Vulnerability Indicators on The Operation of Electric Motorcycle - Battery Swapping Station

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Abstract

The use of electric motorcycle-battery swapping stations (EM-BSS) is one of the efforts to accelerate the adoption of electric motorcycles in Indonesia. The EM-BSS system can be viewed as a digital supply chain (DSC) that utilizes Internet of Things (IoT) technology to carry out system activities. The system certainly deals with the issue of supply chain operational vulnerability, which is a concern for supply chain practitioners today. A *causal inference* approach is used to estimate the supply chain operational vulnerability level. The first step in using the *causal inference* approach is to create a structural causal model based on the expert knowledge domain. Structural causal modeling started with identifying vulnerability indicators: consequences, drivers, and threat sources. The vulnerability indicator on the EM-BSS system obtained 12 vulnerability performance indicators as consequences, 21 vulnerability drivers, and four potential threat sources.

Keywords

Battery Swapping Station, *Causal inference*, Electric Motor Cycle, and Vulnerability Indicators.

1. Introduction

1.1 Background of the study

The vulnerability of supply chains has reemerged as a concern for practitioners and researchers after COVID-19, warfare in several countries, and natural disasters (Khan et al. 2022; S. K. Sharma et al. 2021). Vulnerability in supply chains can arise due to a lack of susceptibility and coping capacity to mitigate disruptions, thus causing various consequences in the system's operations (Nowakowski et al. 2015). Supply chain vulnerability can also be driven by the rapid development of digital technology, such as Industry 4.0 (Qader et al. 2022). The evolution of digital technology has transformed supply chains into digital supply chains (DSC), characterized by multidimensional systems, nonlinear relationships between entities, the need for faster adaptation, and the utilization of artificial intelligence (Ageron et al. 2020; Garay-Rondero et al. 2020; Schmidt et al. 2015). Vulnerability in supply chain systems can decrease the system's performance (Nowakowski et al. 2015). System vulnerability can also reduce customer service effectiveness. On the other hand, a system's vulnerability can measure how sensitive the supply chain faced disruptions (S. K. Sharma et al. 2021).

The Indonesian Government has been trying to accelerate the adoption of electric vehicles (Republik Indonesia 2019). The government provides purchase incentives and regulations to establish electric charging infrastructure: (i) Public Electric Vehicle Charging Stations (SPKLU) and (ii) Public Electric Vehicle Battery Swapping Stations (SPBKLU) (Pemerintah Indonesia 2023). The infrastructure for electric motorcycle battery swapping stations (EM-BSS) offers convenience for electric motorcycle users to quickly obtain fully charged batteries, thereby enhancing mobility. The EM-BSS infrastructure can be managed by vehicle manufacturers or other business entities (Pemerintah Indonesia 2023).

The EM-BSS operation can be viewed as a digital supply chain (DSC) operational model. The DSC has characteristics such as non-linear relationships between entities, e.g. the relationship between the EM-BSS provider, the battery supplier, and the consumers who lease the battery (Büyüközkan & Göçer 2018; Garay-Rondero et al. 2020). Other characteristics involve automation in the battery-swapping process, the use of digital technology, and the Internet of Things (IoT). Another notable characteristic is the utilization of information system platforms and big data analytics to transform operational battery swapping data into information and knowledge for the decision-making process to the EM-BSS management. In the context of the supply chain, big data analytics is commonly referred to as supply chain analytics (SCA) (Büyüközkan & Göçer 2018).

While providing benefits to consumers or vehicle owners, the EM-BSS operation also presents potential issues. These issues include concerns related to infrastructure, battery degradation, battery ownership, the ability to exchange batteries between vehicles, and the transparency of the service system (Ahmad et al. 2020). Other potential problems include operational vulnerabilities in the provision of swapping stations, battery usage, and the battery swapping and charging processes (Emeric 2019; Glombek et al. 2018). The consequences of vulnerabilities can be influenced by other vulnerability consequence indicators or by vulnerability-driving factors triggered by system disruptions. Vulnerable conditions can reduce the service performance of the EM-BSS system, disadvantaging EM-BSS management and impacting service quality for consumers. From an optimistic view, vulnerability monitoring can be part of mitigation efforts (El Baz & Ruel 2021). However, EM-BSS provider currently need to fully explore the operational vulnerability aspect by leveraging the availability of big data from IoT platforms. Therefore, this article aims to analyze the causal structure of vulnerabilities in the supply chain operation of the EM-BSS system.

1.2 Objectives

The studied objectives in the article are as follows:

1. Operational characterization of the electric motorcycle battery swapping system in Indonesia from the perspectives of digital supply chain and system vulnerabilities.
2. Constructing a theoretical supply chain analytic framework to aid in estimating the operational vulnerabilities of the electric motorcycle battery swapping system, examined through the Body of Knowledge of Industrial and System Engineering.
3. Developing a conceptual framework for estimating supply chain vulnerability in the operational electric motorcycle battery swapping system using a big-data analytical approach, specifically a diagnostic analytics task.

