



Blockchain adoption factors for SMEs in supply chain management

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Abstract – Blockchain-based applications can enhance the sharing of information in processes involving multiple types of stakeholders, as in Supply Chain Management (SCM). A supply chain network can benefit from the visibility of the flow of goods, money, and information enabled by blockchain technology. So far, only limited evidence is available on the perspective of Small and Medium-sized Enterprises (SMEs) on the adoption of blockchain-based applications in their business processes. This may lead to a heavily diminished role for SMEs in SCM if large consortia unilaterally decide to adopt a blockchain-based architecture to improve the performance of the entire supply chain. Therefore, we conducted a study to explore which factors influence SMEs' intention to adopt blockchain technology. Based on a literature review into technology adoption frameworks, we derived the technological, organizational, and environmental (TOE) factors that can play a role in their decision-making process. We distributed a survey amongst European SMEs using the multi-criteria decision-making method of the Best-Worst Method (BWM) to elicit the relative weights of these factors. The data analyses show that in contrast to other studies into technology adoption, the SMEs' intention to adopt blockchain-based applications is primarily influenced by organizational rather than by technological and environmental factors. This implies that SMEs are best supported by showing blockchain's organizational benefits and by training senior executives at their company.

Keywords: Blockchain; Supply Chain Management; Best-Worst Method; Adoption Factors, SMEs

1. Introduction

Blockchain has gained the recognition of the general public due to the increasing popularity of Bitcoin and cryptocurrencies, which were the protagonists of a meteoric rise in value between 2015 and 2018, catching the attention of speculative investors and the media. The aforementioned digital coins employ blockchain as their enabling technology due to the distributed ledger's immutability and transparency, which removes the need for a trusted third party that oversees and validates all transactions. The underlying properties of blockchain make it an attractive use case for transacting all kinds of goods, including properties and consumer products. In particular, one of its most promising applications is in Supply Chain Management (SCM), as members of a supply network can benefit from the visibility of the flow of goods, money, and information enabled by blockchain. Nonetheless, several barriers (technological, organizational, and environmental) stand in the way of blockchain's large-scale adoption in SCM. These barriers can become insurmountable mountains for Small and Medium-sized Enterprises (SMEs) which often lack the ICT infrastructure and capabilities to join a blockchain-based network and, hence, face a concrete risk of being left behind in this transformative journey (Olsen et al. 2018, Wang et al. 2019). Furthermore, as SMEs presently occupy a prominent role in the functioning of supply chains and logistics in particular (Velthuis et al. 2018), they need to be able to participate in blockchain-based applications so that not only their performance can be improved but also the performance of the entire supply chain.

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However, despite blockchain's promise, "scholars have barely begun to systematically assess the effects of blockchain technology on various organizational activities" (Kshetri 2018), with the study of its interplay with supply chains still in an embryonic stage. Only one article by Wong et al. (2019) addresses the integration of blockchain for SCM from the perspective of SMEs so far. Furthermore, Fosso Wamba and Queiroz (2020) and Wong et al. (2019) both emphasize the need to further investigate the adoption challenges of blockchain as a distributed ledger technology (DLT) as only a marginal percentage of studies have reported with empirical approaches use cases in the domain of SCM.

In order to bridge this knowledge gap, we conducted an exploratory research project to explore how SMEs with a logistics operation can be supported in the adoption of blockchain for SCM. In this article, we use the term "SMEs with logistics operation" to identify SMEs that are part of an extended supply chain (they do not necessarily handle the entire logistics of it) or that are involved with logistics (e.g., as consultants). In particular, the objective of our research is to discern the factors that play a role for SMEs when deciding to adopt blockchain-based applications for SCM. This study is conducted in collaboration with the Spark! Living Lab (SLL), a Dutch-based open-innovation ecosystem that supports interested stakeholders in developing use cases with blockchain in SCM and Logistics, with the selection of those that directly involve SMEs (Spark! Living Lab 2020). The SLL comprises several stakeholders, including the Netherlands Organization for Applied Scientific Research (TNO), Delft University of Technology, the Windesheim University of Applied Sciences, the Block Field Lab in Rotterdam, and multiple Supply Chain and Logistics (SCL) training centers (Spark! Living Lab 2020). The members of the consortium, and TNO above all, were instrumental in providing a platform for data collection, which was hence directed towards a European audience, as mentioned below.

In our study, we used a mixed-methods approach, comprising of both qualitative and quantitative methods. We started with a literature review in the initial exploratory stages of the project to develop a conceptual model with adoption factors. Following the guidelines of the Best-Worst method (BWM), we developed an online questionnaire that was administered among European SMEs with a logistics operation. The BWM enabled us to determine the weights of all factors based on the respondents' preferences. The obtained weight-wise ranking was used to formulate recommendations to the SLL on how SMEs can be supported in the adoption of blockchain for SCM. Moreover, the factors' ranking can assist the SLL but also blockchain platform providers in determining which elements they should focus on when advertising their respective projects and initiatives. Lastly, the present research aims to increase SMEs' awareness of the determinants they should consider when making a decision to adopt a blockchain-based application and which determinants are weighted more heavily by their peers.

The structure of this article is as follows. In Section 2, we introduce the challenges in SCM, the characteristics of blockchain technologies, and how they can contribute to SCM. Then, in Section 3, a conceptual model with adoption factors is developed based on existing literature on technology adoption by SMEs. Section 4 sheds light on the method(s) that were used to compute the factors' weights, which are then presented in Section 5. In Section 6, the findings of the present study are discussed, along with their managerial implications. Finally, in Section 7, we present our conclusions and formulate future research topics.

2. Blockchain Technology in SCM

In this section, we first introduce the general characteristics of blockchain technology. Thereafter we define the concept of Supply Chain Management (SCM), and we set forth its main issues. Finally, we present a literature overview of blockchain-based applications for SCM purposes.

2.1. Challenges in SCM

A supply chain can be referred to as "the network of organizations that are involved, through upstream and downstream linkages, in the different processes and activities that produce value in the form of products and services delivered to the ultimate consumer" (Christopher 2011). These multi-actor systems are increasingly complex due to the globalization of supply, which requires additional efforts to coordinate the flow of materials into and out of the company (Mentzer et al. 2001). Furthermore, customers have become accustomed to fast and seamless deliveries of their products, which are now requirements to compete in the market (Mentzer et al. 2001). Thus, to manage the intricacy in the flow of goods and information while maintaining exceptional levels of customer service, a new perspective, Supply Chain Orientation, was born. This perspective comprises "a set of

beliefs that each firm in the supply chain, directly and indirectly, affects the performance of all the other supply chain members, as well as ultimately, the overall supply chain performance” (Cooper et al. 1997, as cited in Mentzer et al. 2001). To optimize the supply chain performance, organizations involved need to establish a set of collaborative practices, including the mutual sharing of information and the integration of critical processes (Mentzer et al. 2001). However, supply chain actors may only be willing to commit to these practices if they trust their counterparties.

