participants reviewed the hypothetical supply chain's role and responsibilities. Participants were requested to provide a hypothetical first name to enhance the hypothetical setting design.

Hypothetical company: "Imagine a hypothetical scenario where a Supply Chain Manager is employed at ABC-Company. ABC-Company operates four plants situated in different states across the USA. Established two decades ago, ABC-Company has successfully supplied a diverse range of products. With a robust and well-organized supply chain, ABC-Company has achieved a stable position in its respective market."

Hypothetical supply chain's role: "The supply chain manager plays a vital role in managing risks within the supply chain. This includes safeguarding against cyberattacks and minimizing their impact to ensure a prompt return to normal operations. By employing risk management strategies, the Supply Chain Manager can prevent and mitigate potential disruptions caused by cyber threats, ensuring the smooth functioning of the supply chain."

In the second phase, 70 participants were randomly assigned to each manipulated independent variable level (AI or XAI) in a between-subjects design. Participants reviewed the scenario in each treatment, which included audio and images (see Table 2). In the third phase, participants answered the questions measuring the variables using a seven-point Likert scale from 1 (strongly disagree) to 7 (strongly agree), as shown in Table 3. The mediators were AI transparency and agile decision-making. The dependent variable was the supply chain's cyber resilience. The control variables in this study included the type of business, with 42 companies involved in goods production, 51 companies in the services sector, and 47 companies engaged in trade and commerce. However, no companies from public administration or other categories were included. Moreover, company size was measured by the

Table 1
Demographic information of the 140 participants.

Area of Responsibility	Frequency	Business Type	Frequency
Production/Operations	36	Goods Production	42
Logistics and Supply Chain	14	Services	51
Marketing/Sales	44	Trade and Commerce	47
Finance/Accounting	33		
Information Systems	13	Company size	Frequency
		<100	25
Education Level	Frequency	Between 100 and 500	44
High school/General Education Diploma	2	Between 501 and 1000	42
Two-Year College	8	Between 1001 and 2000	26
Four-Year College	86	>2000	3
Graduate Degree (e.g., MS and PhD)	44		

Table 2
Independent variable: AI vs. XAI.

Artificial intelligence (AI)	Explainable artificial intelligence (XAI)
"Imagine you are working on optimizing a company's inventory management. AI, or artificial intelligence, can help you manage the company's inventory. Using historical sales data, customer demand patterns, and other factors, AI algorithms can predict future demand more accurately. This AI capability helps you to plan inventory levels efficiently, avoiding costly stockouts or excessive inventory. AI can suggest the best shipping routes, considering costs, delivery times, and real-time traffic data. Therefore, you can make better decisions in managing inventory and optimizing logistics. It is like having a helpful assistant that uses data analysis to improve supply chain performance." [with audio]	"XAI, or Explainable Artificial Intelligence, is all about making AI systems understandable to regular folks like you and me. You know, when AI suggests things or makes decisions, it can feel like a total mystery, right? Well, XAI changes that. It opens up that mystery box and gives clear explanations for why AI does what it does. Let us say you are using a voice assistant AI, like the one on your phone. When you ask it, 'Hey, what is the weather like today?' instead of just saying, 'It is going to rain,' XAI would provide an explanation like, 'Based on the data from weather sensors and historical patterns, there is a high chance of rain today.' By making AI more transparent, we can trust it and make better choices based on its suggestions. In a nutshell, XAI makes AI less of a confusing enigma and more like a helpful sidekick that explains its thinking in a way we can understand." [with audio]
"In this AI system, you cannot understand why we have certain results and why not. You cannot recognize when AI succeeds and when it fails. You cannot determine when to trust AI and cannot understand the reasons behind any errors it may make."	"In this AI system, you can understand why we have certain results and why not. You can recognize when AI succeeds and when it fails. You can determine when to trust AI and understand the reasons behind any errors it may make."
	

Table 3
Measured variables.