4. Identifying relevant vulnerability indicators to be employed for estimating the operational vulnerabilities of the EM-BSS.

2. Literature Review

Supply chain vulnerability (SCV) can generally be defined as potential factors that could lead to risks or losses within the supply chain (Hashim et al. 2021). However, supply chain risk is distinct from supply chain vulnerability. Risk is the negative outcome that arises when disruptions occur in the supply chain, whereas supply chain vulnerability is the driving force that directs risk within the supply chain (Adetunji 2014; Marvin et al. 2020). Another definition of SCV is the propensity that drives supply chain vulnerability beyond the ability to mitigate or address supply chain system risks, thus resulting in detrimental or hazardous consequences for the supply chain's capacity to serve consumers effectively (Wagner & Bode 2006). Elleuch et al. (2016) has resumed some definition of the vulnerability.

There are some models of SCV, and in this article, the SCV model refers to Nowakowski (Nowakowski et al. 2015; Nowakowski & Werbinska-Wojciechowska 2014). The SCV is defined as the weakness of system susceptibility and the lack of coping capacity (considered in terms of technology, workforce, and information management) to confront various threats, such as natural disasters, human actions, and operational difficulties, resulting in a range of vulnerability consequences (indicators of system vulnerability). They also grouped four categories of vulnerability consequences: duration, operational, economic, and social. Susceptibility factors and coping capacity are referred to as vulnerability drivers. Their model aligns with Sharma's model (S. K. Sharma et al. 2021) that supply chain consequences are outcomes, vulnerability is a precondition for the emergence of consequences within the supply chain, and disruptions can influence this precondition. The supply chain vulnerability model illustrates a cause-and-effect relationship between sources of threats, vulnerability drivers, and vulnerability consequences. Vulnerability can be used to measure how sensitive a supply chain is in facing disruptions (S. K. Sharma et al. 2021). Several studies utilize SCV measurement in both qualitative and quantitative forms. Commonly used methods for measuring vulnerability include Failure Mode and Effect Analysis (FMEA), Failure Mode, Effects and Critically Analysis (FMECA), Cause-Consequence Analysis (CCA), Supply Chain Event Management (SCEM), Supply Chain Risk Management (SCRM), Supply chain risk drivers, and Simulation models (Nowakowski et al. 2015).

Supply Chain Analytics (SCA) is a concept of data analytics in DSC (Büyüközkan & Göçer 2018). It has been utilized to process big data, which is generated by intelligent logistics technology and Internet of Things (IoT) devices (MacCarthy & Ivanov 2022). Data analytics enhanced decision-making capabilities and quality ((Cao & Duan 2015; financesonline 2022). Data analytics encompasses four activities: descriptive, diagnostic, predictive, and prescriptive, for delivering value in hindsight, insight, and foresight in supporting decision-making (Erl et al. 2016). Data analytics has also driven the transformation of Decision Support System (DSS) frameworks into broader forms based on data analytics, artificial intelligence, and machine learning (Phillips-Wren et al. 2021).

Utilizing machine learning has limitations, one of which is its tendency to offer insufficient cause-and-effect explanations between attributes (Gonfalonieri 2020). Machine learning has a limited capability to predict causal relationships between datasets, even when there might be no actual connection between the two datasets due to differing relevant system contexts (Neal 2020; Pearl 2009; Pearl & Mackenzie 2018). Because correlation doesn't always indicate the presence of a cause-and-effect relationship, the application of the causal inference concept to machine learning has progressed (Arti et al. 2020; Moraffah et al. 2020). Causal inference methods within machine learning examine cause and effect through two stages: causal discovery and causal inference. Causal discovery aims to acquire knowledge about causality from observed data directly, while causal inference is focused on predicting the outcomes that result from altering specific treatment variables in relation to response variables (Nogueira et al. 2022). In general, causal inference utilizes approaches like Pearl's Ladder of Causation or the Three Layers of Causal Hierarchy (Pearl & Mackenzie 2018)), which have become prevalent in various programming libraries to address queries such as "why does changing the treatment of one attribute impact another," or to validate cause-and-effect relationships (A. Sharma & Kiciman 2020). Both the causal discovery and causal inference stages coincide with the predictive and diagnostic roles of data analytics, where both seek to answer "what will happen" and "why did it happen" questions (Erl et al. 2016). Causal inference methods in machine learning prioritize the accuracy and precision of prediction outcomes and aim to enhance the elucidation and interpretation of these results.