In particular, transparency and visibility of operations are crucial to trust development (Akyuz and Gursoy 2020). First, a significant distinction has to be made between visibility and transparency, which are often used interchangeably in the Supply Chain context. Supply Chain Visibility is a precondition for Supply Chain Transparency, and it entails mutual sharing of data between stakeholders internal to the company, such as managers and immediate suppliers (Sodhi et al. 2018). On the other hand, Supply Chain Transparency is achieved when product and supply chain information is disclosed to a broader set of external stakeholders, such as customers as well as investors and regulators (Sodhi et al. 2018). With customers paying more attention to companies’ social responsibility practices, being more transparent represents a marketing tool to increase the public’s trust, which can, in turn, increase sales (Kraft et al. 2019). This practice has been especially popular in the apparel industry, with Nike becoming the first major company to publicly disclose its factory base (Nike 2005). Nonetheless, the prospective benefits of Supply Chain Visibility are not merely limited to improving a company’s image, as gaining visibility has the potential to reduce a firm’s exposure to risk and, at the same time, improve efficiency (Sodhi et al. 2018). Supply Chain Risk may arise due to external factors, such as natural disasters, or internal ones, such as product recalls or supply shortages. If a disruption was to occur, its severe consequences might be avoided if the stakeholders hold a holistic view of the entire supply chain (Tang et al. 2009). Furthermore, Supply Chain Visibility may discourage the actors involved from engaging with opportunistic behaviors and thus prevent fraud and counterfeiting across the supply network (Akyuz and Gursoy 2020). Lastly, as firms gain visibility into their supply chains, they will eventually have access to real-time information and use it to make real-time decisions (Sodhi et al. 2018). For instance, this enables firms to timely respond to supply-demand mismatches and can potentially reduce the impact of the so-called bullwhip effect, which is “the effect by which slow-moving consumer demand creates larger swings in production for suppliers at the other hand of the supply chain” (Akyuz and Gursoy, 2020, Wang and Disney 2016). While the value of Supply Chain Visibility in enhancing trust between the stakeholders, reducing a firm’s exposure to risk, and enabling real-time decision-making is clear, sharing information between supply chain partners is still a cumbersome process (Vyas et al. 2019). Indeed, despite technological advances and the role of logistics information brokers, shared data is often redundant and inaccurate, with many organizations managing the same order (Vyas et al. 2019). However, a paradigm shift in information sharing across the supply chain and between the organizations involved may be possible with the arrival of blockchain technologies (Akyuz and Gursoy 2020).

2.2. Blockchain Technology

A blockchain is a digital ledger that is distributed across all members of a computing network (Carson et al. 2018). This concept was first introduced in 2008 when the article “Bitcoin: A Peer-to-Peer Electronic Cash System” (Nakamoto 2008) was published. In this article, Nakamoto (2008) argues for the value of blockchain as the underlying technology for two parties to transact with each other without the need for a trusted third party. A blockchain, as the name would suggest, is a chain of blocks. Transactions occurring between the members of a blockchain-based network are recorded in chronological order on each block. Every user is assigned a pair of keys, one public, and one private, respectively, which cannot be traced back to their owner and are frequently updated (Nakamoto 2008, van Engelenburg et al. 2018). The public key of each user is known to everyone in the network as transactions are announced publicly in the blockchain. In contrast, private keys are only known to their owners and are used for encrypting each transaction. Once a block has reached its maximum capacity, all the nodes in the network (or a few elected nodes, depending on the algorithm employed) attempt to solve a complex and irreversible computational problem, which takes the transaction data stored on the block and the hash of the previous block as an input to generate the hash of the current block. A hash is generally defined as a function that takes objects as inputs and as outputs a string or number, and, in the blockchain context, it represents the solution of the computational problem that has to be solved to validate a block of transactions (Nakamoto 2008). When a node in the network finds the solution to the puzzle the block is broadcasted to all nodes and has to be accepted by the

majority of the network, in a process known as consensus (Tasca and Tessone 2019). This consensus mechanism is called Proof-of-Work (PoW). Once consensus is reached, the block is finally added to the chain. The original blockchain-based applications were cryptocurrencies based on public permissionless blockchain architectures: anybody can join and act as a node in the blockchain network (Ølnes et al. 2017).

One of blockchain's fundamental features, its immutability, stems from the properties of cryptographic hash functions. A cryptographic hash function has three crucial attributes: it is deterministic, which means that given the same input, one and only one output can be obtained; it is irreversible, which means that given the output, it is not possible to determine the input; it is collision-resistant, which means that no input can ever have the same output (Badev and Chen 2015). From these properties, it follows that if a malicious user tampers with a block in the chain, the block's hash will change, and since every block's hash is included in the subsequent blocks' hashes, a hacker would need to change every single block after that on the blockchain. Accomplishing the latter would take a disproportionate amount of computational power, which makes altering a block extremely difficult (Landerreche and Stevens 2018). Over time other consensus mechanisms have been introduced to cope with the inherent shortcomings of the computationally heavy PoW approach, such as its slow speed of transaction verification and high electricity consumption (Mingxiao et al. 2017). Notably, Proof-of-Stake (PoS) and Proof-of-Authority (PoA) consensus mechanisms were developed in parallel with the rise of private and permissioned blockchain architectures in which only a selected set of stakeholders can take part in the consensus process. These new frameworks dramatically improved the scalability and feasibility of using blockchain-based applications in all kinds of domains in which transactions take place, amongst which the domain of SCM (Segers et al. 2019).

2.3. Blockchain in SCM

Despite being initially developed to favor the exchange of financial assets without the need of a trusted third party (Nakamoto 2008), any transaction of hard or soft assets can be supported by a blockchain-based system (Swan 2015). For instance, an RFID (Radio Frequency Identification) chip, a barcode, or a QR code can be linked to a physical product and used to record its digital counterpart on a distributed ledger (Hepp et al. 2018). Then, each time the product is scanned, its ownership is transferred, and the transaction is recorded with a timestamp on the blockchain (Hepp et al. 2018). Akyuz and Gursoy (2020) argue that blockchain's decentralization, transparency, and immutability provide for "a trusted transactional database for the network for providing real-time, accurate and visible transactions among partners" (Akyuz and Gursoy 2020), which positively matches the needs of the SCM domain. The increased visibility gained with blockchain technology supports applications in product traceability, which can benefit both firms and their consumers (DHL 2018). The former can use the track-and-trace capabilities to provide proof of legitimacy for their products and, hence, identify those that are counterfeit (Akyuz and Gursoy 2020). On the other hand, consumers can exploit the newly available information on the products they buy to make more responsible choices (Kraft et al. 2018). Furthermore, having a holistic view of a supply chain enables all of its members to make more accurate forecasts and to promptly react if demand shocks or disruptions occur (Sodhi et al. 2018, van Engelenburg et al. 2018). Indeed, by sharing their demand data, inventory levels, and work in progress levels in near real-time, all the members of a supply chain can make predictions based on the same data, rather than on the purchase orders from the previous party only (van Engelenburg et al. 2018). Moreover, blockchain can be used as a tamper-proof repository for digitalizing and sharing the bill of lading, customs documents, and other data (Segers et al. 2019). The bill of lading is considered one of the most important documents in ocean shipping, as it contains "the shipment description, quantity, and destination, as well as how the goods must be handled and billed" (Addison et al. 2019, Takahashi 2016). According to international logistics company DHL, using blockchain to replace the bill of lading documentation alone would lead to millions of dollars of cost savings across the supply chain (DHL 2018). Moreover, blockchain can be used to automate manual and inefficient customs-related processes, which are prone to error and cost up to one-fifth of the actual physical transportation costs (Segers et al. 2019). Customs-related processes are the activities needed to obtain clearance for exporting, such as obtaining export licenses or permits and registering with customs and border security agencies (Okazaki 2018). These activities are heavily paper-based and require customs' employees to cross-check manually the documents submitted by traders and transporters for compliance (Okazaki 2018). If customs became part of an embedded blockchain-based network, the information submitted digitally by the exporter and its associates could be automatically checked, and the examined goods could be cleared without human intervention (Okazaki 2018). Lastly, blockchain technology can ease many of the frictions

in trade finance (DHL 2018, Kim et al. 2019). Indeed, as a trail of all trades and transactions is visible on the blockchain, financing institutions would have a reliable information source to assess the credit risks of the actors involved, which can in turn speed up the payment process and guarantee easier access to funds, especially for small businesses (Olsen et al. 2018).

