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Joint Blockchain Service Vendor-Platform Selection using Social Network Relationships: A Multi-Provider Multi-User Decision Perspective

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Abstract:

Blockchain technology has been widely touted for building and supporting supply chain management capabilities. The technology has substantial potential to enhance operational effectiveness and profitability. Blockchain platform evaluation and selection still requires investigation. Blockchain platform selection and adoption decision making in a multi-organizational supply chain context is complex. Effective blockchain adoption and operations requires consideration of multiple vendors—service providers—and platforms while satisfying multiple users and stakeholders. This study introduces a managerial decision support method to assist organizations evaluate and select joint blockchain service vendor and platforms for multiple organizational functions and organizations. Using the literature and practice, we introduce blockchain service vendor and platform attributes from user, vendor, and platform perspectives. A social network theory lens sets the foundation for an innovative group decision-making method—a DEMATEL-based hierarchical best-worst method—integrating characteristics from this decision environment. The technological and distributed network nature of blockchain technology requires evaluation by decision makers from various levels of a supply chain network. These decision makers will likely have varying blockchain technology knowledge and subjective preferences that need integration. The proposed method helps to operationalize social network relationships to comprehend partial and idiosyncratic expert opinions about blockchain technology. An illustrative example and various scenarios are presented to identify managerial and research implications. Methodological limitations and future research are presented for this emergent managerial and technological concern across supply chains.

Keywords: Supply Chain Management, Blockchain, Service Platform Selection, Social Network Theory, DEMATEL, Hierarchical Best-Worst Method

1. Introduction

Blockchain technology proponents have argued for its use across numerous use cases (Zile and Strazdina, 2018). Supply chain application potential for blockchain is substantive (Saberi, et al., 2019a, b). Blockchain technology was introduced as the fundamental platform for bitcoin transactions (Nakamoto, 2008). Beginning as a financial tool, researchers and practitioners sought to explore its potential to improving business and supply chain productivity (Bai and Sarkis, 2020; Saberi et al., 2019; Pearson et al., 2019).

Today's supply chains have initiated promising blockchain pilot projects for their information technological infrastructure and data governance. There are many complexities in the management of potential blockchain applications within a supply chain environment (Bai et al., 2020; Kouhizadeh, et al., 2021; Wamba et al., 2020). As the blockchain vendors evolves and different service packages emerge, organizations in different sectors of multiple level of supply chain networks will face potentially controversial array of issues. Technology giants as IBM, Microsoft, and Oracle develop software that utilizes Blockchain technology to track products for organizations and their supply chains. Such services allow supply chains to leverage cloud-based solutions to enhance transaction traceability and security. For example, Walmart tested an application using IBM infrastructure that traces pork production and transportation processes, by authenticating transactions improving the accuracy and efficiency of global supplier and logistical partner record keeping. For Walmart, fining the expertise to develop and maintain the technology platform; and integrating inter- and intra-organizational stakeholders within the legacy systems are complex and difficult decisions. Critical managerial questions include what problems or opportunities one organization shares with

others within a supply chain; what are the challenges that might prevent broader adoption and collaborative execution; and what are the common standards should be established. All these questions relate to one important issue - how organizations may select and justify the selection of blockchains when multiple organizations are involved. How to select the best blockchain service vendor and platform has yet to be effectively addressed—although it is a critical issue in blockchain design, development, and implementation (Bai and Sarkis, 2020).

The joint blockchain service vendor-platform selection decision is difficult. It is especially complex in the supply chain context. Multiple supply chain companies and multiple providers are involved. An operating blockchain will likely require multiple vendors and satisfy multiple users to be effective. There are also other complex considerations related to life-cycle aspects, from implementation, operation, development and maintenance (Farshidi et al., 2020). The vendor-platform selection process includes steps to evaluate the most fitting blockchain vendor and service platform using managerial preferences and business requirements for blockchain design, constructing the blockchain, and integrating the systems needed—such as application, software providers, internet or service platform, and blockchain managers.

The blockchain service vendor-platform selection process is complicated because many vendors, platforms, and supply chain users are involved. Varied criteria such as security, inter-organizational interoperability, and consensus mechanisms must be considered and fitted to the supply chain network characteristics. Blockchain adoption in a supply chain is a critical and strategic decision for multiple supply chain actors. The decision—depending on blockchain purposes—can well determine future collaborations in product, material, financial, and information flows associated with inter-organizational and intra-organizational activities. A

multi-provider, multi-user, group decision method greatly benefits this business and decision environment.

Group decision-making has gained popularity in the study of multi-attribute decision-making (MADM) methods (Bai et al., 2019). It has been applied to the evaluation of blockchain technology (Bai & Sarkis, 2020)—although it was a focused approach on one characteristic of a blockchain, transparency, and didn't consider partner and technology elements and complexity fully.

Building an effective group decision-making method for the blockchain service vendor-platform selection problem faces two major challenges. First, due to limited understanding and varying priorities, each decision maker (DM) can only provide partial and idiosyncratic evaluation information. Therefore, we need to construct effective methods to eliminate inaccuracies caused by human biases and incomplete information. Second, the inter-related influence of relationships among DMs need to be considered.

According to social network theory (SNT), how people think and act in social situations will be influenced by others in the relationship networks (Krause et al., 2007). Evaluating and selecting a blockchain service platform involves many supply chain actors, and the decision will exacerbate the connectivity and interoperability of these actors in a supply chain. Therefore, the opinions of neighboring department DMs will also influence each other's opinions. The social network relationships among DMs have not been effectively considered and applied to decision-making methods in the blockchain technology evaluation literature.

The group decision-making methods proposed in this study will consider the evaluation behavior of decision makers (DMs), such as judgment uncertainty, the psychological

characteristics of DMs, and relative importance of DMs (Bai and Sarkis, 2020). We introduce a new group decision-making method using a DEMATEL-based hierarchical best-worst method (BWM) for blockchain service platform evaluation and selection. A hierarchical BWM is introduced to determine attribute weights and candidate blockchain service platforms weights under each attribute and will eventually rank those platforms. DEMATEL—the decision-making trial and evaluation laboratory—is introduced in the method to determine the social network relationships (impact degree) among DMs which complements BWM by addressing interconnectivity limitations.

This work contributes to the body of knowledge on blockchain management in supply chains. It provides insights into the necessary factors for blockchain adoption from multiple perspectives for the blockchain service vendor-platform selection decision. A new analytical modelling approach is also introduced that considers important decision environment dimensions missing in other models and approaches. It expands BWM to include hierarchical relationships amongst factors and alternatives. We also provide practical guidance on applying the analytical approach.

The remainder of the paper begins with providing a background on related literature and issues that set the foundation to inform later sections; this section also clarifies and develops a framework for factors to consider in the evaluation. The proposed methodology is then introduced with an overview of the DEMATEL and BWM methods. Detailed aspects of the methodology with specific analytic developments and calculations are presented using an illustrative application. Some scenarios for sensitivity analysis are then introduced to determine the robustness of initial solutions. The penultimate section provides some discussion and

implications of the methodology. The final section summarizes the study, results, and implications. It also provides insights into the limitations of the study which inform future research directions.

2. Background

This section provides some theoretical and practical foundation for this study. We firstly summarize the key characteristics of blockchain technology and its application in supply chain management. We propose a list of key criteria that may be included in strategic blockchain platform selection in a supply chain management context. Next, we thematically review the extant decision methods that have been used in blockchain technology—or strategic technology—evaluation and selection decisions. In this review we will also identify gaps in modeling this decision and environment and how we propose to bridge these gaps and advance the body of knowledge.

2.1 Blockchain Platform Selection Criteria

As a reliable decentralized infrastructure, blockchain technology has started to receive significant attention in supply chain management (Saberi et al., 2019; Kouhizadeh & Sarkis, 2018). Blockchain technology is an emergent and rapidly developing technology with the potential to disrupt supply chains across industries. Blockchain technology, as a type of inter-organizational technology, can potentially change the governance and management structure of the entire supply chain and enable supply chain integration (Bai & Sarkis, 2020). Therefore, organizations are paying greater attention to blockchain technology promises. Multi-functional

teams are usually used to evaluate these pervasive strategic technologies that influence multiple organizations and tiers in the supply chain. Different from traditional supply chain innovations including digital technologies and information systems, blockchain technology can have disruptive and revolutionary implications for supply chains. Table 1 summarized the major differences between blockchain technology adoption and traditional supply chain innovations using the technology, organization, and environment (TOE) theoretical lenses.