Variables	Items	λ
AI Transparency (AIT) adapted from (S. [37]):	AIT01: AI system provides information to stakeholders about its failures, not just successes.	0.83
	AIT02: AI system informs stakeholders about its failures, and there is nothing to hide.	0.79
	AIT03: AI system informs stakeholders about both positive and negative information regarding its activities.	0.88
Agile decision-making (ADM) ([4]; [33]; [81]):	ADM01: The best information is available for making decisions.	0.92
	ADM02: Everyone is involved in business planning.	0.71
	ADM03: Quick responses are made to changes in the environment.	0.75
	ADM04: Current circumstances do not limit decision-making capability.	0.85
Supply chain cyber resilience (SCCR) adapted from Ambulkar et al. [7]:	SCCR01: We can identify potential cyber disruptions for avoidance.	0.71
	SCCR02: We can cope with changes brought by cyber disruptions.	0.77
	SCCR03: We can maintain control over structure and function during cyber disruptions.	0.79
	SCCR04: We can provide a quick response to cyber disruptions.	0.73

number of employees, with 69 companies classified as small-sized, 42 as medium-sized, and 29 as large-sized.

4. Results

We employed regression analysis to test the hypothesized relationship between research model variables. We conducted required tests relating to the experimental design along with method assumptions and bias checks.

4.1. Design check

To check the design, the scenario test, the realism test, the validity test, and the manipulation test were performed. We conducted the scenario check to measure the participants' learning process regarding the provided information. The results showed that participants' learning was strong enough to support the scenario design (in the first scenario, the Mean = 5.3 out of 7, with a Standard Deviation = 0.99, and in the second scenario, the Mean = 5.5 out of 7, with a Standard Deviation = 0.85). The realism check was conducted through a face validity process and tested using the quantitative approach proposed by Thomas et al. [65]. Participants supported the realism check by agreeing that the scenarios were close enough to reality (Mean = 4.08 out of 5; Standard Deviation = 0.44). Similarly, the validity check supported the scenario design (Mean = 4.07 out of 5; Standard Deviation = 0.43). The manipulation test supported the manipulation by showing a significant difference between the two manipulated levels (p-value <0.001, the first level, the low level of XAI: Mean = 2.68 out of 7; Standard Deviation = 0.12; and the second level, the high level of XAI: Mean = 5.9 out of 7; Standard Deviation = 0.10).

4.2. Bias check

Since this paper used Amazon M-Turk to recruit participants, there was an incentive to complete the survey, and the recruitment process was completely anonymous. Therefore, there was no primary concern about a non-response bias. This paper employed the marker variable technique to check the common method bias (CMB; [40]). We selected social desirability as a marker variable not conceptually related to the research model [63]. The marker variable test failed to reject the null hypothesis of the chi-square (χ^2) test for the model with and without the marker variable ($\left(\Delta\chi^2\right)[\Delta df]$, *p-value* > 0.05). Therefore, the result provided evidence that mitigates concerns regarding the presence of CMB. Moreover, we addressed the influence of social desirability bias by concealing the research objective and using indirect questioning techniques. Besides, participants were assured of anonymity and confidentiality [52].

4.3. Validity and reliability: confirmatory factor analysis

We employed confirmatory factor analysis (CFA) to provide statistical support for the validity and reliability of the measurement model. We used a free and accessible library called the Lavaan in the R programming environment (Version 4.2.2) to perform CFA. Table 3 shows the factor loadings (λ), which are higher than 0.7. The ratio is within an acceptable range, $\chi^2/df = 75/41$, with a p-value = 0.001, which is lower than 3. Other fitness indices were strong enough to support the measurement model, including the comparative fit index (CFI) = 0.96 > 0.90 and the standardized root mean square residual (SRMR) = 0.064 < 0.08, and root mean square error of approximation (RMSEA) = 0.07 < 0.08 ([28], p. 452).

Table 4 presents the composite reliability (CR) values, which are high enough to support the reliability of items ([38], p. 313). CRs are calculated by compRelSEM function of semTools package in R environment. The convergent validity is supported by the average variance extracted (AVE) values higher than 0.5 [24]. Moreover, the discriminant validity is upheld by the square root of AVE explanatory variables ($\sqrt{\text{AVE}}$), which are higher than φ or the inter-construct correlations [24]. Thus, there is enough evidence to support the measurement model [38].

4.4. Hypotheses testing

The regression assumptions were satisfied. The normality assumption is supported by the insignificant Shapiro-Wilk test results (p-values >0.097). The Breusch-Pagan test does not reject the null hypothesis of constant error term variance (9.5, df = 6, and p-value = 0.14), indicating that homoscedasticity is not a concern. Multicollinearity is addressed by ensuring that the variance inflation factors (VIF) are below two.

We tested four regression models in Table 5 to provide more details about the hypothesized relationship in the research model. We included business type (converted to the dummy variables) and company size in the models to control their possible impacts on the outcomes.