In order to profit from the benefits that blockchain technologies can offer to SCM, all stakeholders involved in a particular process need to join the same blockchain-based application. Currently, these blockchain-based applications in SCM and international logistics are developed by large stakeholders. For example, the blockchain-based architecture for international logistics for container transport Tradelens was originally initiated by one of the largest international shipping firms, Maersk, and technology provider IBM (Rukanova et al. 2021). Another example is the blockchain-based platform Vinturas, initiated by large players in the automotive industry to support reliable information sharing amongst organizations in the international logistics of vehicles transportation (Vinturas 2019). Whereas these platforms are open to all supply chain organizations to join, these consortia are still mostly made up of large organizations. The adoption of blockchain-based applications by SMEs has not materialized yet, whereas the added value of supply chain transparency and visibility applies to them as well. Hence, barriers to blockchain adoption for SMEs need to be addressed to avoid the risk of being left out if a network of larger supply chain stakeholders decides to base their processes on a distributed ledger architecture. In the following section, we develop a conceptual model to investigate the barriers that SMEs may experience in adopting blockchain-based applications for supply chain visibility and transparency.

3. Conceptual Model

In this section, we present the conceptual model that we used to discover the barriers to blockchain adoption in SCM by SMEs. We started with a systematic literature review to make an inventory of available frameworks for investigating blockchain adoption by SMEs. After a critical review of these frameworks, we selected the Technology, Organization, and Environment (TOE) framework to identify the factors that influence the SMEs' intention to adopt blockchain for SCM. These factors are described in full before we present our research method in Section 4.

3.1. Literature Review Protocol

To gather data on available frameworks for investigating blockchain adoption intention in SCM by SMEs and to identify a set of explanatory factors, a systematic literature review was performed. The main literature repository that was used for this systematic review is Scopus, the largest abstract and citation database of peer-reviewed literature. The search results were compared and complemented with the results from Web-of-Science (WoS), to make the review more rigorous. Only the studies accessible in full-text were selected for the literature review. A constraint was also placed on the publication type (only peer-reviewed journal articles and conference proceedings) and on the language of the sources (only sources written in English), the year (after 2015), and on the relevance to our research topic. A limit on the publication year has been imposed due to the novelty of the topic, as the majority of the publications on blockchain technologies published before 2015 were solely related to cryptocurrencies/Bitcoin applications. The studies returned by Scopus and WoS were thoroughly examined by looking first at the abstract and then to the full article when in doubt to determine its suitability for developing a conceptual model of technology adoption factors.

Two distinct queries were formulated, as shown in Table 1, but the results were examined jointly due to the scarcity of sources on the topic and substantial overlap in the research output. Initially, the keywords that were used in Search 2 included the words from Search 1 plus "factors OR drivers OR determinants". Nevertheless, the output yielded only one additional article, hence the constraint on the SMEs' focus was removed at this time, and the query shown in the second row of Table 1 was used instead.

Table 1. Search terms for our systematic literature review.

Query number	Search Term(s)
1	SMEs OR “Small and medium-sized enterprises” OR “Small and medium-sized businesses” OR “Small enterprises” OR “Small businesses” OR “Small firms” AND (“Supply Chain” OR “Logistics” OR “Supply Chain Management”) AND (“Blockchain” OR “Blockchain” OR “Distributed ledger” OR “ICT” OR “Information Technology”) AND (“Benefits” OR “Advantages” OR “Opportunities” OR “Positive” OR “Impact”) AND (“Adoption”) OR “Appropriation”)
2	("Supply Chain" OR "Logistics" OR "Supply Chain Management") AND ("Blockchain" OR "Block chain" OR "Distributed ledger") AND ("Adoption") AND ("factors" OR "drivers" OR "determinants")

The first query from Table 1 returned 24 articles, of which 13 were discarded based on the title alone, and three were discarded as we could not gain access to them despite using several means to do so. Of the remaining results, two were rejected after reading the full text, as shown in Figure 1. The output of the second query consisted of 11 documents, which were all published in 2019, which shows the novelty of this topic. The paper by Wong et al. (2019) was already present in the first query. Moreover, one paper was rejected based on the title alone, whereas three articles were judged as not suitable topic-wise after reading the abstract, and one article was discarded as it was not written in English. Subsequently, 11 papers were found that complied with our search terms. These are reviewed in the next paragraphs in order to select a conceptual framework for our study.