[INSERT TABLE 1 ABOUT HERE]

Blockchain service vendors are companies that provide service packages to other businesses or startups aiming to adopt blockchain technology. Not every vendor can provide an end-to-end solution. Besides, the variety of service packages means different application approaches for dynamic business environment. Many companies including IBM, Microsoft, Hewlett Packard Enterprise, and Oracle are developing and introducing blockchain service packages for a broad spectrum of business operations, transactions, and purposes. These software development companies will typically need to select a blockchain platform with optimal functionality, adaptability and compatibility, to create best value to their business clients (Farshidi et al., 2020). For example, IBM may select the best fitting blockchain infrastructure from companies like Ethereum, JM Morgan Quorum, Hyperledger, BigchainDB, or MultiChain. Understanding the business environment, defining the selection process, and evaluating the vendor and platform alternatives using appropriate method are critical to successful blockchain service adoption.

Organizations are seeking reliable software companies and appropriately capable service platform to achieve their competitive goals. This evaluation and decision-making process becomes more complicated from the perspective of supply chain organizations and partners as the number of decision makers, software vendors and platform alternatives and criteria increase. Figure 1 presents a generalized decision-making environment when firms within a supply chain collaboratively select the best software vendor and supporting blockchain service platform.

[INSERT FIGURE 1 ABOUT HERE]

Numerous blockchain platforms have emerged and covering diverse business applications. Platforms are often designed to fit application. For example, although Hyperledger and Ethereum both offer public blockchain service platforms, there exist fundamental differences in design layers. Hyperledger is an open-source platform that enables the functioning of multiple blockchain platforms and facilitates a collaborative development of blockchain-based distributed ledgers (Kinory et al., 2020). Whereas Ethereum is also an open source distributed public blockchain service platform but primarily designed for smart contracts implementation (Linoy et al., 2020). As the number and diversity of blockchain platforms in the market increases, selecting the best blockchain service platform is becoming significant yet complex especially for supply chain application users and service providers (Bai and Sarkis, 2019). Therefore, different characteristics such as compatibility, maturity, and functionality of blockchain platforms need to be critically identified, organized, and evaluated for platform selection, development, monitoring and maintenance.

A variety of studies have developed different analytical tools to facilitate blockchain adoption and selection decisions, for example multicriteria decision-making techniques has been utilized in decision support systems (Ar et al., 2020; Çolak et al., 2020; Öztürk and Yildizbaşi, 2020). However, few studies have considered these decisions from multiple-user and organizational perspectives. In this paper, we propose a blockchain service platform selection framework that aims to assist decision-makers from a supply chain perspective using a two-stage evaluation and selection process – first, selecting a blockchain infrastructure vendor; second selecting a blockchain service platform. Criteria at three levels are introduced and analyzed in the decision-making process. Table 2 entails the criteria dimensions, evaluation factors, their descriptions and literature support.

[INSERT TABLE 2 ABOUT HERE]

The first dimension represents the supply chain partner—users—perspective. These users are organizations engaged in a supply chain network. When they consider blockchain service adoption, factors to consider include: participation by each firm in supply chain information governance (Gordon & Catalini, 2018; Hardjono et al., 2019; Lewis et al., 2017); level of expertise and blockchain knowledge; scope of operations of the blockchain technology (Akoka & Comyn-Wattiau, 2017; Grover et al., 2019); the security needs of the blockchain service (Saberi et al., 2019; Kouhizadeh et al., 2019); the related blockchain technology adoption rate (Lou & Li, 2017; Lian et al., 2020; Folkinshteyn & Lennon, 2016); the require organizational or supply chain change management (Tapscott & Tapscott, 2017; Apte & Petrovsky, 2016); and the current information structure—legacy systems—of the supply chain users (Feng et al., 2020; Liu & Li, 2020). We also include sustainability factors, such as policy adaptability (Sheel

& Nath, 2019; Yeoh, 2017), job creation (Vovchenko et al., 2017; Ozdemir et al., 2019) from social factor dimension, and return on investment from economic sustainability dimension (Till et al., 2017; Stranieri et al., 2020).

The second dimension set of criteria focus on blockchain vendors– the infrastructure providers – and their characteristics. Companies such as IBM and SAP are early adopters of blockchain technology and constantly engaging in blockchain innovation and software development. When comparing these blockchain vendors, the first factor is trustworthiness and expertise that the vendor company provides (de Leon et al., 2017; Garrard & Fielke, 2020). We also include selection criteria relating to blockchain features, such as the adaptability of the system to a changing supply chain environment (Farshidi et al., 2020; Sheel & Nath, 2019); the ability to connect blockchains that may also exist across organizations (Zhang et al., 2018; Holmgren et al., 2017); scalability capabilities due to increases in the number of nodes, transactions, users, and geographic dispersion change, accessibility such as user interfaces, geographic availability (Malik et al., 2018; Zhang et al., 2018); and complexity of the development, maintenance, and operation of blockchain service (Dasaklis & Casino, 2019; Wang et al., 2019).

Cost factors also play an important role in blockchain adoption and selection decisions. Fixed costs and variable costs both need to be evaluated, for example the initial investment cost (Woodside et al., 2017; Prewett et al., 2020); and the cost of periodic operating and maintenance (Kouhizadeh et al., 2019; Dai & Vasarhelyi, 2017; Andoni et al., 2019). Technical

support availability and reliability correspondingly need to be considered (Zhang et al., 2018; Woodside et al., 2017; Zachariadis et al., 2019).

The third factor set focuses on the blockchain service provider dimension – the platforms. The dominating factors that differentiate the platform alternatives include transaction speed (Geneiatakis et al., 2020; Oh & Shong, 2017; Carson et al., 2018); market acceptance and popularity (Crosby et al., 2016; Guo et al., 2020); the maturity of the service platform depending on the year of foundation, revenue size, and firm size (Farshidi et al., 2020; Kietzmann & Archer-Brown, 2019); level of innovation of each platform in terms of integration with internet-of-things, artificial intelligence, and technological innovation such as technology and consortium-research support (Morabito, 2017; Risius & Spohrer, 2017; Angelis & da Silva, 2019); as well as the amount and the efficiency of energy consumption of the service platform running, development and maintenance (Khatoon et al., 2019; Fu et al., 2019; Imbault et al., 2017).

In real world applications, depending on different industries, firms and stakeholders involved, the inclusion of the three sets of factors is flexible and should be unique in dynamic business environment. For example, if firms shortlist qualified blockchain service platforms to Ethereum, JM Morgan, Hyperledger and BigchainDB. Considering all these platforms share the premium interoperability, scalability and accessibility, the company can select a specialized set of attributes from Table 2 to enhance the practical usefulness and cost effectiveness. As an illustrative example, we provide Table 3 as a comparison among four popular blockchain service platforms, respectively Ethereum, JM Morgan Quorum, Hyperledger and BigchainDB.

Ethereum service platform provides 15 second confirmation time, and processes 15 transactions per second as the speed of consensus mechanism – its transaction speed will be evaluated as “Low”, compared to Hyperledger that only needs 1 second in confirmation and completes 170 transactions per second in its consensus mechanism.

[INSERT TABLE 3 ABOUT HERE]

2.2 Decision Methods for Blockchain Technology Evaluation and Selection

Researchers have only recently initiated research on blockchain technology evaluation and selection modeling; realizing the industry is seriously considering the technology and there is great uncertainty for these potentially strategic decisions. Various tools and perspectives have been utilized. Entropy analysis and TOPSIS have been used to evaluate general public blockchain evaluation with results showing that Bitcoin, Ethereum, and EOS viewed as the top three public blockchains (Tang et al., 2019). There have also been proposed organizational evaluations using group decision methods for blockchains and the chain value provided (Yu, 2019). A multi-attribute decision-making model using Pythagorean fuzzy linguistic information measures have been proposed to evaluate blockchain products within a general sustainability context (Jin et al., 2019). Expanding on these works included using group decision methods with integrated hesitant fuzzy set and regret theory, for blockchain technology evaluation and selection, but specifically evaluating it from an important although singular blockchain supply chain characteristic—transparency (Bai and Sarkis (2020). A multi-criterion decision analysis method under development has been used to determine the most

suitable blockchain solution from company provided requirements and preferences (Six et al., 2020).

These few but emerging techniques and applications show many possibilities for further development. Utilizing a multicriteria, multistage, and multi-stakeholder decision perspective is lacking; especially considering a comprehensive set of evaluation criteria and characteristics. There are emergent methods and considerations that could benefit some of these initial published works.

In order to understand the holistic potential value of blockchain technology, an effective group decision-making method should evaluate the behavior of managers and entities within the broader supply chain. Group decision-making methods can support the evaluation behavior of decision makers (DMs) across different dimensions including the importance of DMs, judgment uncertainty, the psychological characteristics of DMs. For example, Yue (2011) presents a new approach for determining weights of DMs in a group decision environment using an extended TOPSIS method. Xia et al. (2013) propose a group decision making method using a hesitant fuzzy environment. Bai and Sarkis (2020) introduce a group decision making method emphasizing decision maker psychological characteristics and variation in decision maker opinions. Each of these inform the technique proposed and serve as the initial foundation for this more holistic evaluation process.