Causal inference has seen extensive utilization in domains such as health and genetics (Friedman et al. 2000), ecology (Arif & MacNeil 2023), astronomy, and neuroscience (Vuković & Thalmann 2022). It has progressively entered the realm of manufacturing and supply chain studies, with each field employing a distinct approach to shaping problems using causal inference (Vuković & Thalmann 2022). Various applications of causal inference in the business and manufacturing sectors encompass predicting the influence of dynamic pricing on hotel room rentals and revenue (Leoni & Nilsson 2021), estimating battery reliability and performance (Hund & Schroeder 2020), forecasting the lead-time vulnerability of aircraft component supplies (Zhao et al. 2019), and predicting the effects of natural disasters on local business economic costs (Yabe et al. 2020).

Causal inference combines human expertise in structural causal models with machine learning models (Bareinboim et al. 2022; Bareinboim & Pearla 2016). The initial challenge in applying causal inference is how to construct structural causal models (SCM), typically represented as causal graphs or directed acyclic graphs (DAGs) (Bareinboim et al. 2022; Hund & Schroeder 2020; A. Sharma & Kiciman 2020). These SCM encompass the domain knowledge of experts, and when there is a growing number of interconnected factors or attributes, it becomes progressively intricate for an expert to validate the accuracy of associative relationships or causal-effects connections. As a result, experts are often requested to compile partial DAGs, which are then subjected to the validation processes of causal inference, involving associations and cause-and-effect relationships that are assessed using observational data and inference mechanisms (Arif & MacNeil 2023; A. Sharma & Kiciman 2020).

Drawing upon the literature review, this research defines Supply Chain Vulnerability (SCV) in the context of the operational aspects of the Electric Motorcycle Battery Swapping System (EM-BSS), with references taken from (Hashim et al. 2021; Nowakowski et al. 2015; S. K. Sharma et al. 2021). SCV in this context refers to potential consequences that could impair the operational performance of the EM-BSS. These consequences manifest as effects stemming from various drivers of vulnerability and exposure factors. To illustrate, consider an operational consequence such as a charging completion time. Charging completion time can reduce the frequency of battery swaps within an EM-BSS and could even lead to decreased revenue. Factors contributing to this prolonged charging time might include the number of batteries currently being charged, the installed electrical power, or the state of charge (SOC) of batteries inserted by customers into battery compartments.

3. Methods

The article simplifies the representation of its four objectives through Figure 1. The initial step involves a system characterization approach. This is achieved by defining a system view from the standpoint of the EM-BSS provider, based on seven system aspects: objectives of observation, system components, behaviors or activities, component relationships, inputs, outputs, and the relevant environment (Daellenbach et al. 2012). These seven elements are visually depicted in a diagram illustrating the EM-BSS system. This characterization process relies on official documents like the Minister of Energy and Mineral Resources Regulation of the Republic of Indonesia Number 1 of 2023, which pertains to the establishment of charging infrastructure for battery-based electric motor vehicles (Pemerintah Indonesia 2023), as well as the Minister of Energy and Mineral Resources Regulation No. 13 of 2020 (Pemerintah Indonesia 2020). The diagram is verified and validated through consultation with business managers of an electric motorcycle manufacturer in Indonesia.

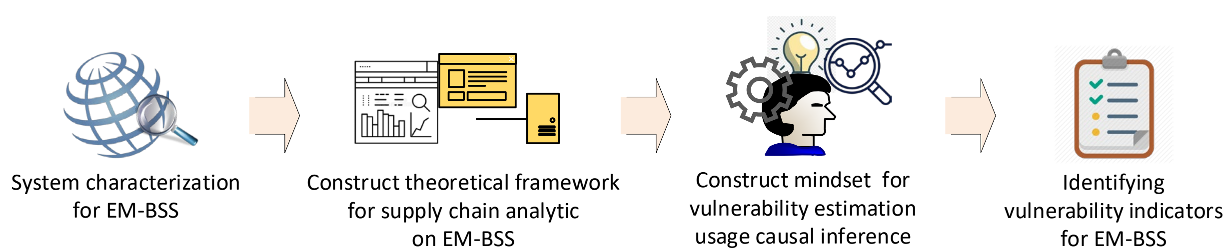

Figure 1. Construction stages to establish a structural causal model

Theoretical construction of supply chain analytics employs a scientific discipline approach, which involves reviewing the body of knowledge (BoK) on Industrial and Systems Engineering (Institute of Industrial and System Engineers 2022). The three components examined are Information Engineering, Supply Chain Management, and Operation Research and Analysis, which are utilized to construct the theoretical framework of supply chain analytics. This theoretical framework is presented in a schema for supply chain analytics to estimate the operational vulnerability of systems. This conceptual framework is validated by considering the availability of datasets within the electric motorcycle battery swapping system, ensuring that supply chain analytic tasks can be executed.