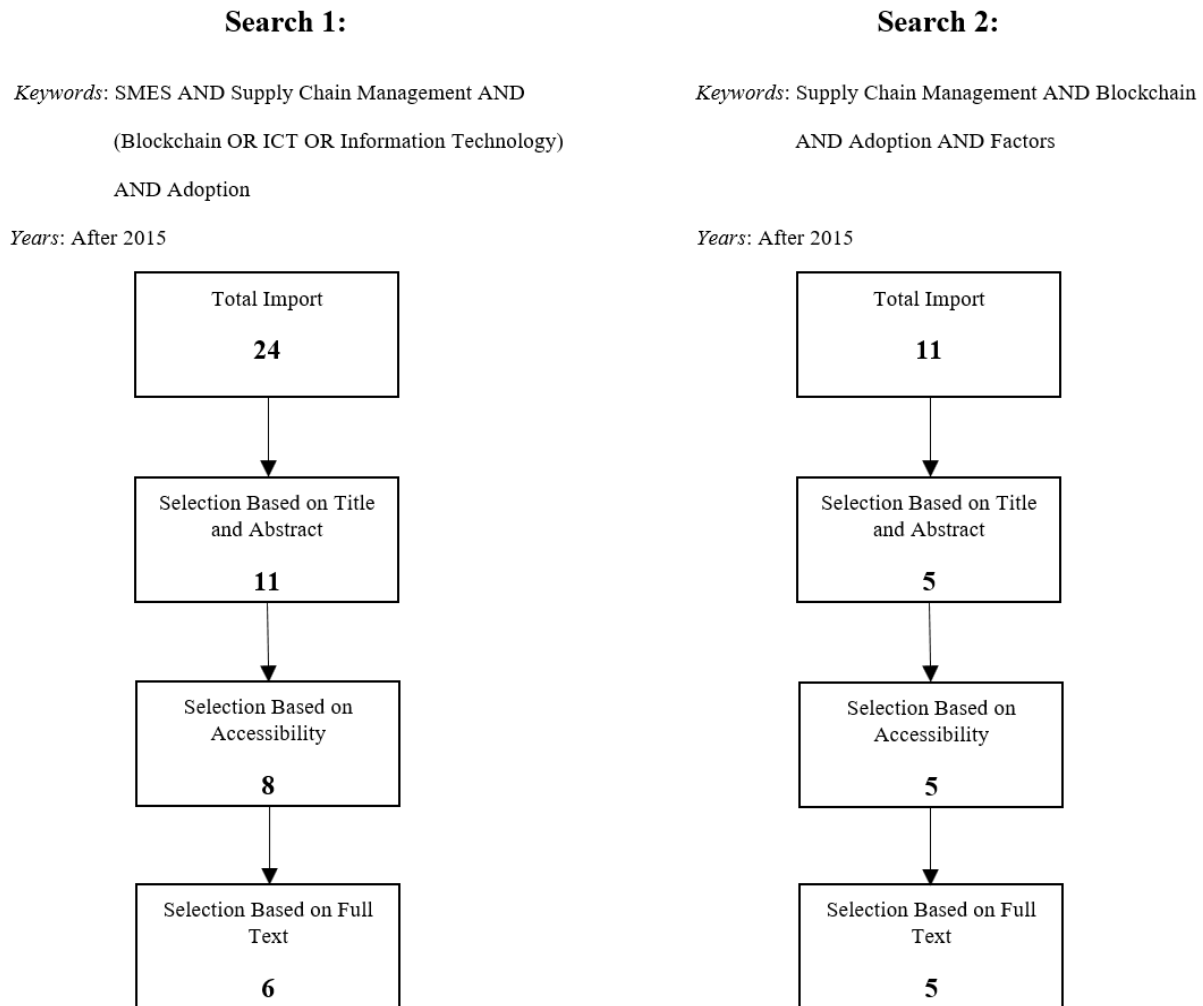


Figure 1. Literature review selection.

3.2. Framework Selection

In the 11 remaining references of our literature review, several frameworks were employed in the study of ICT adoption, including the Technology Acceptance Model (TAM), the Diffusion of Innovation Theory (DoI), the Technology, Organization and Environment framework (TOE), and the United Theory of Acceptance and Use of Technology (UTAUT).

Whereas the DoI and the TOE frameworks both examine technology adoption at a company's level, the TAM and UTAUT frameworks focus on the adoption by individual users and, as such, excluded from this study. The DoI Theory framework has been demonstrated to be consistent with the Technology-Organization-Environment Framework (Baker 2011). Indeed, the DoI adoption predictors individual leader characteristics and internal characteristics of the organizational structure have been compared to the TOE's organizational context. Whereas the external characteristics of the organization and Rogers's (1962) technology focus have been compared to the TOE's environmental and technological contexts, respectively. Nonetheless, the TOE framework provides a more holistic picture of adoption factors (Awa and Ojiabo 2016) and has often been praised for its adaptability (Baker 2011, Kühn et al. 2019), which allows researchers to adjust the set of adoption factors depending on the situation. Moreover, the TOE framework has been used for many ICT adoption inquiries, which strengthens its empirical validity (Awa and Ojiabo 2016, Baker 2011) and demonstrating an explanatory power that encompasses sectors and nations (Baker 2011). In particular, the TOE framework has been applied to explain the adoption of electronic data interchange (EDI), inter-organizational information systems, e-business, and a broad spectrum of general IS applications (Awa and Ojiabo 2016, Baker 2011, Wong et al. 2019). Although the influence of DoI is evident, especially in the technology context, which comprises determinants such as Perceived Compatibility and Complexity as introduced by Rogers in his seminal work on technology adoption (1962), we selected the TOE framework to categorize the identified factors for the reasons mentioned above.

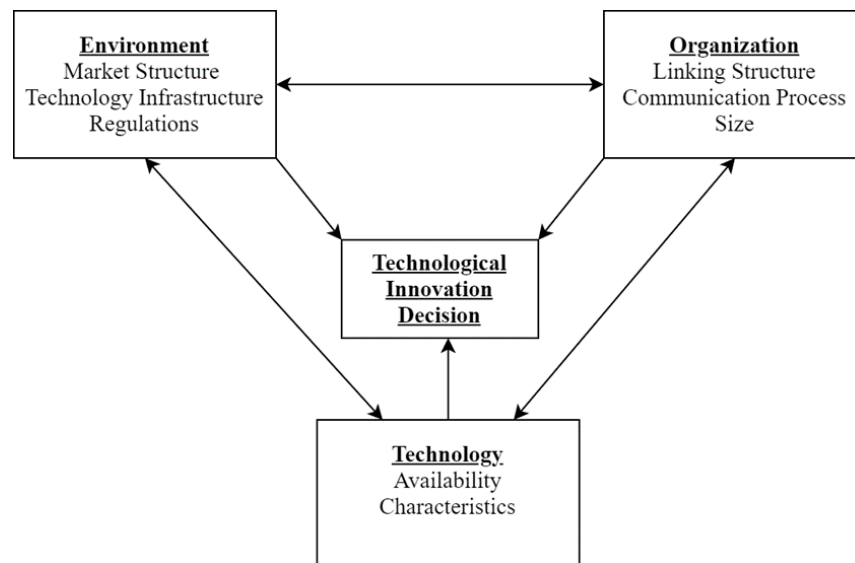


Figure 2. TOE Framework, based on DePietro et al. (1990).

As illustrated in Figure 2, the TOE framework implies that “the organizational adoption of technological innovation is influenced by the context's technology, organization, and environment, which can be constraints and opportunities for technological innovation” (DePietro et al. 1990). The Technology context includes the technologies that are relevant to the firm, both internal and external, with their perceived availability and characteristics (e.g., Perceived Usefulness) (Awa and Ojiabo 2016, Baker 2011). The Organization context concerns the attributes and resources of the company, including linking structure between the employees (Baker 2011), a firm's communication processes, and size (Anjum 2019, Awa and Ojiabo 2016). Lastly, the Environment context depicts the market structure, the presence of ICT infrastructure providers, and the regulatory environment (Baker 2011).

3.3. Conceptual Model Construction

Following the concept-centric matrix for a literature review described by Webster and Watson (2002), the factors that we retrieved from the reviewed articles are presented in Table 1 and categorized according to the TOE framework. The initial version of the matrix was validated by means of an interview with a blockchain expert at TNO that yielded three additional factors, namely Governance, People's Readiness, and Process Readiness (Hofman 2020). In the following paragraphs, we provide a description of each factor in more detail.

Table 1. Concept-Centric Matrix of Factors.