A blockchain service platform will involve various levels of expertise and interest; and cover multiple functional departments within an organization. Potential challenges of multi-organization and multi-department participation in blockchain vendor platform selection decision making include issues related to connectivity and interoperability of existing

information systems, data privacy and security compliance, access authentication and data encryption methods as well as personally perception of blockchain adoption urgency and effectiveness. Built upon social network theory (SNT), in this paper, to address the complexities and issues not yet addressed by other models and applications, we introduce a group decision-making method using DEMATEL-based hierarchical BWM for the blockchain service platform evaluation and selection problem.

SNT explains how information and relationships interact in the context of active social groups in organizations (Kadushin, 2004). Through these network connections, changes such as new technological innovations, for example, diffuse throughout the network (Krause et al., 2007). The rate and extent of such diffusion depends on two factors: the structure and the connectivity of the network. Strategic blockchain platform and vendor selection is comprised of a variety of network agents including cross-functional decision-making individuals of adopting firms, blockchain infrastructure vendors, blockchain service platform providers, and other entities (Queiroz and Wamba, 2019). These agents interact in different ways and hold diverse knowledge, value, motivations, and performance measures to technological changes (Swan, 2019), in this case, blockchain vendor and platform selection decisions. According SNT, the impact degree among DMs and their needs should consider understanding the potential value of blockchain service platform. Each DM's opinion will be influenced by other DMs who are closely related in functional duties. The implementation of blockchain will promote the integration of supply chain partners, however, the network connections between decision makers should be considered in blockchain adoption decisions—since buyers or sellers or any partner may have diverse knowledge and wield significant power. Such degree of impact on

cross-functional decision makers and their relationships has not been effectively considered and applied to group decision-making methods in the extant literature.

The proposed DEMATEL-based hierarchical BWM in this study is informed by a number of recent developments. Nie et al. (2018) constructed a multistage decision support framework integrated with multi-criteria decision making techniques including BWM, DEMATEL and TOPSIS, for water security sustainability evaluation. Kumar et al. (2019) used BWM to prioritize green supply chain management oriented intangible dimensions and employed DEMATEL to extract interrelationships among them. Yazdi et al. (2020) integrated DEMATEL with BWM and Bayesian networks to capture risk factor dependency with information source. These methods simply utilize these methods separately and not integrated into one single approach to address the limitations of the other method.

Some issues include BWM suffering from DM biases, incomplete information, and judgment uncertainty. Many scholars have applied grey numbers and fuzzy numbers to solve uncertainty problems (Bai et al., 2019). We will apply social network relations to lessen DM biases and incomplete information. DEMATEL is introduced to develop the social network relationships (impact degree) among DMs. This impact degree among DMs will be used to will supplement missing values and correct a DM's initial evaluation information in preference comparisons associated with BWM. A unique—developed for this study—hierarchical BWM is introduced to determine attribute weights and candidate blockchain service platforms weights under each attribute and finally ranks those platforms.

Thus, there is not only contribution in terms of application to a blockchain platform and vendor selection, but also factor development, and introduction of a unique and novel

methodology to address blockchain adoption challenges when involving broader stakeholders. The methodology has a multiplicity of future potential group decision making applications.

3. Methodology

The selection methodology process refers to the steps involved in selecting the best fitting blockchain infrastructure provider and blockchain service platform. This section will illustrate a detailed application procedure of the proposed methodology. Initially, some background is required for general aspects of the methodology including BWM and DEMATEL.

3.1 The Best-Worst method

The BWM, introduced by Rezaei (2015), is a simple and effective multi criteria decision making (MCDM) method to determine attribute weights. BWM uses fewer pairwise comparisons than the analytic hierarchy process (AHP) method and improves the consistency and the accuracy of judgment (Bai et al., 2019). The five steps of BWM include (Rezaei, 2015):

Step 1. Construct the attribute set $\{c_j | j = 1, \dots, m\}$, where m represents the number of attributes.

Step 2. Identify the best attribute B and the worst attribute W based on the opinions of DMs.

Step 3. Develop the preference comparisons of DMs for the best attribute over other attributes based on a 9-point Likert scale. The scale range goes from a value of 1 meaning *equal importance* between factors to a value of 9 meaning one factor is *extremely more important* than another.

Step 4. Develop the preference comparisons of DMs for other attributes over the worst attribute based on a 9-point Likert scale.

Step 5. Build the minimax model and solve optimal weights for the attributes.

3.2 DEMATEL

DEMATEL is suited for developing and analyzing the interrelationship and interdependencies between the factors by using matrices or digraphs of a system (Gabus and Fontela, 1973). It can quantify the strength of relationship while considering dependency among the factors. The basic stages of DEMATEL include four main steps (Bai and Sarkis, 2013).

Step 1. Construction of the initial direct-relation matrix $M = \{m_{ij}\}$ between a set of factors $a = \{a_i \,|\, i = 1, 2, \ldots, n\}$ by the DM using the six-level linguistic scale from "No Influence" to "Very High Influence".

Step 2. Computation of the normalized direct-relation matrix using expression (1) and (2).

$$N = s \cdot M \tag{1}$$

$$s = \frac{1}{\max\limits_{1 \le i \le n} \sum\limits_{j=1}^{n} m_{ij}}, \; i, j = 1, 2, \cdots, n. \tag{2}$$

Step 3. Computation of the total-relation matrix using expression (3).

$$T = N + N^2 + N^3 + \cdots = \sum_{i=1}^{\infty} N^i = N(I - N)^{-1} \tag{3}$$

The total-relation matrix represents the final relationship among factors after continuous iteration of direct and indirect relations. In this paper, we use DEMATEL method to capture social network relations (total relation matrix) among DMs, which can be used in BWM, to eliminate DM biases and incomplete information. The next two steps will not be covered in

this paper, since these DEMATEL results are not needed for the methodology. We mention these stages for completeness.

Step 4. Computation of the row (R_i) and column (D_j) sums from the total-relation matrix (T).

Step 5. Evaluation of the causal/effect diagram using the overall prominence (P_i) and the net effect (E_i).

Methodological details and calculations utilizing both techniques appear in the illustrative case described in the next section.

4. An Illustrative Case for Blockchain Service Platform Selection

In this section, the integrated DEMATEL and BWM method is applied to evaluate and select the best blockchain service platform using a practical illustrative application.

BWM is a simple and effective multi criteria decision making (MCDM) method to determine attribute weights or candidate weights with fewer pairwise comparisons. But it is difficult to use it in group decision-making, especially to balance different opinions among DMs. Especially for the decision-making of blockchain service platform selection, there is an influence relationship between group DMs, which makes it difficult to deal with by BWM directly. We will use DEMATEL method to overcome these gaps of BWM from the following two aspects. First, DEMATEL is introduced in the method to determine the social network relationships (impact degree) among DMs. This relationship can effectively correct the bias and incomplete information in BWM. Second, DEMATEL method can effectively confirm the weight of DMs. This weight can be used to balance the different opinions among DMs.

Therefore, the combination of these two methods can solve the group decision problem of blockchain service platform selection.

A hierarchical BWM is introduced to determine attribute weights and candidate blockchain service platforms weights under each attribute and will eventually rank those platforms. DEMATEL—the decision-making trial and evaluation laboratory—is introduced in the method to determine the social network relationships (impact degree) among DMs which complements BWM by addressing interconnectivity limitations.

In this illustration an organization seeks to adopt blockchain technology to connect their suppliers and customers. The deployment and operation of the blockchain service platform needs to involve various firms and functional departments across the supply chain. The opinions of critical DMs need to be considered when evaluating and selecting the optimal blockchain solution – a combination of blockchain infrastructure vendor and a specific blockchain platform. Their opinions and future operations will be influenced by other DMs through social network relations.

In the illustrative scenario, a focal firm and its upstream and downstream business partners collaboratively engage in a blockchain service provider selection decision. We assume two cross-functional teams from each of four firms are most directly involved in the decision-making process. Respectively we can assume a distribution department of supplier 1 (DM1 or DM d_1), customer service department of supplier 1 (DM2 or DM d_2); sourcing department of focal firm (DM3 or DM d_3), marketing department of focal firm (DM4 or DM d_4); supply chain department of distributor 1 (DM5 or DM d_5), sustainability department of distributor 1

(DM6 or DM d_6); finance department of distributor 2 (DM7 or DM d_7) and the procurement department of distributor 2 (DM8 or DM d_8).

Each decision alternative represents a combination of one vendor and one blockchain service platform. The top management teams shortlisted five blockchain service vendor-platform alternatives, respectively, IBM-Ethereum (x1), IBM-Hyperledger (x2), Microsoft-Ethereum (x3), Oracle-Hyperledger (x4), and SAP-Hyperledger (x5). As a methodological illustration, we only demonstrate use of 6 criteria from Table 2: scope of operations (C1), acceptance rate (C2), operating cost (C3), interoperability (C4), transaction speed (C5), and energy efficiency (C6). The model is easily generalizable to larger data sets including additional DMs, alternatives, and criteria/factors.