The framework for conducting a diagnostic analytic task (exploring the reasons behind occurrences and performing what-if analysis) to estimate the supply chain's vulnerability in the operational electric motorcycle battery swapping system adopts a causal inference approach. This approach follows the concept of the three ladders of causation (Pearl 2009), which offers a structured way to comprehend cause-and-effect relationships at three levels: association, intervention, and counterfactual. Domain knowledge plays a pivotal role in conducting accurate causal estimation. The dataset from the swapping system can serve two purposes: validating cause-and-effect relationships derived from expert domain knowledge, or conducting causal discovery without any prior domain knowledge. Creating well-formulated business questions is fundamental to effectively applying the causal inference approach. These questions should consider the availability of datasets maintained by the administrators of the EM-BSS.

The last section identifies relevant vulnerability indicators for the operational electric motorcycle battery swapping system. The identification method considers the limitations of available datasets, as assessed in the second stage during the development of the theoretical framework for Supply Chain Analytics (SCA). Additionally, the identification process draws from vulnerability models, system vulnerability indicators, and vulnerability index measurement models in supply chain, logistics, manufacturing, and warehousing systems (Hashim et al. 2021; Nowakowski et al. 2015; S. K. Sharma et al. 2021; Vlajic et al. 2013). Validation of these indicators is carried out with stakeholders in an EM-BSS provider, as well as domain experts (academics) in the field of supply chain, as presented in Table 1.

Table 1. *Stakeholders* for identifying vulnerability indicators

#No	*Stakeholders*	Roles	
(1)	(2)	(3)	
1.	Director of Operations and Business Development	EM-Manufacture	Industry
2.	Staff in the Data Management and Information System Division of EM-BSS.	EM-Provider	Industry
3.	Manager of IoT Platform Development and Data Center Manager.	Developer of IoT Platform	Industry
4.	Director of PT Batex Energi Mandiri	Producer of Lithium-ion batteries and its derivative product	Industry
5.	Researcher at Industrial Engineering and Techno-Economics (RITE) Research Group	Researcher	Academician
6.	Researcher at Centre of Excellence for Electrical Energy Storage Technology, Universitas Sebelas Maret	Researcher at	Academician

4. Results and Discussion

4.1 System Characterization

System characterization of the EM-BSS system in accordance with Minister of Energy and Mineral Resources Regulation No. 1 of 2023 is presented in Table 2 and depicted in Figure 1.

There are two forms of business entities providing EM-BSS: (1) businesses that provide batteries for rent to vehicle users and simultaneously own the battery swapping cabinets (Battery Provider Cabinet Owner - BPCO), and (2) businesses that offer battery rentals to battery users but lease cabinets from other business partners (Battery Provider, Cabinet Lessee - BPCL) (Pemerintah Indonesia 2023). In addition to supplying batteries, EM-BSS providers are responsible for offering a mobile application for electric motorcycle users, operating a data center to manage transaction data and information related to battery exchange, and sharing data with the data exchange system managed by the Ministry of Energy and Mineral Resources.

There are four main activities within the battery swapping operation, all interconnected through the Internet of Things (IoT) technology. Firstly, battery usage in electric motorcycles (BM) generates various data such as the user's location, battery state of charge (SOC), estimated remaining range of the vehicle, and other data points. The second activity is the battery swapping process (SP). This is carried out by consumers at Battery Swapping Stations (BSS) by exchanging a battery from their electric motorcycle with a fully charged one from the BSS. This activity can be done if at least one fully charged battery is available in a BSS compartment. The battery that goes into the compartment is then recharged by the BSS in the third activity (charging process - CP). The fourth activity involves the use of a mobile application (mobile application usage - MA) that assists electric motorcycle users in swapping batteries, making battery rental payments or exchanges, accessing information about BSS locations with available batteries, and other informational services.

Table 2. *EM-BSS system characterization*

System view	***System characterization***
The purpose of viewing an entity as a system	The managers of EM-BSS aim to conduct regular assessments of the vulnerability factors within the battery exchange system's operations, with a periodic frequency of either weekly or monthly intervals.
System components	Battery charging stations (including battery compartments), batteries, vehicles, mobile applications, and IoT devices (including IoT platforms).
Behavior or activities of the system	Battery swapping, battery charging, battery utilization in vehicles, and mobile application usage by vehicle users.
Relationships between components	Exposure and driver vulnerability indicators are correlated or causally related to consequence vulnerability indicators within the system.
Input	Indicators of triggers and drivers of operational vulnerability in the EM-BSS system.
Output	Indicators of consequences of vulnerability in the EM-BSS system.
Relevant environment	Battery supply system from battery manufacturers to EM-BSS administrators, or vehicle manufacturers to/from EM-BSS provider.

The data management components within the IoT platform serve the purpose of conducting supply chain analytics activities. This data can be utilized to monitor system performance or, from another perspective, to observe how vulnerability indicators within the system change or shift due to the influence of internal system activities or external factors that can be observed.