Factors	Authors
<i>Technology</i>	
Cost (C)	Dinca et al. (2019); Kühn et al. (2019); Surjandy et al. (2019); van Hoek (2019); Y. Wang et al. (2019); Wong et al. (2019)
Governance (G)	Hofman (2020)
Results Observability (RO)	Anjum (2019)
Perceived Compatibility (PC)	AL-Shboul (2019); Anjum (2019); Awa & Ojiabo (2016); Dinca et al. (2019); van Hoek (2019); (Walker et al. (2016)
Perceived Ease-of-Use (PEOU)	AL-Shboul (2019); Anjum (2019); Dinca et al. (2019); van Hoek (2019); Walker et al. (2016); Wong et al. (2019)
Perceived Usefulness (PU)	AL-Shboul (2019); Anjum (2019); Awa & Ojiabo (2016); Dinca et al. (2019); Kühn et al. (2019); Queiroz & Fosso Wamba (2019); Surjandy et al. (2019); van Hoek (2019); Wong et al. (2019)
Privacy (P)	Dinca et al. (2019); Surjandy et al. (2019); van Hoek (2019)
Security (S)	AL-Shboul (2019); Awa & Ojiabo (2016); Dinca et al. (2019); Surjandy et al. (2019); van Hoek (2019)
Trialability (T)	Anjum (2019); Dinca et al. (2019)
<i>Organization</i>	
People's Readiness (PEO)	Hofman (2020)
Process Readiness (PR)	Hofman (2020)
Technology Readiness (TR)	AL-Shboul (2019); Awa & Ojiabo (2016); Dinca et al. (2019); Kühn et al. (2019); Queiroz & Fosso Wamba (2019)
Top management Enthusiasm (TMEN)	Walker et al. (2016)
Top management Expertise (TME)	Anjum (2019); Dinca et al. (2019)
Top Management Support (TMS)	Anjum (2019); Walker et al. (2016); Wong et al. (2019)
<i>Environment</i>	
Customers' Influence (GUS)	Kühn et al. (2019); van Hoek (2019); Wang et al. (2019);
Competitive Pressure (CP)	Awa & Ojiabo (2016); Dinca et al. (2019); van Hoek, (2019); Walker et al., (2016); Wong et al. (2019)
Cooperation with ICT Providers (CICT)	Dinca et al. (2019); Kühn et al. (2019); Walker et al. (2016)
Environmental Impact (EI)	Anjum (2019);
Government Support (GS)	Anjum (2019); Awa & Ojiabo (2016); Dinca et al. (2019); Wong et al. (2019)
Regulatory Status (RS)	Kühn et al. (2019);
Reputation (R)	Anjum (2019); Wang et al. (2019)
Trading Partners' Readiness (PR)	Awa & Ojiabo (2016); Kühn et al. (2019); Wang et al. (2019)

3.4. Technology

As Table 2 shows, the Technology factors occupy a prominent role in the adoption models that have been employed so far, accounting for 9 of the 23 identified factors. In particular, Perceived Usefulness (PU) has been mentioned as a driver for adoption in nine articles. PU is defined as the perception that the innovation has a relative advantage over the incumbent practices (Anjum 2019, Awa and Ojiabo 2016) and several authors (Anjum 2019, Awa and Ojiabo 2016, Kühn et al. 2019, Queiroz and Fosso Wamba 2019, van Hoek 2019, Wong et al.

2019) recognize its significance in predicting an organization's adoption intentions. Furthermore, the Cost (C) of the technology may also have a decisive impact on behavioral intentions (Dinca et al. 2019, Kühn et al. 2019, van Hoek 2019, Y. Wang et al. 2019, Wong et al. 2019). Another determinant, with six citations, is Perceived Compatibility (PC). PC "refers to the extent to which a given innovation is regarded to be consistent with the present values, past experiences and the needs of the potential adopters" (Anjum 2019). Several authors (AL-Shboul 2019, Awa and Ojiabo 2016, Walker et al. 2016) advocate for the importance of this variable for adoption intention, whereas Anjum (2019) claims that Perceived Ease-of-Use (PEU) exercises a greater influence. PEU is defined as the degree to which a technology is perceived as simple to use and easy to understand (Davis et al. 1989).

Additional factors are Security (S) and Privacy (P). Security is described as one of the highest risks in ICT adoption (Awa and Ojiabo 2016), and it refers to the ability of the utilized technology to protect the user's information and assure a transaction's integrity during transmission (Awa and Ojiabo 2016, van Hoek 2019). Privacy, which is often used interchangeably with Security and is sometimes referred to as a part of it, represents the level of anonymity that technology can guarantee to the user (Dinca et al. 2019). Awa and Ojiabo (2016) include Security as the most influential predictors for ERP adoption, whereas Surjandy et al. (2019) claim that both S and P are cited as significant factors in over 57.5% of the studies into blockchain adoption.

Anjum (2019) adds that Results Observability (RO) and Trialability (T) should be considered among the determinants for technology adoption. RO is defined as the degree to which the results of an innovation are visible to the adopter, whereas T represents the possibility to experiment with technology on a limited basis before making any commitment (Anjum 2019).

Finally, the Governance of the technology (G) comprises the rules that define who will be responsible for making decisions concerning data ownership and the further development of the blockchain-based platform on behalf of its users (van Engelenburg et al. 2020).

3.5. Organization

The Organization component of the TOE Framework accounts for 6 out of the 23 identified factors, with three of them being related to the top management and their attitude towards technological innovations. According to Anjum (2019) the decision-maker is in all probability a member of the upper management team in the context of SMEs. Top Management Support (TMS), which is referred to as the degree "to which upper management understands the importance of the technology and is involved" (Ooi et al. 2018) is recognized as a significant positive predictor by Walker et al. (2016). Top Management Expertise (TME) is also considered as a critical adoption factor by multiple authors (Anjum 2019, Dinca et al. 2019). TME is defined as the managers' knowledge of the advantages, deployment models, and the cost of the technology of interest (Dinca et al. 2019). According to Anjum (2019) and Dinca et al. (2019) a firm with an owner with IT experience may be keener to explore disruptive paradigms and to take risks to adopt new technologies than a firm whose owner without IT experience. Top Management Enthusiasm (TMEN) for an innovative technology is also included by Walker et al. (2016) as a component of Organizational Readiness in their explanatory framework.

Technology Readiness (TR) is defined as an organization's preparedness in terms of technological infrastructure and IT human resources (AL-Shboul 2019). TR is deemed a significant predictor of adoption intention by all five authors that included this factor in their models (AL-Shboul 2019, Awa and Ojiabo 2016, Dinca et al. 2019, Kühn et al. 2019, Queiroz and Fosso Wamba 2019).

The *Organization* category is completed by adding People's Readiness (PEO) and Process Readiness (PR), which along with Technology, make up the Golden Triangle for organizational change (Chen and Popovich 2003, Hammer and Champy 1993). PEO represents the acceptance of the technology by an organization's employees, while PR depicts the goodness of fit of the technology with the tasks it supports (Goodhue and Thompson 1995).

3.6. Environment

The Environment component depicts the setting in which an organization acts. In this study, eight environmental factors were retrieved from the literature review. The first one is the Customers' Influence (CUS). Wong et al. (2019) claim that the pressure from customers who demand to know the provenance of the products they buy appears to be one of the main drivers for blockchain adoption. In addition, several authors (Awa and

Ojiabo 2016, Walker et al. 2016, Wong et al. 2019) agree that Competitive Pressure (CP) has a significant effect on adoption intentions. CP is described as the desire to keep up with the competitors and eventually gain an advantage over them (van Hoek 2019, Wong et al. 2019). Equally critical for blockchain adoption is the Trading Partners' Readiness (PR) as for a blockchain to work in the supply chain, all related actors have to be involved (Y. Wang et al. 2019). Furthermore, Government Support (GS) may aid SMEs in solving ICT-related issues (Anjum 2019, Awa and Ojiabo 2016). Dinca et al. (2019) define GS as the manager's perception of government interventions such as tax incentives for ICT investments, subsidies for ICT training, financing, or the creation of legal frameworks (Dinca et al. 2019). The latter is also considered as a separate factor Regulatory Status (RS) due to its utmost importance. Indeed, Kühn et al. (2019) position that legal uncertainties are a serious impediment to blockchain adoption, especially referring to the validity of smart contracts that can be created with blockchain technologies. Furthermore, Dinca et al. place Cooperation with ICT Providers (CICT) among the main factors that influence ICT adoption (Dinca et al. 2019).