Now, we introduce how to apply the proposed group decision method, using a range of identified factors based on the social network relations of DMs to evaluate blockchain service platforms and eventually achieve an alternative ranking for selection purposes.

Step 1: Construct a group decision system.

The decision table for blockchain service platform evaluation and selection is defined by $T = (X, C, E)$, where $X = \{x_1, x_2, ..., x_n\}$ is a set of n candidate blockchain service vendor and platform combinations, $C = \{c_1, c_2, ... , c_m\}$ is a set of m attributes which are used to evaluate the performance of blockchain service alternatives, $D = \{d_1, d_2, ... , d_e\}$ is a set of e decision makers (DMs).

In our case, the illustrative firm considers 8 DMs $D = \{d_k \mid k = 1, \ldots, 8\}$ across multiple organizations and functions as defined in the illustrative case scenario. They will evaluate the 5 candidate blockchain vendor-service platform pairs $X = \{x_i, i = 1, 2, ..., 5\}$ based on the 6

performance attributes $C = \{c_j, j = 1, 2,...,6\}$. All attributes are distilled from both academic investigations and practical applications as summarized in Table 2.

Step 2: Determine the impact degree among DMs.

Impact degree is defined by a pattern of interaction among DMs in daily operations or future blockchain service platform operation. To measure the impact or influence degree among DMs, each DM was asked to evaluate the extent to which other DMs influence them using a 6-point linguistic scale. For example, "How much influence does other DMs have on you in the business and in the decision-making process. Please evaluate using the following linguistic scale." The linguistic scale is: 0 indicates no influence, 1 means very low influence, 2 means low influence, 3 is medium influence, 4 means high influence, 5 means very high influence. Next, all DMs were invited to evaluate, to get the impact degree matrix $M = \{m_{kl}\}$ among DMs. m_{kl} refers to the influence of DM d_k to DM d_l.

In our case, the impact degree matrix M among DMs is initially for all DMs in the supply chain (m_{kl}) included in a 8*8 matrix. An initial direct-relation matrix for DMs in the illustrative case is shown in Table 4.

[INSERT TABLE 4 ABOUT HERE]

Step 3: Establish the total direct influence matrix by DEMATEL.

In this step, we first standardize and obtain the normalized direct influence matrix using expressions (1) and (2). Second, we determine total relation matrix with expression (3). Then, the total relation matrix T among DMs is shown in Table 5.

[INSERT TABLE 5 ABOUT HERE]

The social network relationship (impact or influence degree) of the DMs is established; this information will be used for improved BWM analysis by providing DM weights in Step 7.

Step 4: Determine the best and the worst attribute and platform under each attribute for each DM.

This step includes two sub-steps. First, each DM d_k evaluates which attribute c_j is the best—*most important*—c_B^k and the worst—*least important*—c_W^k attribute for the blockchain service platform evaluation problem. Second, each DM d_k evaluates which blockchain service platform x_i is the best x_B^k and the worst x_W^k for each attribute.

In our case, the best and worst attributes and blockchain service platforms under each attribute for each DM are shown in Table 6. For example for DM d_1 the c1 is the most important or best for DM d_1, while the least important is c5; also the values show how much more important c1 is when compared to the other factors—a value of 1 meaning the factors are of equal importance to c1—while a 9 means that c1 is extremely more important than the column factor. Under attribute c1 the Best Service Provider Platform pair for DM d_1 is x_2, the worst is x_5.

[INSERT TABLE 6 ABOUT HERE]

Step 5: Establish hierarchical BO matrices for attributes or platforms under each attribute.

First, each DM d_k is responds to a 9-point measurement scale to express the preference degree of the best attribute c_B^k over the other attribute c_j. For example, each DM will be asked "How much do you think the best attribute c_B^k is more important than the attribute c_j? Please use 1-9 to evaluate." If the DM d_k is not sure, he can use a null value $\varnothing$ instead. The

comparison judgement is denoted by as a_{Bj}^{k}. Then the individual attribute Best-to-Others (aBO) matrix is formed as follows: $aBO^{k} = \{a_{Bj}^{k} \mid j = 1,\ldots,6\}$.

Second, each DM d_k is also asked to use a 9-point measurement scale to express the preference degree of the best blockchain service platform x_B^k over other blockchain service platforms x_i under each attribute c_j. The comparison judgement is denoted by as $a_{Bi}^{k,j}$. Then the individual platform Best-to-Others (pBO) matrix is formed as follows: $pBO_j^k = \{a_{Bi}^{k,j} \mid j = 1,\ldots,6;\ \ i = 1,\ldots,5\}$.

In our illustrative case, DM d_1 believes that the best—most important—attribute c_1 is slightly more important than attribute c_2 and assigns a value: a_{B2}^{1} = 3. In addition, DM d_1 also thinks that the best blockchain service platform x_2 is slightly more important—or doing better—then platform x_1 for attribute c_1 and given a value as: $a_{B1}^{1,1}$ = 3. In our example case, the aBO matrix and pBO matrices for the DM d_1 are presented in Table 7. Due to limited space, the evaluation results of other DMs are no longer displayed in our illustrative example.

[INSERT TABLE 7 ABOUT HERE]

Step 6: Establish hierarchical OW matrices for attributes or platforms under each attribute.

This step is very similar to the Step 5. First, the each DM d_k is asked to express the preference degree a_{jW}^{k} of the other attribute c_j over the worst attribute c_W^k using a 9-point measurement scale. The individual attribute Others-to-Worst (aOW) matrix is formed as follows: $aOW^{k} = \{a_{jW}^{k} \mid j = 1,\ldots,6\}$. Second, the each DM d_k is also asked to express the preference degree $a_{iW}^{k,j}$ of other blockchain service platforms x_i over the best blockchain service platform

x_W^k under each attribute c_j. Then the individual platform Others-to-Worst (pOW) matrix is formed as follows: $pOW_j^k = \{a_{iW}^{k,j} \mid j = 1,\ldots,6;\ \ i = 1,\ldots,5\}$.

In our example case, the aOW matrix and pOW matrices for the DM d_1 are presented in Table 8.

[INSERT TABLE 8 ABOUT HERE]

Step 7: Fill in missing value in BO matrices and OW matrices.

Due to the limited understanding if the technologies or vendors by each DM, they may not be able to provide all the detailed preference information for all alternatives and attributes for various BO matrices and OW matrices resulting in missing data. In this step, we will fill in missing values using DM similarity and impact degrees; with the belief through SNT that DMs will be greatly influenced to arrive at similar conclusions as other DMs. This step will be completed into two sub-steps.

Sub-step 1: Compute the similarity degree among DMs.

We first give the definition of the similarity degree among DMs.

Definition 1: Let a_{Bj}^k and a_{Bj}^l be the matrices given by the DM d_k and the DM d_l. Some of the elements in matrices are missing values and are set at $\varnothing$. The similarity degree (q_{kl}) between DM d_k and DM d_l is defined by equation (4) as follows:

$$q_{kl} = (4 - \frac{1}{NES} \sum_{a_{hj}^k, a_{hj}^l \notin \varnothing} | a_{hj}^k - a_{hj}^l |) - (\frac{m \times m}{NES} - 1) \tag{4}$$

where NES is the number of non-empty elements for a_{hj}^k and $a_{hj}^l \notin \varnothing$. $a_{hj}^k = \frac{a_{Bj}^k}{a_{Bh}^k}$ is the preference degree of the attribute c_h over another attribute c_j for DM d_k. $a_{hj}^l = \frac{a_{Bj}^l}{a_{Bh}^l}$ is the

preference degree of the attribute c_h over the other attribute c_j for DM d_l. Therefore, the first formula $(4-\frac{1}{NES}\sum_{a_{hj}^k, a_{hj}^l \notin \varnothing} | a_{hj}^k - a_{hj}^l |)$ refers to the similarity degree of the evaluation information given by two DMs. 4 is the maximum average deviation of each element because 9 point scale is used BO matrices and OW matrices. The second expression in (4), formula $(\frac{m \times m}{NES} - 1)$ refers to the proportion of the missing value and is used to describe the uncertainty degree of evaluation information given by the two DMs. *m* is the number of attributes. It is used to prevent artificial similarity degree increases caused by too many missing values and is distributed between [0, m-1] because the diagonal *m* elements are known and equal 1. When q_{kl} <0, we set it equal to 0.