The findings from Model-1 (Adjusted R2 = 0.42) demonstrate a significant and positive relationship between XAI and supply chain cyber resilience, supporting H1. The coefficient value for this relationship is 1.35 (β = 0.64), with a high level of statistical significance (t = 9.7, p < 0.001). The confidence interval (CI) for the coefficient ranges from 1.079 to 1.632, further reinforcing the strength of the association.

Model-2, which has an Adjusted R2 value of 0.05, shows that XAI is positively associated with AIT, thereby providing support for H2. The coefficient value for this relationship is 0.601 (β = 0.23), and it is statistically significant with a t-value of 2.7 (p = 0.007). The CI for the coefficient ranges from 0.171 to 1.030.

We investigated the association between AIT and ADM by examining Model-3, which achieved an Adjusted R2 value of 0.51. The results of the analysis present robust empirical evidence in support of H3. The coefficient for this relationship is 0.49 (β = 0.54), demonstrating a strong positive correlation. The statistical analysis indicates high significance, with a t-value of 8.7 (p < 0.001). The coefficient's confidence interval (CI) ranges from 0.381 to 0.602, providing additional confidence in the precision and accuracy of the estimated relationship.

Table 4
Validity and reliability results: Construct correlations.

Constructs	AIT	ADM	SCCR	√AVE	AVE	CR (Ω)	α
AI Transparency (AIT)	–	0.633	0.548	0.842	0.708	0.881	0.87
Agile decision-making (ADM)	0.633	–	0.636	0.808	0.653	0.891	0.87
Supply chain cyber resilience (SCCR)	0.548	0.636	–	0.75	0.563	0.837	0.83

Table 5
The regression results for 140 responses.

	Model01	Model02	Model03	Model04
(Intercept)	3.349*** t = 10.571 p ≤0.001	3.776*** t = 7.660 p ≤0.001	1.659*** t = 4.323 p ≤0.001	1.989*** t = 5.520 p ≤0.001
Explainable artificial intelligence (XAI)	1.355*** t = 9.702 p ≤0.001	0.601** t = 2.763 p = 0.007	0.849*** t = 5.848 p ≤0.001	1.023*** t = 7.146 p ≤0.001
AI Transparency (AIT)	– – –	– – –	0.492*** t = 8.792 p ≤0.001	0.175** t = 2.831 p = 0.005
Agile decision-making (ADM)	– – –	– – –	– – –	0.199** t = 2.616 p = 0.010
Company Size	−0.081 t = −1.266 p = 0.208	−0.180+ t = −1.794 p = 0.075	−0.035 t = −0.525 p = 0.600	−0.026 t = −0.442 p = 0.659
Services	−0.238 t = −1.418 p = 0.158	0.027 t = 0.103 p = 0.918	−0.066 t = −0.387 p = 0.700	−0.232 t = −1.555 p = 0.122
Trade and Commerce	0.007 t = 0.041 p = 0.967	0.379 t = 1.382 p = 0.169	−0.076 t = −0.422 p = 0.674	−0.081 t = −0.513 p = 0.609
Dependent Variable	SCCR	AIT	ADM	SCCR
R^2 Adj.	0.427	0.059	0.512	0.546

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001.

Model-4 (Adjusted R2 = 0.54) assessed the relationship between ADM and SCCR. The results yield substantial empirical evidence supporting H4. The coefficient for this relationship is 0.19 (β = 0.21), indicating a positive correlation. The statistical analysis reveals significance with a t-value of 2.6 (p = 0.01). The CI for the coefficient ranges from 0.048 to 0.349, providing a reliable estimate of the relationship's magnitude.

We performed the serial mediation analysis using the sixth design in the Hayes Process models shown in Fig. 2 [31]. Table 6 presents the mediation analysis of 5000 bootstrap samples for percentile confidence intervals. According to the results, the mediation analysis supports the serial mediation in which the indirect effects of XAI on SCCR are significant (0.333 with p-value <0.001).