Finally, a manager's awareness of the Environmental Impact (EI) brought about by an innovative technology may be positively associated with its adoption (Anjum 2019). A technology's EI may impact a firm's Reputation (R) as well, depending on the environmental awareness of its consumers. In addition, a firm's managers may exploit the adoption of innovative technology as a source of differentiation to create a new and improved company image (Winter et al. 2010).

We used this list of factors to determine the relative weights that SMEs attribute to them in the context of blockchain adoption. In the next section, we present the method that we applied to assess the ranking of the factors.

4. Best-Worst Method Protocol

We used the Best-Worst Method (BWM) to compute the weights of the identified factors and, hence, to rank them based on their importance.

Among the available Multi-Criteria Decision-Making (MCDM) techniques, pairwise comparisons methods were preferred over rank-ordering weighting methods, as the former contemplates that two or more criteria may have equal importance in the eyes of a decision-maker (DM) (which is likely going to occur if he/she is presented with a broad range of attributes, as in this case) and take into account the strength of a DM's preferences (Caballero and Go 2010, Sureeyatanapas 2016). Several pairwise comparison methods exist to compute the weights of a set of criteria, including the Simple Multi-Attribute Technique (SMART) (and its variations), the Analytic Hierarchy Process (AHP), and the BWM (Edwards 1971, Saaty 1980). The SMART technique is the most efficient one as it only requires the DMs to produce a single $1 \times n$ vector that contains the numerical score of each criterion, in ascending order from the least important one (Edwards 1971, Németh et al. 2019, Rezaei 2020b). However, this efficiency comes at a cost as "the consistency of the provided pairwise comparisons cannot be checked" (Rezaei 2020a). On the other hand, the AHP calls for the DMs to perform $n(n - 1)$ pairwise comparisons, which are generally represented with a $n \times n$ matrix, as shown in Equation (1) (Herman and Koczkodaj 1996).

$$\begin{bmatrix} 1 & a_{12} & \cdots & a_{1n} \\ 1/a_{12} & 1 & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 1/a_{1n} & 1/a_{2n} & \cdots & 1 \end{bmatrix} \quad (1)$$

The weights of the criteria are then estimated as the elements of the right principal eigenvector of the matrix (Saaty 2008).

On the other hand, the BWM stands in the middle as it only requires the DMs to carry out $2n - 3$ pairwise comparisons to produce two $1 \times n$ vectors, and it provides the possibility of monitoring the consistency of the submitted pairwise comparisons (Rezaei 2020a). The BWM's pairwise comparisons are referred to by Rezaei (2015) as reference comparisons, as the DMs are required to express their preference of the most important criterion over all the other criteria and the preferences of all the criteria over the least important criterion. The fact that the DMs are asked to identify the Best and Worst attributes at an early stage (before conducting the actual comparisons) leaves the DMs with a clear understanding of the range of evaluation, which could lead to more consistent pairwise comparisons (Rezaei 2020a). In addition, the use of two opposite references (best and worst)

could alleviate the anchoring bias that DMs might have during the process of carrying out the pairwise comparisons, hence increasing his/her consistency (Rezaei 2020a). Finally, the BWM only utilizes integers in the comparison matrix, making it considerably simpler to deploy compared to AHP (Rezaei 2015).

For the aforementioned reasons, the BWM has been preferred to AHP and SMART (and its variations) in this study. In the following paragraphs, we address our choice for the Bayesian BWM, the design of our questionnaire, and our sampling approach.

4.1. Bayesian Best-Worst Method

For computing the weights of the identified factors, we choose the Bayesian BWM over the original BWM. In both approaches, the DM is asked to carry out $2n-3$ pairwise comparisons to produce two $1 \times n$ vectors (Best-to-Others and Others-to-Worst), as will be explained in more detail below, but the final step in the two methods differs. The original BWM employs a constrained optimization problem to determine the factors' weights for each decision-maker (shown in Equation (2) below) and then combines them with an aggregation method such as the arithmetic mean (Mohammadi and Rezaei 2020).

$$\begin{aligned} & \min_w \max_j \left\{ \left| \frac{w_B}{w_j} - a_{Bj} \right|, \left| \frac{w_j}{w_W} - a_{jW} \right| \right\} \\ \text{s.t. } & \sum_{j=1}^n w_j = 1, \quad w_j \geq 0 \quad \forall j = 1, 2, \dots, n \end{aligned} \quad (2)$$

Whereas the BWM already outperforms alternative approaches such as the AHP in terms of ease-of-use and consistency (Rezaei 2015), much information may be lost due to aggregation, as averages are sensitive to outliers and they are not appropriate for highly dispersed datasets (Mohammadi and Rezaei 2020). The Bayesian BWM, on the other hand, models the inputs (pairwise comparisons) and outputs (the singular and aggregated weights) of the problem as probability distributions and uses the Bayesian Estimation to find the posterior probability density function (pdf) of the final aggregated weights. (Mohammadi and Rezaei 2020, Rezaei 2016). The latter is not a precise value point but a distribution, which yields more information regarding the events under study (Mohammadi and Rezaei 2020). For instance, the standard deviation of such a distribution can be an indicator of uncertainty regarding the problem at hand (Mohammadi and Rezaei 2020).

The Bayesian BWM also generates a Credal Ranking which describes the relation ($>$ or $<$) of each pair of criteria with a confidence level. The latter “represents the extent to which one can be certain about the superiority of a criterion over one another” (Mohammadi and Rezaei 2020), which can significantly improve the DM's decisions.

Step 1: All DMs need to agree on a set of decision criteria $C = \{c_1, c_2, \dots, c_n\}$ for the problem at hand. Once the first step is completed, the next three steps have to be performed separately by each DM involved.

Step 2: Each DM selects the best (c_B) and the worst (c_W) criteria from C .

The best criterion is the most important or most desirable criterion according to the DM, whereas the opposite is true for the worst criterion.

Step 3: Each DM conducts the pairwise comparison between the best (c_B) and the other criteria from C .

The preferences of the DM have to be calibrated based on a scale that ranges between one and nine, where one means equally important and nine means extremely more important. The pairwise comparison generates the *Best-to-Others* vector A_B as

$$A_B = (a_{B1}, a_{B2}, \dots, a_{Bn})$$

where a_{Bj} represents the preference of the best (c_B) to the criterion $c_j \in C$.

Step 4: Each DM conducts the pairwise comparison between the worst (c_W) and the other criteria from C .