In our case, the sum deviation $\sum_{a_{hj}^k, a_{hj}^l \notin \varnothing} | a_{hj}^k - a_{hj}^l |$ between DM d_1 and DM d_2 for the aBO matrix is 31.539. Since there are ten missing values in a_{hj}^k and zero missing values in a_{hj}^l, then $(4-\frac{1}{NES}\sum_{a_{hj}^k, a_{hj}^l \notin \varnothing} | a_{hj}^k - a_{hj}^l |) = (4-\frac{31.539}{36\text{-}10}) = 2.787$. We also get $(\frac{m \times m}{NES} - 1) = (\frac{6 \times 6}{36\text{-}10} - 1) = 0.385$. Finally, we get q_{kl} = 2.787-0.385=2.402.

Sub-step 2: Fill in missing value in BO matrices and OW matrices.

For this missing value situation, we obtain the estimated value $a_{Bj}^{k\,*}$ of missing value a_{Bj}^k for DM d_k using equation (5).

$$\begin{aligned} a_{Bj}^{k\,*} &= \sum_{l=1, a_{B_k j}^l \notin \varnothing}^{K} w_l \times a_{B_k j}^l \\ &= \sum_{l=1, a_{B_k j}^l \notin \varnothing}^{K} \frac{q_{lk} \times t_{lk}}{\sum_{h=1, a_{B_k j}^h \notin \varnothing}^{K} q_{hk} \times t_{hk}} \times a_{B_k j}^l \end{aligned} \tag{5}$$

where w_l is the weight of the DM d_l for the estimated value a_{Bj}^{k*} of DM d_k. Its calculation takes into account the two dimensions of similarity degree and impact degree. $a_{B_k j}^{l} = \frac{a_{Bj}^{l}}{a_{BB_k}^{l}}$ is the preference degree of the attribute c_{B_k} over the other attribute c_j for DM d_l. The attribute c_{B_k} is the best attribute for DM d_k.

In our example case, the incomplete aBO matrix and pBO matrices for the DM d_1 are changed to the complete matrices shown in Table 9. Due to limited space, the evaluation results of other matrices are no longer displayed but would be similarly complete.

[INSERT TABLE 9 ABOUT HERE]

Step 8: Adjust evaluation information in BO matrices and OW matrices according to impact degree among DMs

According social network theory, the opinions of each DM will influence other DMs due to their relationships. We consider this influence degree among DMs and adjust their evaluation values using expression (6).

$$\tilde{a}_{Bj}^{k} = \sum_{l=1}^{K} (t_{lk} \times (a_{B_k j}^{l} - a_{Bj}^{k})) + a_{Bj}^{k} \quad (6)$$

where t_{lk} is the impact degree of DM d_l on DM d_k. $(a_{B_k j}^{l} - a_{Bj}^{k})$ is the knowledge level differences value between DM d_l and DM d_k.

In our example case, the adjusted aBO and pBO matrices for DM d_1 appear in Table 10.

[INSERT TABLE 10 ABOUT HERE]

Step 9: Calculate the weights w_j^k for each attribute and $w_i^{k,j}$ for platforms under each attribute of DM d_k.

The weights of the attributes are calculated by solving the minmax model for each DM d_k using expression (7).

$$\min \ \max_j \{|\frac{w_B^k}{w_j^k} - a_{Bj}^k|, |\frac{w_j^k}{w_W^k} - a_{jW}^k|\} \tag{7}$$

$$\text{s.t. } \sum_{j=1}^{m} w_j^k = 1, \ w_j^k \geq 0 \text{, for all } j.$$

The weights of the platforms under each attribute are calculated by solving the minmax model for each DM d_k using expression (8).

$$\min \ \max_i \{|\frac{w_B^{k,j}}{w_i^{k,j}} - a_{Bi}^{k,j}|, |\frac{w_i^{k,j}}{w_W^{k,j}} - a_{iW}^{k,j}|\} \tag{8}$$

$$\text{s.t. } \sum_{i=1}^{n} w_i^{k,j} = 1, \ w_i^{k,j} \geq 0 \text{, for all } i.$$

In our case, the weights for each attribute c_j and DM d_1 are obtained and appear in Table 11. ξ is a parameter for $|\frac{w_B^k}{w_j^k} - a_{Bj}^k| \leq \xi$, $|\frac{w_j^k}{w_W^k} - a_{jW}^k| \leq \xi$ that represents the reliability of the comparisons. The consistency ratio ξ^* is small, hence the comparisons are highly consistent and reliable. The weights of each blockchain service platform x_i under each attribute and DM d_1 are calculated by the same process using expression (8), with results shown in Table 12.

[INSERT TABLES 11 AND 12 ABOUT HERE]

Step 10: Determine overall platform selection weights w_i based on the w_j^k and $w_i^{k,j}$ of all DMs.

We determine a weight w_i of each blockchain service platform x_i for all DMs d_k using expression (9).

$$w_i = \frac{\sum_{k=1}^{e} \sum_{j=1}^{m} w_j^k \times w_i^{k,j}}{\sum_{o=1}^{n} \sum_{k=1}^{e} \sum_{j=1}^{m} w_j^k \times w_o^{k,j}} \tag{9}$$

In our case, as an example, the weight (w_1) for blockchain service platform x_1 is: $w_1 = \frac{\sum_{k=1}^{e}\sum_{j=1}^{m} w_j^k \times w_1^{k,j}}{\sum_{o=1}^{n}\sum_{k=1}^{e}\sum_{j=1}^{m} w_j^k \times w_o^{k,j}} = \frac{2.935}{8} = 0.367$. The blockchain vendor service platform overall ranking weights are shown in Table 13.

[INSERT TABLE 13 ABOUT HERE]

The results show that the first blockchain service platform x_1 has the highest-ranking weight with a score of 0.367 using all DMs and attribute values. The fifth blockchain service platform x_5 has the lowest weight with a score of 0.071.

5. Sensitivity Analysis

In order to complete the sensitivity analysis, the basic values and assumptions related to the illustrative examples are altered to determine the robustness of the results.

5.1 Not consider social network relationships among DMs

When we do not consider the impact degree amongst DMs in the social network relationships. This lets us observe whether the social influence degrees amongst DMs will affect the final result.

First, we still use similar methods to incorporate missing values in BO and OW matrices. Second, we put the complete *n* BO matrices and OW matrices using the BWM method to calculate the weight of attributes and platforms. Finally, we arrive at the results without social network influences amongst DMs as shown in Table 14. The results show that although the rankings of the top three have not changed, the rankings of the last two have changed. Therefore, considering social network influences among DMs in group decision-

making can likely affect the final result. Although x1 was still the selected alternative, without the social influencing results it can be seen that it is an even stronger choice. If the weights were initially closer between x1 and x2 there may have been a change in the top alternative. Alternative x1 decreased by 0.016 in weight, while alternative x2 increased by 0.008 in weight when social network influence is included. This is a shift in different of 0.024 (or almost 10% of the x2 weight).

[INSERT TABLE 14 ABOUT HERE]

5.2 Similarity degrees among DMs not considered for filling in missing values

When we do not consider the similarity degree among DMs—used to fill in missing values. This will allow us to determine whether the estimated value will affect the final result and the relative influence of missing values. As a comparison, we can determine an estimated value $a_{Bj}^{k\,*}$ for a missing value a_{Bj}^{k} for a DM d_k using expression (10); which leaves out the similarity degree variable q_{kl} from expression (5):

$$a_{Bj}^{k\,*} = \sum_{l=1, a_{B_k j}^{l} \notin \emptyset}^{K} \frac{t_{lk}}{\sum_{h=1, a_{B_k j}^{h} \notin \emptyset}^{K} t_{hk}} \times a_{B_k j}^{l} \qquad (10)$$

Using this alternative approach for missing value determination, we may compare the two prediction results for the aBO matrix and pBO matrices of DM d_1. The comparison results are shown in Table 15. We found that when similarity degree is replaced, the predicted missing value $a_{Bj}^{k\,*}$ will be smaller. There is slightly larger bias in the missing data valuations and should be considered when using similarity rather than the alternative approach. Yet, given that there are multiple decision makers, the values are not off by more than 10%, which could be substantial with many missing values. Which implies that alternative approaches and their influence can be large depending on the number of missing values. But too many missing

values will likely make any data set invalid. Arguably the results did not change to an extent that the relative relationships change much to the next level of comparison (e.g. from 1 to 3, or 3 to 5) which would mean a relatively substantial difference in comparisons.

[INSERT TABLE 15 ABOUT HERE]

6. Discussion and Implications

This study has important managerial and methodological innovation implications. These implications are now summarized.

6.1. Managerial and practical implications

Supply chain or technology managers will find the results and methodology important for their organizations.

First, identifying, evaluating and adopting blockchain service platform vendors and providers requires numerous and diverse inputs and considerations including technical and sustainability characteristics. We have identified a general series of concerns and dimensions for evaluating blockchain technology adoption in organizations. An organization can benefit from the various factors identified as well as the various viewpoints that are offered to the decision. Organizations should realize that blockchain and interorganizational technologies should not just consider only their evaluation criteria but incorporate other stakeholders in a collaborative decision process (Ojala and Hallikas, 2006; Zhang and Cao, 2019). As diverse blockchain service vendors emerges and the adoption costs increases, it is critical to comprehend the differences of different vendors and avoid any form of a lapse in understanding the impact and scope of blockchain platforms in specific application sceneries.