4.5. Post hoc analysis: text analysis method

We employed text analysis to conduct a post hoc analysis of tweets containing the hashtag "*Decision*" in combination with "*XAI*," "*ExplainableArtificialIntelligence*," and "*ExplainableAI*." The text sample includes a collection of 1133 tweets covering the period from January 1, 2022, to June 1, 2023. In this text analysis, we carried out three steps: data

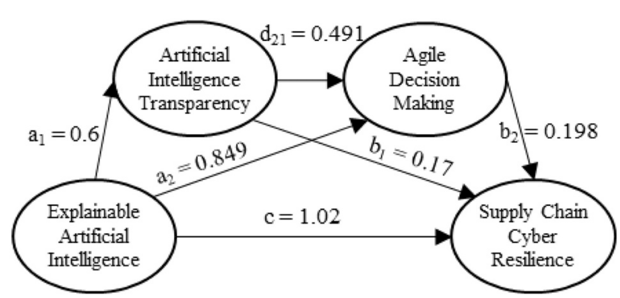

Fig. 2. The Hayes process model.

Table 6
Direct and indirect effects of 5000 bootstrap samples.

Direct effect of XAI on SCCR	Effect	Error	LLCI	ULCI
XAI ➔ SCCR	1.023	0.14	0.740	1.306
Indirect effects of XAI on SCCR	0.333	0.091	0.157	0.514
XAI ➔ AIT ➔ SCCR	0.105	0.056	0.013	0.228
XAI ➔ ADM ➔ SCCR	0.169	0.062	0.052	0.296
XAI ➔ AIT ➔ ADM ➔ SCCR	0.059	0.033	0.008	0.137

cleaning, descriptive analysis (word cloud and sentiment analysis), and topic modeling.

In the first step, data cleaning, we removed retweets and non-English letters and identified the hashtags ("decision," "XAI," "explainable artificial intelligence," and "explainable AI") and website links. Moreover, we lowered all capital words to have a consistent corpus. Utilizing the Natural Language Toolkit Python (Version 3.9) library, we used the Lemmatize technique to convert inflected words to their root forms (e.g., supplying to supply; [25]). We excluded the stemming technique due to its inaccuracy (e.g., converting caring to car).

In the second step, we created a corpus from the collected texts to draw the bigram word cloud analysis shown in Figs. 3 and 4. The findings reveal that machine learning algorithms, including neural networks, are often perceived as black boxes within decision support systems. This need for more transparency in understanding AI processes poses a current challenge, specifically the slow adoption of AI in decision-making processes. XAI has the potential to foster daily collaborations among decision-makers, facilitating a better understanding of AI processes and thereby fostering trust. In addition, we performed sentiment analysis using the TextBlob Python library to evaluate the emotional tone of the tweets [39,62]. The outcomes revealed a prevailing positive attitude towards XAI within decision support systems, which is shown in Fig. 5.

In the third step, we employed the latent Dirichlet allocation (LDA) algorithm for topic modeling to uncover the primary themes and emerging trends [26]. We utilized the coherence score to identify the optimal number of topics in the considered text. As shown in Fig. 6, we select two topics for the LDA algorithm because it has a higher coherence score (0.34) than other alternatives. We ran the LDA algorithm to see primary themes. The first topic included "system," "understand," "learning," "data," "process," "algorithm," "trust," "human," "tree," and

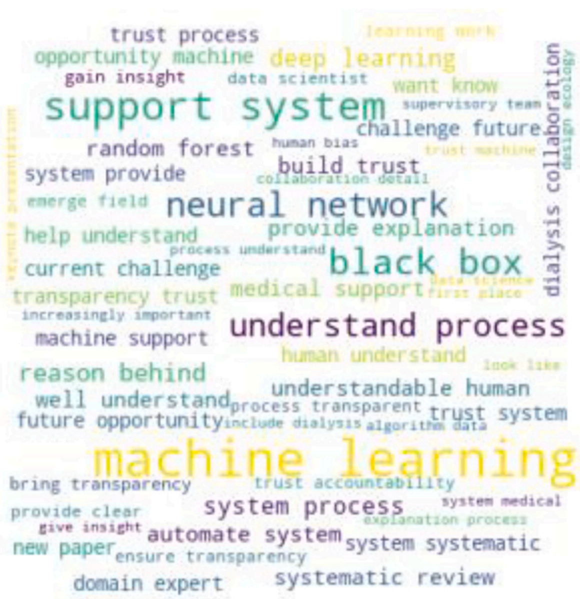

Fig. 3. The Bigram word cloud analysis.

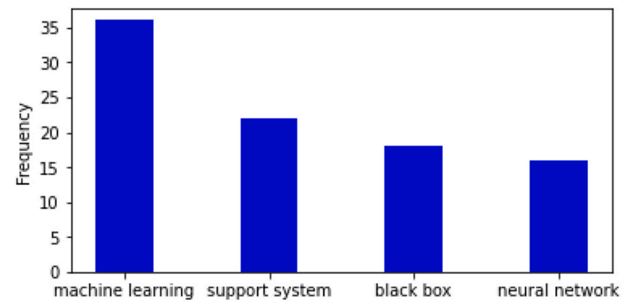

Fig. 4. The Bigram frequency.