Similar to the previous step, the DM has to calibrate his/her preferences on a scale that ranges between one and nine. The result of this step is the *Others-to-Worst* vector A_W as

$$A_W = (a_{1W}, a_{2W}, \dots, a_{nW}) \quad (3)$$

where a_{jW} represents the preference of the criterion $c_j \in C$ over the worst criterion (c_W).

Step 5: Bayesian estimation.

The Bayesian BWM models the inputs (A_B and A_W) and outputs (the criteria's weights) of the problem as probability distributions. In particular, the criteria are seen as random events, with their weights as their occurrence likelihood (Mohammadi and Rezaei 2020). This interpretation is, mathematically speaking, in line with the MCDM, since $w_j > 0$ and $\sum_{j=1}^n w_j = 1$ according to the probability theory as well.

According to Mohammadi and Rezaei (2020), A_B and A_W can be modeled with multinomial distributions. The latter can be used to depict experiments involving repeated and independent trials (e.g., rolling the dice five times) with n possible outcomes (in the dice experiment, six). In the case of A_W , the weight vector is set to represent the probability distribution, and A_W itself the number of occurrences of each event (or possible outcome).

$$P(A_W|w) = \frac{(\sum_{j=1}^n a_{jW})!}{\prod_{j=1}^n a_{jW}!} \prod_{j=1}^n w_j^{a_{jW}} \quad (4)$$

The multinomial distribution, despite being completely different from what is expected for the BWM, fulfills its underlying idea (Mohammadi and Rezaei 2020). Based on the multinomial distribution, the probability of the event j is proportionate to the number of occurrences of the event to the total number of trials, i.e.,

$$w_j \propto \frac{a_{jW}}{\sum_{i=1}^n a_{iW}} \quad \forall j = 1, \dots, n \quad (5)$$

Similarly, one can write the same equation for the worst criterion as

$$w_W \propto \frac{a_{WW}}{\sum_{i=1}^n a_{iW}} = \frac{1}{\sum_{i=1}^n a_{iW}} \quad (6)$$

By using the prior two equations, one obtains

$$\frac{w_j}{w_W} \propto a_{jW} \quad \forall j = 1, \dots, n \quad (7)$$

which is the relation that is sought after in the constrained optimization problem of the BWM.

Likewise, A_B can also be modeled using the multinomial distribution. Nonetheless, since A_W is the vector of the preferences of the other criteria over the worst and A_B represents the preferences of the best over the other criteria, A_B yield the inverse of the weight, i.e.,

$$A_B \sim \text{multinomial}(1/w) \quad (8)$$

Identical to the worst criterion, one can write

$$\frac{1}{w_j} \propto \frac{a_{Bj}}{\sum_{i=1}^n a_{Bi}}, \frac{1}{w_B} \propto \frac{a_{BB}}{\sum_{i=1}^n a_{Bi}} = \frac{1}{\sum_{i=1}^n a_{Bi}} \rightarrow \frac{w_B}{w_j} \propto a_{Bj} \quad \forall j = 1, \dots, n \quad (9)$$

Which is again the exact relation we seek in the objective function (minmax) of Equation (2).

Concerning the output of the model, the weight vector must satisfy the non-negativity and sum-to-one properties (Mohammadi and Rezaei 2020). Thus, the Dirichlet distribution has been chosen as an appropriate distribution to model the weights.

$$\text{Dir}(w|\alpha) = \frac{1}{B(\alpha)} \prod_{j=1}^n w_j^{\alpha_j-1} \quad (10)$$

The distribution has only a vector parameter $\alpha \in R^n$ and the weight vector w satisfies the aforementioned properties ($w_j \geq 0$ and $\sum_{j=1}^n w_j = 1$), as it is a probability distribution.

Modeling the inputs and outputs of the problem as probability distribution makes statistical inference techniques suitable to determine the optimal weights (Mohammadi and Rezaei 2020).

One widely accepted inference technique is the Bayesian estimation, which is the method of choice for the last step of the Bayesian BWM. However, given the complexity of the problem at hand, a hierarchical model (shown in Figure 3) had to be defined before the Bayes' rule could be applied to infer the optimal weights.

In the hierarchical model proposed by Mohammadi and Rezaei (2020), w^{agg} represents the overall optimal weights, w^k identifies the optimal weights of the k th DM, and A_W^k and A_B^k depict the k th Others-to-Worst and Best-to-Others vectors. Furthermore, the superscript $1:K$ will be used to indicate the total of all vectors in the base.

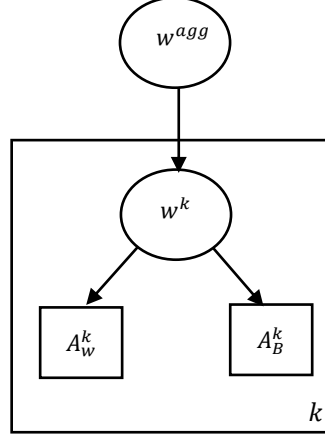


Figure 3. The probabilistic graphical model of the Bayesian BWM, based on Mohammadi and Rezaei (2020).

In the hierarchical model, the rectangles represent the observed variables, which are the inputs to the original BWM (Mohammadi and Rezaei 2020). On the other hand, the circular nodes are the variables that must be estimated, and the arrows indicate that the node in origin is dependent on the node at the other hand. Lastly, the plate that surrounds all variables except w^{agg} signals that the corresponding variables are iterated for all DMs.

After computing the joint probability distributions* of all variables given the available data, and taking into account all independence among different variables per the hierarchical model in Figure 3, and the fact that each DM provides his/her preference independently, it follows that

$$\begin{aligned}
 P(w^{agg}, w^{1:K} | A_B^{1:K}, A_W^{1:K}) &\propto P(A_B^{1:K}, A_W^{1:K} | w^{agg}, w^{1:K}) P(w^{agg}, w^{1:K}) \\
 &= P(w^{agg}) \prod_{k=1}^K P(A_W^k | w^k) P(A_B^k | w^k) P(w^k | w^{agg})
 \end{aligned} \tag{11}$$

Mohammadi and Rezaei (2020) specify the distribution of every element in Equation 2 according to their probabilistic interpretation, i.e.

$$\begin{aligned}
 A_B^k | w^k &\sim \text{multinomial}(1/w^k), \forall k = 1, \dots, K \\
 A_W^k | w^k &\sim \text{multinomial}(w^k), \forall k = 1, \dots, K \\
 w^{agg} &\sim \text{Dir}(\alpha), \alpha = 1 \\
 w^k | w^{agg} &\sim \text{Dir}(\gamma \times w^{agg}), \forall k = 1, \dots, K
 \end{aligned} \tag{12}$$

Unfortunately, the resulting equation does not bear a closed-form solution. As a result, the Markov-chain Monte Carlo (MCMC) technique, based on *just another Gibbs sampler* (JAGS) sampling, is employed to compute the posterior distribution of weights for every DM and the aggregated w^{agg} (Depaoli et al. 2016, Kass et al. 1998, Mohammadi and Rezaei 2020). For more information on this last step, we refer to Mohammadi and Rezaei (2020).

4.2. Online Questionnaire

* A joint probability distribution is a probability distribution for two (or more) variables. In the context of the Bayesian BWM, Mohammadi and Rezaei (2020) refer to the joint probability distribution of w^{agg} and $w^{1:K}$, which will be computed at the same time. Clearly, this also applies to $w^{1:K}$, which represents the optimal weights of the k decision makers, which will also be computed simultaneously.