The factors and dimensions presented in Table 2 can prove to be a valuable starting point for managers involved in the decision process. But each of these factors, as identified by the many sources, can have a series of subfactors that can be utilized. Another aspect of the factors is that many are subjective. The subjectivity needs to be carefully managed since evaluation could be heavily dependent on issues such as recency of experience, lack of supporting data, and surety of the situations. It is for these reasons that careful sensitivity analysis of this and any model is necessary.

Second, this paper considers the impact degree among multiple DMs through a social network relationships construct. The opinions of cross-departmental and functional, as well as inter-organizational, DMs can influence opinions in a multiplicity of ways. In order to select the appropriate blockchain service platform, firms should explicitly consider the decision influence degree among multiple DMs. However, this social network relationship has not been effectively considered in group decision-making methods and practices previously--a research implication, but also a practical implication. Managers and decision analysts can now effectively implement this influence weighting into the analysis.

Third, blockchain vendor-service platforms, as a type of inter-organizational technology, will involve multiple processes and multiple departments. Therefore, each DM cannot have the most comprehensive understanding and evaluation of this platform. We need DMs to choose not to evaluate without knowing much about the technology. This will cause incomplete information. Firms need to construct scientific methods to calculate this unknown information through known information. This is particularly important for investing in these inter-

organizational technologies; given a variety in expertise. Methodologies that allow this opt-out measure now have a way to determine values for missing data using similarity indices.

6.2. Methodological and research implications

The proposed group decision making method can overcome some existing group decision making method limitations for blockchain vendor-service platform evaluation; and other group inter-organizational decisions that may include such items as adoption of other technology, standards, sustainability practices, and other multi-tier supply chain projects such as investment in R&D projects (e.g. Manning, 2017; Grimm, et al., 2018; Sarkis, et al., 2019; Stejme et al., 2019).

First, through DEMATEL and mutual evaluation between DMs, the proposed method has analytically established a social network relationship between them. The social network relationship among DMs is one of the important dimensions that the group decision-making method need to consider in DM decision-making behavior. DM weights, psychological characteristics, and fuzzy judgments are the main dimensions of group decision-making methods to consider decision-making behavior, but the social network relationships between DMs has not been well established in the literature (Aaldering et al., 2018). This social network relationship can have serious impact on the final decision.

Second, the proposed method applies DEMATEL to develop a social network influence relationship that may explicitly consider group dynamics and potentially reduce DM knowledge deficiencies and incomplete information. BWM is an emerging popular and simple method that has been applied to evaluation and decision-making in various fields (Ahmadi et al., 2017; Mohammadi, and Rezaei, 2020). However, BWM may suffer from DM biases based

on ignorance of situation, incomplete information, and judgment uncertainty in a group decision making decision situation. Blockchain vendor-service platform, as an inter-organizational technology, will exacerbate the impact of DM bias and incomplete information on the application of BWM. This social network relationship among DMs will be used to supplement the missing value and correct the DM's initial evaluation information in preference comparisons of BWM by considering other DM influences. In addition, we also developed a hierarchical BWM to determine attribute weights and candidate blockchain service platforms weights under each attribute and finally rank those platforms.

Third, we proposed a new way to integrate DEMATEL and BWM, merging DEMATEL information into BWM, and then improve BWM incorporating a hierarchical evaluation characteristic. Although there are studies that use these two methods together, they are used in a parallel relationship, and there is no real integration of the two methods. We regard the total-relation matrix of DEMATEL as part of the BWM to correct the deficiencies and biases in DM evaluation. We proposed DEMATEL-based hierarchical BWM that can not only overcome the limitations of BWM, but also integrate the opinions of different DMs in BWM.

7. Summary and Conclusion

Blockchain technology can aid supply chains govern inter-organizational interactions and transactions with a secure, transparent, immutable information service infrastructure (Koh, et al., 2020). Much is still to be learned and evaluated in blockchain technology and supply chain management (Wamba, et al., 2020). Existing studies—albeit still in their early phases—have investigated the promising benefits and barriers of adopting blockchain for organizations and

their supply chains (Kouhizadeh et al., 2021). Yet blockchain adoptions and the bureaucracies formed to develop, manage, and maintain them have not been systematically evaluated; this evaluation is necessary to facilitate comprehensive supply chain digital transformation.

Few studies have examined blockchain adoption and selection from an integrated perspective of multiple supply chain users and service vendors and platforms. In this paper, a blockchain service platform selection framework that can assist decision-makers from a supply chain perspective using a joint evaluation and selection process is introduced – first, selecting a blockchain infrastructure vendor; second selecting a blockchain service platform. A comprehensive list of strategic criteria from multiple perspectives are introduced and can aid organizations and researchers seeking to further investigate the blockchain adoption managerial phenomenon. Some of these factors and characteristics are used in an evaluation of the methodology through an illustrative application.

A DEMATEL-based hierarchical BWM method—a novel group decision making method—is proposed and designed to be practicable for managers to evaluate and select a multi-tier blockchain vendor-service platform. The integrated methodology is built on social network theory to help integrate decision maker cross-influences and missing information. Inter-organizational and cross-functional decision making will likely have conflicts and diverging opinions each decision maker's social identity and network interactions; the methodology considers these important, yet less investigated group decision making aspects. The inter-relationships and relative influence amongst decision-makers, departmental functions, and organizations have been illustrated in this study using a DEMATEL-based hierarchical BWM method. This method helps to address the complexity and uncertainties in

practical interorganizational business decisions while enhancing collaborations and inter-relationships of supply chain users. The resulting decision is meant to be inclusive across these various stakeholders. Although numerous practical and theoretical—research—implications are evident and from this study, limitations exist.

Study limitations also give rise to future research opportunities. First, in introducing the list of proposed decision-making factors, we meant to be comprehensive and not necessarily exhaustive. Many of the factors are at strategical level rather than operational and tactical decision and management levels. There are additional factors that need to be considered in a real scenario depending on country-, industry-, firm characteristics. Sub-factors will likely be important in each of the categorizations and can also be utilized.

There may also be an issue with method generalizability and managerial application complexity. We only include a selective list of critical factors. Future studies can apply the method and evaluate it in empirical settings and determine the inclusion of critical factors as well as contingent factors. It will also be necessary to determine how feasible and understandable this technique is to managers.

Factors of one dimension may also affect factors of another dimension. We have not considered the multiple inter-relationships of factors at different dimensions and levels. For example, the proposed factors at the supply chain user level assume the users are all equal in one supply chain, meaning they are equally empowered in decision making. However, if we consider one user performs as the downstream product and information receipt of another user, the inter-relationships between these two users may alter the optimal decision at a certain point. The analytical network process (ANP) integrated with BWM and/or DEMATEL may be a

promising research direction for furthering the complex study of evaluating joint blockchain service provider-platform decisions.

Third, BWM may suffer from decision making biases. Such biases may come from the incomplete information and judge uncertainties given by the decision makers. The impact of such biases may be exacerbated especially in blockchain vendor-service platform decisions concerning the technological nature of a disruptive innovation – because the expertise, knowledge level, acceptance rate and personal preference may diverge in supply chain users and firms. Though the integration of hierarchical BMW aims to overcome such methodological limitation, biases still may not be eliminated. Future studies can explore other methodologies to retain decision making biases at minimal level.

The research on blockchain technology management in a supply chain setting is emerging. Considering the variety of offerings and use-cases, there is room for further development of decision tools and aids. We extend the work on decision aids for technology selection and evaluation in this context. We believe there are more explicit and important concerns depending on use-cases such as environmental sustainability, resilience, coordination, collaboration, and other emergent supply chain management topics and concerns. This work helps to further build on this research foundation.