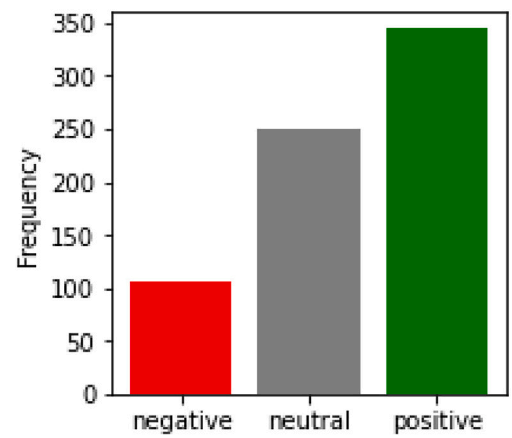

Fig. 5. The Bigram word cloud analysis.

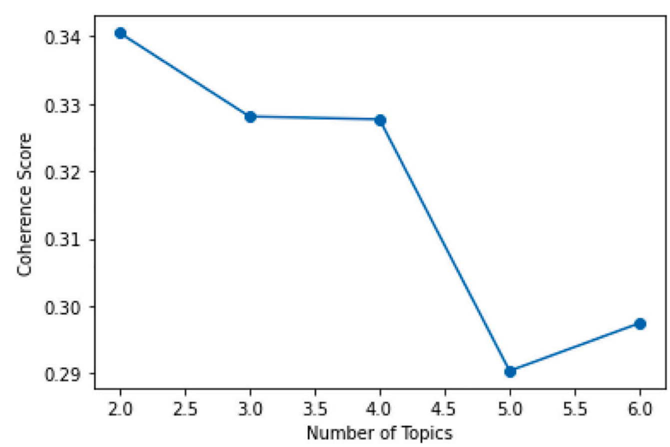

Fig. 6. LDA's number topic comparisons.

"machine," and the second topic included "process," "learning," "system," "transparency," "work," "explanation," "trust," "help," "human," and "data." According to the first topic, XAI can help decision-makers understand machine learning algorithms in decision support systems, highlighting the explainability principle in XAI. Moreover, based on the second topic, XAI plays a vital role in supporting transparency in AI. By shedding light on the inner workings and decision-making mechanisms of AI systems, XAI can significantly improve trust, facilitating collaborative efforts with decision-makers. The second topic highlights transparency and interpretability in XAI.

5. Discussion and conclusions

Using two studies, we addressed the research question, *how can XAI* *impact decision-making processes*? This study built upon previous research by introducing a theoretical framework that explains the influence of XAI on cyber resilience, mediated sequentially by transparency and agile decision-making. To support the proposed relationships, this paper employed a between-subjects experimental design, gathering empirical evidence for analysis. Moreover, a post hoc analysis presented a positive attitude towards XAI in industries. Text analysis revealed two main themes that emphasized the importance of transparency, explainability, and interpretability in XAI.

The findings show that XAI can contribute to cyber resilience by offering decision-makers clear and comprehensible AI-based alternatives during cyberattacks, thereby expediting the decision-making process (H1). One of the critical elements of building an XAI is transparency [82]. XAI can play a crucial role in enhancing the transparency of AI systems by providing understandable explanations of their decision-making processes (B. [36]). We tested the relationship between XAI and transparency, in which a positive correlation was supported (H2). The post hoc analysis results, moreover, support H2 by highlighting transparency in the identified topic. AI transparency can enhance the criteria used in decision-making and boost the effectiveness of AI algorithms. As a result, an agile decision-making system that incorporates transparency into its AI methods can render AI-based decisions easily comprehensible for all parties involved. This system promotes clarity and understanding by fostering a collaborative atmosphere that promptly addresses modifications, which are shown in the post hoc analysis as well. This paper supports this relationship with empirical data (H3). Finally, the empirical model supported the positive correlation between agile decision-making and supply chain cyber resilience (H4). The ability to quickly change and respond to unexpected situations can significantly benefit supply chain management [35]. In competitive industries, agile decision-making enables quick responses to uncertain situations [49]. By employing agile decision-making approaches, businesses can promptly react to disruptive environments [5].