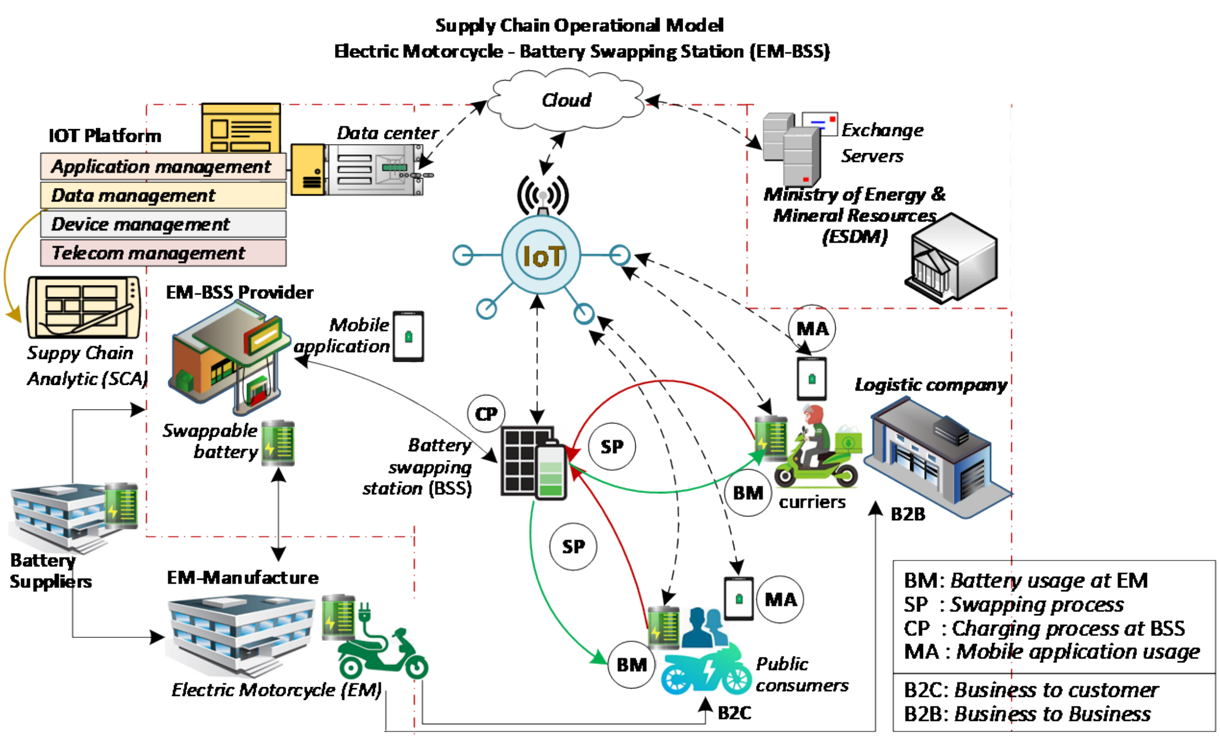

Figure 2. Supply chain operational model on EM-BSS

4.2 Supply Chain Analytic at the EM-BSS

The theoretical concept of supply chain analytics within EM-BSS is examined through the Industrial and System Engineering BoK components: Information Engineering, Operations Research and Analysis, and Supply Chain Management (Institute of Industrial and System Engineers 2022). This theoretical framework is presented in Figure 3. Information Engineering involves an approach to planning, generating, distributing, analyzing, and utilizing data collections in systems to facilitate decision-making and business communication. The Data-Information-Knowledge-Wisdom (DIKW) model by Ackoff is supported by information technology up to the Knowledge stage (Baškarada & Koronios 2013; Frické 2018; Liew 2013). This can be observed in how decision support systems (DSS) serve as decision-making aids, but the final actions taken by individuals are not necessarily bound to DSS outcomes. Therefore, wisdom represents the application of decision outcomes. Wisdom updates the tacit knowledge of decision-makers and can result in system changes that impact shifts or trends in data patterns, distinct from data before the implementation of a decision.