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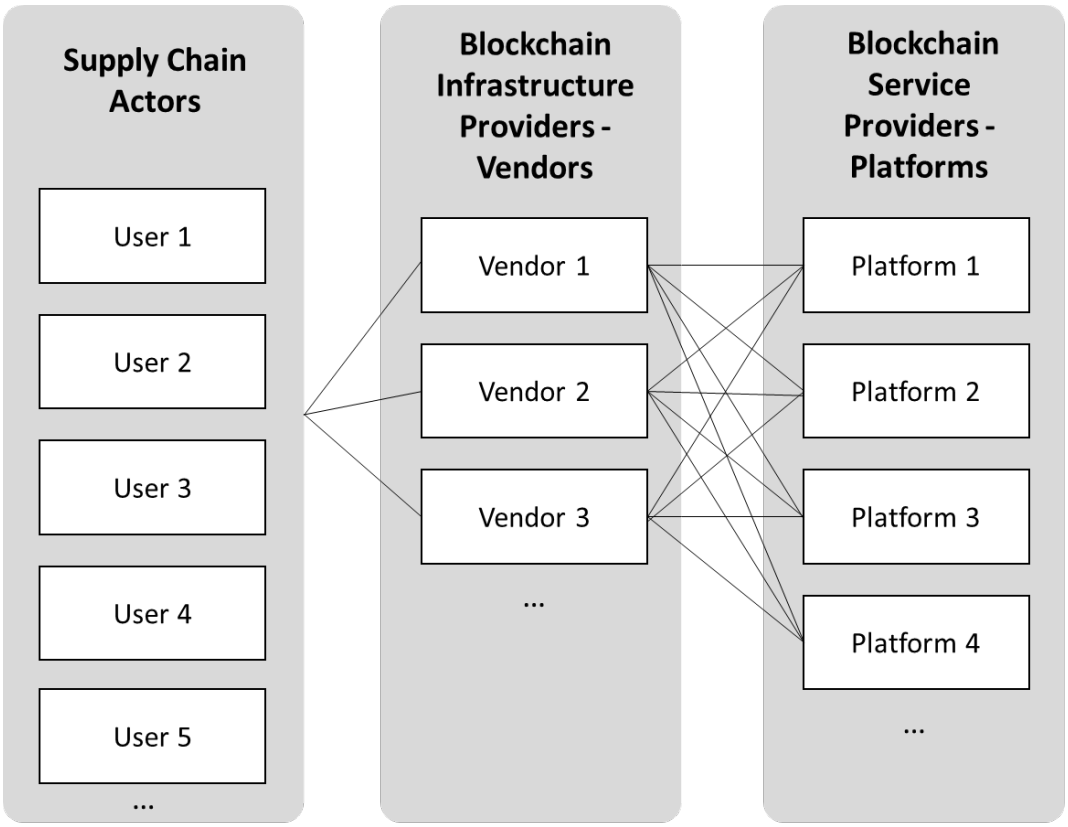
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Figure 1. Blockchain Service Vendor-Platform Decision Environment



Note: This blockchain platform decision environment is from the perspective of supply chain actors – firms and cross-functional teams that collaborate within a supply chain. The first stage of decisions is assumed to select the best software vendor – blockchain infrastructure providers – for instance, IBM Blockchain, Hewlett Packard Enterprise, Microsoft, Oracle, or SAP. The following decision stage is to select the best fitting blockchain service platforms, for example, Ethereum, JM Morgan Quorum, Hyperledger, BigchainDB, or MultiChain.

Table 1. Comparisons of Blockchain Technology and Traditional Supply Chain Technology Adoption

TOE View	Comparison Dimension	Blockchain Vendor-Platform Adoption	Traditional Supply Chain Technology Adoption
Technological context	Technology characteristics	Disruptive; Network based; Decentralized; Distributed ledger; Encryption/cryptography.	Centralized database; client-server based.
	Scalability and interoperability	Medium	High
	Disintermediation	Yes	No
	Technological maturity	Low	High
	Adoption cost	High	Low
	Supply chain coordination	High	Low
Organizational and supply chain context	Transformation complexity	High	Low
	Knowledge and expertise	Limited	Proficient
	Cross-functional stakeholder involvement	High	Low
	External stakeholders' involvement	High	Low
	Policy adaptability	Low	High
Environmental context (External view)	Regulations, legislation and effective governance	No	Yes
	Participation degree and adoption motivation	Low	Depends
	Awareness and understanding	Low	High

Table 2. Blockchain Service Vendor-Platform Selection Criteria

Dimension	Factor	Description	Sources
Supply chain ***users***	Participation degree	The ability for participation for all parties on the supply chain.	(Hardjono et al., 2019); (Lewis et al., 2017); (Gordon & Catalini, 2018).
	Level of expertise	Knowledge and familiarity of blockchain technology amongst supply chain actors.	(Akoka & Comyn-Wattiau, 2017); (Grover et al., 2019).
	Scope of operation	Supply chain organizations share all relevant or partial information with other participants.	(Filimonau & Naumova, 2020); (Helo & Hao, 2019).
	Security needs	Security needs will decide on the type of blockchain service adopted to the supply chain. For instance, permissioned vs Permission-less, and other security and privacy granularity.	(Saberi et al., 2019); (Kouhizadeh et al., 2019).
	Acceptance rate	The level of blockchain technology adoption amongst supply chain actors.	(Lou & Li, 2017); (Lian et al., 2020); (Folkinshteyn & Lennon, 2016).
	Change management	Unique change management requirements due to the nature of the technology.	(Tapscott & Tapscott, 2017); (Apte & Petrovsky, 2016).
	Information structure	Quality of documentation, data structure of supply chain actors.	(Feng et al., 2020); (Liu & Li, 2020).
	Policy adaptability	Social sustainability consideration: the adaptability of existing inter-organizational polices under the inclusion of blockchain technology – the level of adaptability to change.	(Sheel & Nath, 2019); (Yeoh, 2017).
	Job creation	Social sustainability consideration: the number of jobs increases after adopting blockchain technology in the supply chain.	(Vovchenko et al., 2017); (Ozdemir et al., 2019).
	Return on investment	Economic sustainability consideration: the efficiency of the investment on blockchain adoption.	(Till et al., 2017); (Stranieri et al., 2020).
Blockchain infrastructure providers - ***vendors***	Trustworthiness	Expertise and reliability of blockchain systems offered by the vendor company.	(de Leon et al., 2017); (Garrard & Fielke, 2020).
	Adaptability	The adaptability skills of the system to the changing environment on the supply chain.	(Farshidi et al., 2020); (Sheel & Nath, 2019).
	Interoperability	Compatibility of connecting blockchains across organizations.	(Zhang et al., 2018); (Holmgren et al., 2017).
	Scalability	The change of system performance leaded by the increase of the number of nodes, transactions, users, and geographic dispersion change.	(Malik et al., 2018); (Zhang et al., 2018).
	Adoption cost	Initial investment of adopting the blockchain service.	(Woodside et al., 2017); (Prewett et al., 2020).
	Operating cost	The cost of operating and maintaining a blockchain solution.	(Kouhizadeh et al., 2019); (Dai & Vasarhelyi, 2017); (Andoni et al., 2019).
	Accessibility	User interfaces, geographic availability, etc.	(Kouhizadeh & Sarkis, 2018); (Kumar et al., 2020).

	Complexity	The complexity of the development, maintenance, and operation of blockchain technology.	(Dasaklis & Casino, 2019); (Wang et al., 2019).
	Technical support	Availability of supporting developer tools to increase the developer experience.	(Zhang et al., 2018); (Woodside et al., 2017); (Zachariadis et al., 2019).
Blockchain service providers – ***platforms***	Transaction speed	The rate at which data is transferred from one account to another. Blockchain transaction speed depends upon various factors such as block time, block size, transaction fees, and network traffic.	(Geneiatakis et al., 2020); (Oh & Shong, 2017); (Carson et al., 2018).
	Popularity in the market	The market acceptance of the blockchain platforms amongst vendors or individual companies.	(Crosby et al., 2016); (ChoiGuo et al., 2020).
	Innovation	The level of innovation of each platform in terms of the involvement of internet-of-things, artificial intelligence, and technological innovation such as proofs technology, consortium-research support, etc.	(Morabito, 2017); (Risius & Spohrer, 2017); (Angelis & da Silva, 2019).
	Blockchain platform maturity	The maturity of the service platform depending on the year of foundation, revenue size, firm size, etc.	(Farshidi et al., 2020); (Kietzmann & Archer-Brown, 2019).
	Energy efficiency	Environmental sustainability consideration: the amount and the efficiency of energy consumption of the service platform running, developing and maintaining.	(Khatoon et al., 2019); (Fu et al., 2019); (Imbault et al., 2017).