5.1. Theoretical implications

The research findings offer four theoretical implications contributing to prior works. First, our research improves the existing body of knowledge on XAI by offering empirical evidence and novel insights into the effective utilization of XAI within supply chain decision-making processes. The empirical evidence better explains how XAI can improve the decision support system during cyberattacks. Second, this paper explored the main concepts in relationships between XAI and cyber resilience, which can result in refining or expanding existing theoretical frameworks. The proposed research model introduces AI transparency and agile decision-making as new mediators that can contribute to developing AI frameworks. These mediators play a significant role in enabling and enhancing the theoretical understanding of AI frameworks. Third, our findings contribute to the development of resilience theory by introducing the role of agile decision-making, which is a key enabler in mitigating cyberattacks. This paper enhances the existing body of knowledge and provides valuable insights into the processes that improve resilience. Moreover, it underscores the need for adaptive and proactive decision-making processes to effectively respond to and recover from cyberattacks. Finally, this paper proposes an experiment-based study for evaluating potential moderators and mediators in future research. By conducting this study, several avenues for further investigation can be explored, offering valuable insights into the complex relationships and dynamics within the research domain. Including various moderators and mediators in future studies can enhance our understanding of the underlying mechanisms and factors influencing the phenomena under investigation. Absorptive capacity at both the individual and organizational levels could serve as potential moderators for the hypothesized relationships. Moreover, the power structure within the supply chain network may influence the effectiveness of AI during cyberattacks. Technology dependency is also identified as one of the potential variables that could moderate relationships within the research model.

5.2. Managerial implications

Supply chain decision-makers must proactively prepare to withstand an increasing number of cyber disruptions as the substantial economic price of data breaches continues to rise. Moreover, supply chain decision-makers must leverage AI systems to enhance resilience. Our findings yield four recommendations supported by empirical data. First, our findings suggest that managers can prioritize adopting and implementing XAI techniques within their supply chain operations to improve cyber resilience capability. By leveraging XAI, managers will have more profound insights into the decision-making processes of AI systems, enabling them to understand the rationale behind AI outcomes and identify potential vulnerabilities. Integrating XAI into supply chain operations can provide transparency and enhance decision-making processes, resulting in improved cyber resilience. Second, the findings herein recommend that managers ensure that decision-making criteria in AI systems are clear and understandable to all stakeholders. By enhancing transparency, managers can build trust and confidence in AI systems, enabling stakeholders to comprehend and articulate the underlying rationale of AI outputs. Transparency enables non-experts to understand and explain the functioning of AI systems. Managers should invest in XAI techniques, such as LIME, RETAIN, or LRP, to enhance the transparency of AI algorithms and facilitate better understanding among stakeholders [9,16,43]. Third, based on our results, transparency will enable decision-makers to access timely and relevant information, facilitating agile decision-making processes. Agile decision-making implies making quick and collaborative decisions to address changes and uncertainties effectively [49]. Finally, according to our findings, managers should prioritize the development of agile decision-making by which they have access to high-quality and timely information and can create collaborations among stakeholders and quickly adapt to changing circumstances. Agile decision-making supports companies in responding quickly to cyber threats [5].

5.3. Limitations

Although past research supports generalizability when using the M-Turk platform [29], there are limitations. One potential limitation is the possibility of capturing only some kinds of industries since some industries may be inactive on the M-Turk platform. The findings were limited to data collected in an experimental study. Future research can use field studies or an interview design to further test the hypothesized relationships, which can provide an understanding of the topic from a different perspective. In future works, longitudinal studies can investigate the causal relationships between XAI, AI transparency, agile decision-making, and supply chain cyber resilience to better understand their relationships over time.

CRediT authorship contribution statement

Kiarash Sadeghi R.: Writing – original draft, Writing – review & editing, Conceptualization, Data curation, Formal analysis. **Divesh Ojha:** Investigation, Methodology, Writing – original draft. **Puneet Kaur:** Writing – review & editing. **Raj V. Mahto:** Writing – original draft, Writing – review & editing. **Amandeep Dhir:** Conceptualization, Resources, Supervision, Writing – original draft, Writing – review & editing.

Declaration of competing interest

We, the authors of the manuscript titled “Explainable Artificial Intelligence and Agile Decision-Making in Supply Chain Cyber Resilience,” have no conflict of interest to declare.

Data availability

The authors do not have permission to share data.

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