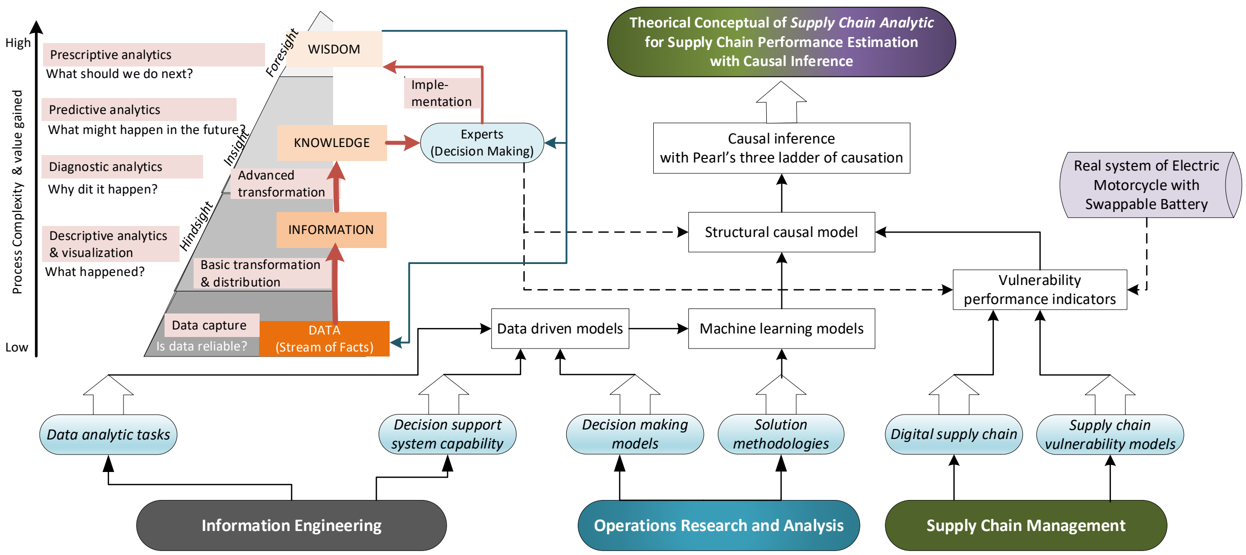

Figure 3. The theoretical concept for *supply chain analytics on EM-BSS*

A DSS (Decision Support System) consists of three components: data component, model component, and interface component. The model base in a DSS can be operation research-driven or data-driven. Currently, supply chain analytics predominantly leverages data-driven approaches through the utilization of data analytics. One of the data analytic tasks is diagnostic analytics, which aims to answer why a particular event occurred (looking at cause-effect relationships). This task can employ causal inference, a specialized form of prediction that predicts an outcome variable due to interventions, actions, or manipulations of other variables. Supply chain analytic tasks that emphasize data analysis can utilize solution methods employing machine learning models.

Utilizing the causal inference approach requires an appropriate structural causal model that fits the context of the study object. When connected with system vulnerability issues, it becomes necessary to construct vulnerability indicators that align with the real system or match the dataset availability within the system. Experts or decision-makers need to organize these indicators into a structural causal model. This Structural Causal Model (SCM) can then be employed to carry out the process of vulnerability estimation.

4.3 Estimation of the Vulnerability with Causal Inference Approach

Each battery swapping station location possesses distinct vulnerability potential, and ideally, the entire system's vulnerability level can be monitored. Different vulnerability potentials may arise due to varying conditions or differing values of vulnerability indicators. However, the question arises as to which indicators can serve as sources for vulnerability estimation and provide insight into which aspects are more susceptible to disturbances and sensitive to slight changes in vulnerability-driving factors.

One of the tasks in supply chain analytics involves diagnostic analysis, which delves into cause-and-effect analyses (Ivanov et al. 2019). The causal inference approach, employing the concept of Pearl's three ladders of causation, can be applied to discern causal relationships or cause-and-effect relationships concerning issues (Pearl & Mackenzie 2018). The application of this concept is illustrated in Figure 4.