Table 3. Exemplary Blockchain Service Platforms Evaluation

Factors	**Ethereum**	**JM Morgan Quorum**	**Hyperledger**	**BigchainDB**
Transaction speed	Low	High	High	High
Popularity in the market	High	Medium	High	Low
Innovation	High	Medium	High	Medium
Platform Maturity	High	Low	High	Medium
Energy Efficiency	High	Medium	High	Medium

Table 4. The direct-relationship matrix for all DMs

	DM1	DM2	DM3	DM4	DM5	DM6	DM7	DM8
DM1	0	5	4	2	2	1	0	0
DM2	4	0	4	3	2	2	1	1
DM3	3	4	0	5	4	5	2	2
DM4	2	3	5	0	3	4	2	1
DM5	2	2	3	3	0	5	1	1
DM6	1	1	2	2	4	0	4	3
DM7	0	1	1	2	2	3	0	5
DM8	0	0	1	1	3	3	5	0

Table 5. The total-relation matrix (*T*) for all DMs

	DM1	DM2	DM3	DM4	DM5	DM6	DM7	DM8
DM1	0.161	0.367	0.371	0.286	0.290	0.288	0.151	0.132
DM2	0.310	0.215	0.396	0.343	0.324	0.358	0.217	0.193
DM3	0.328	0.414	0.345	0.487	0.486	0.566	0.333	0.298
DM4	0.263	0.341	0.458	0.273	0.402	0.476	0.291	0.233
DM5	0.231	0.270	0.351	0.334	0.252	0.457	0.229	0.203
DM6	0.171	0.207	0.287	0.280	0.373	0.272	0.327	0.275
DM7	0.104	0.163	0.207	0.233	0.266	0.327	0.168	0.316
DM8	0.093	0.120	0.190	0.191	0.284	0.315	0.325	0.142

Table 6. The best and worst attributes and platforms under each attribute determined by each DM

DMs	Attributes		Blockchain Service Vendor-Platform Decision Criteria											
			c1		c2		c3		c4		c5		c6	
	Best	Worst	Best	Worst	Best	Worst	Best	Worst	Best	Worst	Best	Worst	Best	Worst
DM1	c1	c5	x2	x5	x1	x4	x1	x4	x1	x4	x1	x5	x1	x5
DM2	c2	c6	x1	x5	x2	x5	x2	x5	x2	x5	x1	x5	x1	x5
DM3	c1	c5	x1	x5	x1	x5	x1	x4	x1	x4	x1	x4	x2	x4
DM4	c4	c5	x4	x5	x4	x5	x4	x3	x3	x4	x3	x4	x3	x4
DM5	c2	c5	x2	x5	x2	x5	x2	x4	x3	x4	x3	x4	x1	x4
DM6	c1	c5	x1	x5	x1	x5	x1	x4	x1	x4	x1	x4	x3	x4
DM7	c2	c6	x2	x5	x2	x5	x2	x5	x2	x5	x1	x5	x1	x5
DM8	c3	c5	x3	x5	x3	x5	x3	x4	x2	x4	x2	x4	x1	x4

Table 7. The incomplete aBO matrix and pBO matrices for DM1

aBO	best	c1	c2	c3	c4	c5	c6
	c1	1	3	4	5	9	∅
	best	x1	x2	x3	x4	x5	
	x2	3	1	4	∅	6	
	x1	1	3	4	5	6	
pBO	x1	1	∅	4	9	6	
	x1	1	3	5	9	6	
	x1	1	4	5	∅	6	
	x1	1	2	3	6	∅	

Table 8. The incomplete aOW matrix and pOW matrices for DM1

aOW	best	c1	c2	c3	c4	c5	c6
	c5	9	∅	3	2	1	2
	best	x1	x2	x3	x4	x5	
	x5	6	3	2	∅	1	
	x4	9	3	2	1	2	
pOW	x4	9	3	2	1	2	
	x4	9	∅	3	1	2	
	x5	5	2	2	1	1	
	x5	5	2	2	∅	1	

Table 9. The complete aBO matrix and pBO matrices for DM1

aBO	best	c1	c2	c3	c4	c5	c6
	c1	1	3	4	5	9	4.007
	best	x1	x2	x3	x4	x5	
	x2	3	1	4	1.626	6	
	x1	1	3	4	5	6	
pBO	x1	1	2.090	4	9	6	
	x1	1	3	5	9	6	
	x1	1	4	5	7.809	6	
	x1	1	2	3	6	4.716	

Table 10. The adjusted aBO matrix and pBO matrices for DM1

aBO	best	c1	c2	c3	c4	c5	c6
	c1	1	2.753	3.586	4.313	8.309	3.944
	best	x1	x2	x3	x4	x5	
	x2	2.592	1	3.484	1.597	5.682	
	x1	1	2.753	3.586	4.313	5.510	
pBO	x1	1	2.038	3.586	8.009	5.510	
	x1	1	2.753	4.313	8.309	5.510	
	x1	1	3.810	4.532	7.807	5.974	
	x1	1	2.007	2.812	5.815	4.632	

Table 11. The attribute weights across DMs

DMs	c1	c2	c3	c4	c5	c6
DM1	0.432	0.177	0.133	0.108	0.050	0.101
DM2	0.385	0.341	0.085	0.061	0.061	0.067
DM3	0.422	0.130	0.144	0.166	0.052	0.087
DM4	0.305	0.172	0.115	0.273	0.038	0.098
DM5	0.161	0.307	0.126	0.305	0.041	0.061
DM6	0.402	0.143	0.149	0.169	0.051	0.086
DM7	0.383	0.343	0.088	0.060	0.060	0.066
DM8	0.154	0.310	0.331	0.089	0.042	0.072

Table 12. The blockchain service vendor-platform weights under each attribute for all DMs

DMs	x1	x2	x3	x4	x5	x1	x2	x3	x4	x5
			c1					c2		
DM1	0.309	0.320	0.066	0.227	0.077	0.484	0.169	0.153	0.112	0.082
DM2	0.489	0.170	0.149	0.135	0.057	0.470	0.308	0.082	0.082	0.058
DM3	0.451	0.151	0.157	0.186	0.055	0.428	0.090	0.101	0.318	0.063
DM4	0.337	0.195	0.126	0.302	0.041	0.384	0.150	0.120	0.288	0.058
DM5	0.170	0.323	0.151	0.314	0.041	0.206	0.261	0.118	0.371	0.045
DM6	0.438	0.161	0.166	0.181	0.054	0.389	0.173	0.181	0.198	0.059
DM7	0.357	0.406	0.105	0.075	0.057	0.442	0.352	0.084	0.057	0.064
DM8	0.171	0.340	0.349	0.096	0.045	0.180	0.352	0.298	0.120	0.050
			c3					c4		
DM1	0.473	0.234	0.147	0.056	0.089	0.517	0.195	0.130	0.060	0.099
DM2	0.419	0.360	0.092	0.059	0.071	0.457	0.355	0.059	0.059	0.070
DM3	0.499	0.157	0.177	0.064	0.103	0.496	0.151	0.192	0.060	0.101
DM4	0.456	0.304	0.081	0.086	0.073	0.346	0.193	0.309	0.043	0.110
DM5	0.238	0.455	0.157	0.060	0.089	0.192	0.366	0.322	0.049	0.072
DM6	0.488	0.169	0.178	0.065	0.099	0.476	0.163	0.201	0.060	0.100
DM7	0.417	0.361	0.095	0.057	0.070	0.454	0.357	0.060	0.060	0.069
DM8	0.165	0.362	0.350	0.046	0.077	0.217	0.496	0.126	0.062	0.099
			c5					c6		
DM1	0.542	0.163	0.132	0.065	0.098	0.466	0.194	0.145	0.086	0.108
DM2	0.552	0.160	0.130	0.089	0.069	0.517	0.177	0.136	0.097	0.073
DM3	0.495	0.179	0.177	0.058	0.090	0.131	0.486	0.194	0.077	0.111
DM4	0.371	0.137	0.329	0.045	0.118	0.248	0.148	0.404	0.056	0.143
DM5	0.365	0.073	0.394	0.057	0.112	0.389	0.133	0.344	0.050	0.083
DM6	0.481	0.183	0.188	0.058	0.089	0.132	0.147	0.537	0.092	0.091
DM7	0.554	0.167	0.118	0.091	0.069	0.500	0.189	0.137	0.100	0.074
DM8	0.232	0.475	0.128	0.061	0.103	0.394	0.387	0.087	0.052	0.080

Table 13. The integrated blockchain service vendor-platform rank weights from all DMs

DMs	x1
x1	0.367
x2	0.258
x3	0.175
x4	0.129
x5	0.071

Table 14. The integrated blockchain service vendor-platform weights for all DMs without social network relationships

DMs	x1
x1	0.383
x2	0.250
x3	0.180
x4	0.079
x5	0.107

Table 15. The aBO and pBO matrices of DM1 when considering similarity degree or alternative to replace missing values

	Consider similarity degree among DMs							Not consider similarity degree among DMs						
aBO	best	c1	c2	c3	c4	c5	c6	best	c1	c2	c3	c4	c5	c6
	c1	1	3	4	5	9	**4.007**	c1	1	3	4	5	9	**3.711**
	best	x1	x2	x3	x4	x5		best	x1	x2	x3	x4	x5	
	x2	3	1	4	**1.626**	6		x2	3	1	4	**1.492**	6	
	x1	1	3	4	5	6		x1	1	3	4	5	6	
pBO	x1	1	**2.090**	4	9	6		x1	1	**1.846**	4	9	6	
	x1	1	3	5	9	6		x1	1	3	5	9	6	
	x1	1	4	5	**7.809**	6		x1	1	4	5	**7.800**	6	
	x1	1	2	3	6	**4.716**		x1	1	2	3	6	**4.326**	