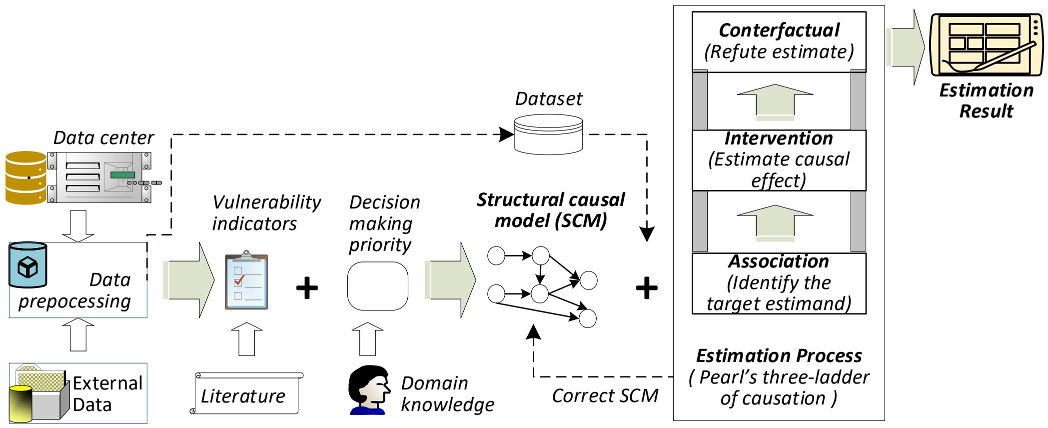

Figure 4. C*ausal inference* for vulnerability estimation on EM-BSS

A crucial aspect of implementing causal analysis is formulating clear statements about the treatment under investigation and its impact on the outcome, the considered outcome itself, and the suspected confounders correlated with the outcome and treatment (Microsoft 2023). These causal analysis statements can be expressed as a Structural Causal Model (SCM). An SCM can be obtained through the processes of causal discovery and causal estimation. In the case of causal estimation, constructing an SCM requires domain knowledge from experts regarding the cause-and-effect relationships among treatments, outcomes, and confounders. In the context of the vulnerability model for EM-BSS, outcomes, treatments, and confounders are referred to as vulnerability indicators.

Vulnerability indicators adopt the model by Nowakowski et al. (2015) as presented in Figure 5. In this model, the indicators are categorized into three aspects: vulnerability triggers (threats/exposures), vulnerability drivers, and vulnerability consequences. The assessment of vulnerability consequences can be reflected in performance as sudden drops or spikes in key performance indicator (KPI) values (Vlajic et al. 2013). Consequently, this study uses the term Vulnerability Performance Indicator (VPI) as a replacement for vulnerability consequences. Evaluating consequences from a performance perspective is more measurable due to dataset availability and is widely used and easily understood by EM-BSS system users (Asih et al. 2020; Hanif et al. 2020; Raut et al. 2021; Vlajic et al. 2013). VPI measurements can include: (1) the magnitude of sudden drops or increases in key performance indicators that are significantly negative or vulnerable, (2) how long the system experiences or maintains the spiked performance indicator value before returning to normal, and how frequently the system encounters spikes within a specific period.

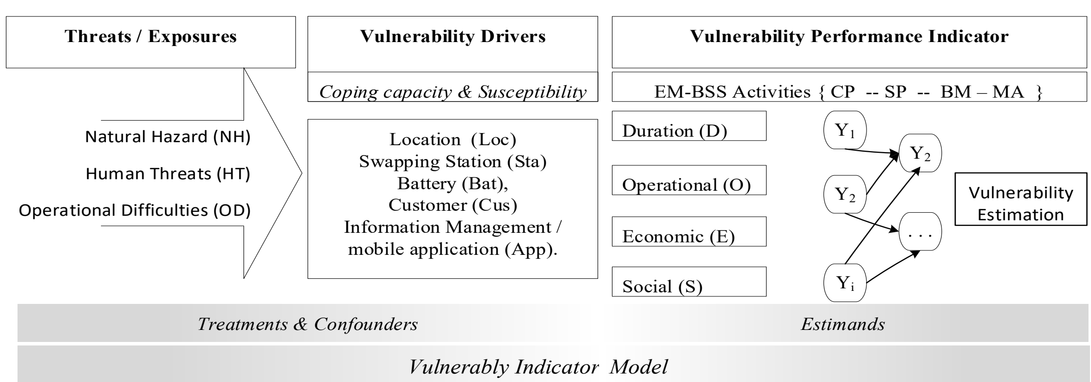

Figure 5. Vulnerability Indicators model on EM-BSS

4.4 Vulnerability Indicators on EM-BSS Operations

VPI is categorized into the aspects of Duration (D), Operational (O), Economic (E), and Social (S). The objective of VPI is confined to the four operational activities of EM-BSS based on system characterization, namely CP, SP, BM, and MA. The vulnerability drivers, on the other hand, adopt the model by S. K. Sharma et al. (2021), with a redefined grouping involving Location (Loc), Battery Swapping Stations (Sta), Batteries (Bat), EM Users (Cus), and Information Management from the mobile application (App). Regarding the sources of threats that can expose system vulnerabilities, they are grouped into natural hazards (NH), human threats (HT), and operational difficulties (OD) (Nowakowski et al. 2015).

Performance indicators from relevant systems like manufacturing, logistics, maintenance, and warehousing are used as reference sources to establish VPI (British Standards 2007; Hashim et al. 2021; S. K. Sharma et al. 2021). The availability of datasets within the operational big data of the EM-BSS system is also a consideration for reviewing VPI (Dev et al. 2019; Kamble & Gunasekaran 2020).

Table 3 presents the Vulnerability Performance Indicators (VPI) in the EM-BSS system. For instance, the charging completion time at a location can signify the ineffectiveness of the BSS service to consumers. This indicator potentially reduces Throughput and Revenue for the EM-BSS provider.

Table 3. Vulnerability Performance Indicators on EM-BSS

No	Vulnerability Performance Indicators	Description	Activities	Category	References
(1)	(2)	(3)	(4)	(5)	(6)
1.	Charging completion time	The time required to reach a 100% state of charge (SOC).	CP	D	(British Standards 2007)
2.	Swap Completion Time	The duration of the battery replacement process.	SP	D	(British Standards 2007)
3.	Throughput	The number of batteries used by consumers from an EM-BSS	SP	O	(British Standards 2007)
4.	Battery availability	The availability of fully charged batteries in the EM-BSS.	SP	O	(Emeric 2019)
5.	Electric power consumption.	The electricity power consumption in the EM-BSS	CP	E	(Pemerintah Indonesia 2023)
6.	Occupancy rate	The ratio of compartment usage in the EM-BSS.	SP	E	(British Standards 2007)
7.	Operational cost	The operational cost of the EM-BSS.	CP	E	(British Standards 2007)
8.	Revenue	The operational revenue of the EM-BSS	SP	E	(British Standards 2007)
9.	Station availability	The availability of the EM-BSS	CP	S	(Emeric 2019)
10.	Response latency	The speed of responding to disruptions from consumers.	SP	S	(British Standards 2007)
11.	Compartment reliability	The percentage of compartment success in serving consumers.	CP	S	(Glombek et al. 2018), (Emeric 2019)
12.	Station reliability	Percentage of BSS success in serving consumers without any disruptions.	SP	S	(Glombek et al. 2018), (Emeric 2019)

The driving factors of vulnerability, as presented in Table 4, are illustrated. For instance, the number of active compartments in the BSS, the quantity of batteries in the process of being charged, and the state of charge of the batteries being put in by the consumers, can affect the VPI.

Table 4. Vulnerability drivers

No	Vulnerability Drivers	Description	Category
(1)	(2)	(3)	(4)
1.	The number of compartment	The number of active compartments in the BSS.	Sta
2.	Maximum compartment	The maximum number of compartments that can be activated in the BSS.	Sta
3.	Electrical power at BSS	The electrical power (in kWh) in the BSS.	Sta
4.	Internet signal strength	Internet signal strength at the BSS	Sta
5.	Battery charging mode.	Battery charging mode at the BSS	Sta
6.	The number of batteries on charging.	The number of batteries on charging.	Sta
7.	Battery replacement time.	Battery replacement time, e.g., peak/ non-peak hours, weekdays/weekends.	Sta
8.	State of charge (SOC)	SOC on the swapping.	Bat
9.	Travel distance	Total travel distance of the battery.	Bat
10.	Total discharge (cycle)	Total discharge (cycle).	Bat
11.	State of Health (SOH)	State of Health (SOH) on charging process.	Bat
12.	BSS location type	BSS category based on the Permen ESDM No.1, 2023.	Loc
13.	The distance between the BSS location	The distance between BSS locations.	Loc
14.	Road type at the BSS	Road type at the BSS	Loc
15.	The number of consumers registered.	The number of consumers registered	Cus
16.	The battery replacement fee.	The battery replacement fee.	Cus
17.	The type of payment used by consumers.	The type of payment used by consumers.	Cus
18.	The type of consumer.	The type of consumer.	Cus
19.	Vehicle type	Vehicle type used by the consumer.	Cus
20.	The number of batteries rented by consumers.	The number of consumers registered	Cus
21.	The type of mobile app used by consumers.	The type of mobile app used by consumers.	App

Conditions that can expose vulnerabilities are referred to as threats. These factors can be categorized into three categories: natural hazards (NH), human-induced disturbances (HT), and operational disruptions (OP) (Nowakowski et al. 2015). Table 5 presents descriptions of these categories along with examples. An example of a natural hazard is a flood event near a BSS location, a human-induced disturbance could be an attack affecting the decision of an EM-BSS provider to make the maximum compartments available in a BSS.

Table 5. Threats/exposure categories

No	Threats / Exposures	Description	Examples
(1)	(2)	(3)	(4)
1.	Natural hazards/disruption (NH)	The type and/or percentage of natural disturbances within a certain period:	Flood
2.	Human threats (HT)	Human threats, both direct and indirect.	Hacker; Demonstration or riot.
3.	Operational disruption (OP)	Operational disruptions	Internet signal; Power outage; Traffic density.

5. Conclusion

There are vulnerability indicators that can represent the consequences of vulnerability, driving factors, and exposure in the operational system of EM-BSS. These indicators can have cause-and-effect relationships based on expert analysis, which can be further extended for diagnostic analytic studies by constructing a structured causal model (structural causal model) and a causal inference approach.

The identified indicators still require more detailed or operational metrics to examine the cause-and-effect relationships among indicators using the causal inference approach. The cause-and-effect relationships among indicators need to be supported by a structural causal model. Developing a structural causal model requires a quantitative approach to justify the assumptions of cause-and-effect relationships. Methods such as DEMATEL, or the combination of Fuzzy-DEMATEL, can be utilized.

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