The input of the Bayesian BWM is a set of k vectors A_B and A_W . To elicit the preferences of a group of DMs and, thus, obtain the desired input data, an online questionnaire was designed with Qualtrics Survey Software. The wording of the questions was based on the principles laid out by Sekaran and Bougie (2016), who state that questions should be phrased in a way that the target group can easily understand. Also, an attempt was made to avoid double-barreled, ambiguous, leading, and socially desirable questions, and it was decided to ask for the respondents' personal information at the end of the questionnaire. This decision was made with the reasoning that the participants may be more inclined to share personal data after they have been persuaded of the validity and truthfulness of the survey (Sekaran and Bougie 2016).

The survey opened with an introductory statement to clarify the objective of the present study and to disclose the identity of the researcher. Next, a brief video introduction to blockchain for SCM (Blockchain Council 2018) was provided to let the respondents familiarize themselves with the technology and its implications.

The questions that followed were designed according to the guidelines provided by Rezaei (2015). First, the DMs were presented with the problem of blockchain adoption. Then, a set of factors (or decision criteria) divided according to the TOE framework from Table 2 was provided to the respondent, who was first asked to express their category preferences. Subsequently, the respondent was asked to compare the best category to all the other categories and all the other categories to the worst category. The comparison was elicited by using a scale ranging between 1 and 9, as in Rezaei (2015). Throughout the survey, this same structure was applied, eliciting separately the factors' preferences of the respondent(s) within each TOE category.

Finally, the participants were asked to fill in multiple-choice questions about themselves (their age, gender, job position, years of experience, and email), the company they were currently employed at (its size, age, location, and sector), and their interest in blockchain technology.

4.3. Sampling

For this research, a purposive sampling approach amongst European SMEs was chosen. The minimum sample size was set at 20 respondents. Despite being arguably a small sample size, the goal of this research was neither to yield generalizable findings nor to statistically test quantitative hypotheses but rather to conduct an exploratory study into a relatively unexplored field. Moreover, previous empirical studies carried out with the BWM involved as low as six respondents (experts) (Ren et al. 2017).

The online questionnaire was distributed through several channels and made available between the 4th of May 2020 and June 8th 2020. First, the survey was shared through the partners of the Spark! Living Lab (SLL), the organization that commissioned this study, and directly sent to the attendees of a webinar hosted by the SLL on the subject of Supply Chain Visibility on May 19th 2020. Secondly, the survey was published on LinkedIn and shared via the SLL's page, and in the closed groups *Inspired Supply Chain and Logistics Executives* and *Logistics and Supply Chain Professionals*, which have more than 60.000 members each.

In total, 36 responses were collected. However, we had to eliminate 16 responses that were either incomplete (14), or that did not fit the firm's profile of interest for this research (company exceeded the SMEs' commonly accepted threshold of 250 employees or the respondent was not interested in blockchain technology).

Eleven of the twenty respondents selected for the analysis identify themselves as Senior Manager or Director, whereas seven hold a Middle Management position. The majority of the respondents' organizations are either located in The Netherlands (eight) or Italy (ten). They operate in various sectors, with Manufacturing being the most prominent one with ten out of twenty selections, followed by Transport and/or Logistics with four. Concerning the respondents' blockchain expertise, the most popular choice was Interested in the technology, which was picked by 13 out of 20 respondents, trailed by Testing the technology, Implementing the technology, and Learning the technology, which were chosen 2, 2, and 1 times respectively.

5. Results

To determine the relative importance of the factors identified in section **Error! Reference source not found.**, we used the Bayesian BWM MATLAB implementation provided by Mohammadi (2019) in their GitHub repository. The aforementioned implementation, given $A_B^{1:K}$ and $A_W^{1:K}$ as inputs, automatically executes the steps laid out in section **Error! Reference source not found.**, to simultaneously determine w^{agg} and $w^{1:K}$.

The final outputs of the model (w^{agg}) are presented in the following section(s). First, we touch upon the category and local weights. The category weights represent the relative importance of each category (T, O, and E), whereas the local factors' weights are the factors' loads within the bracket to which they belong. Then, we compute each factor's global weight by multiplying its local weight by its corresponding category load. Finally, we compare the weights for the two most prevalent clusters among the respondents (Dutch and Italian firms), accounting for any statistically significant differences. The Bayesian BWM's Credal Rankings are also presented in this section.

5.1. Local Weights

In Table 3, we present the weights that the respondents attributed to the categories. As can be noticed from the column Category Weight, Organization is by far the relatively more important category, with a weight of 0.4263. Technology follows as the second most important category, with a weight of 0.3058, whereas Environment comes in last with a weight of 0.2679. The ordering of the categories is also visualized in Figure 3, which depicts the Credal Ranking of Technology, Organization, and Environment. The Credal Ranking has been introduced by Mohammadi and Rezaei (2020) to provide more information on the confidence of the relation (> or <) between each pair of criteria.

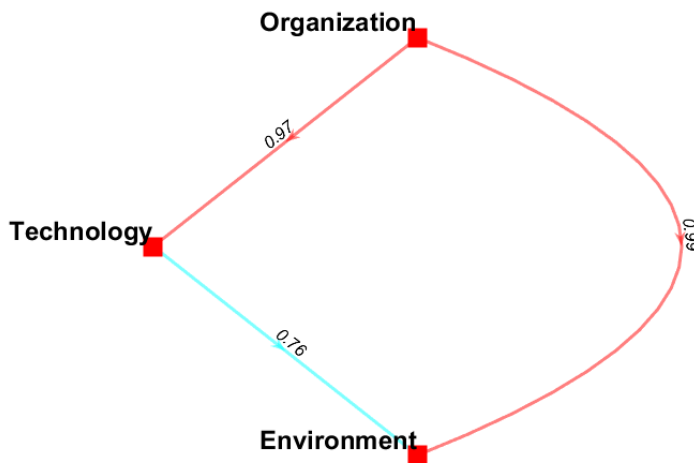


Figure 3. Categories' Credal Ranking.

In Figure 3, each arrow has a specific direction, which identifies the relation (>) between each pair. Moreover, the numbers that appear above each arrow represent the confidence (0-1) of that relation. In this case, Organization is the utmost category beyond any reasonable doubt. Indeed, the confidence that the weight of Organization is higher than the weights of Technology and Environment is 97% and 99%, respectively.

Within the Organization category, it can be seen from the Local Weight column that Process Readiness (PR) leads the way with a weight of 0.2015, with People's Readiness (PEO) and Top Management Support (TMS) closely following with weights of 0.1961 and 0.1891 respectively. The latter constitutes a balanced three-factors tier, which is separated by a wider gap from the rest of the determinants. The Credal Ranking in Figure 4 confirms the closeness of PR, PEO, and TMS, which can be depicted from the arrows connecting the three factors. Indeed, the confidence values above the links that connect PR & PEO, PR & TMS, and PEO & TMS are of 0.58, 0.68, and 0.61 respectively. On the contrary, the confidence that PR, PEO, and TMS are superior to each of the remaining factors is always above 83% (TMS & TR).

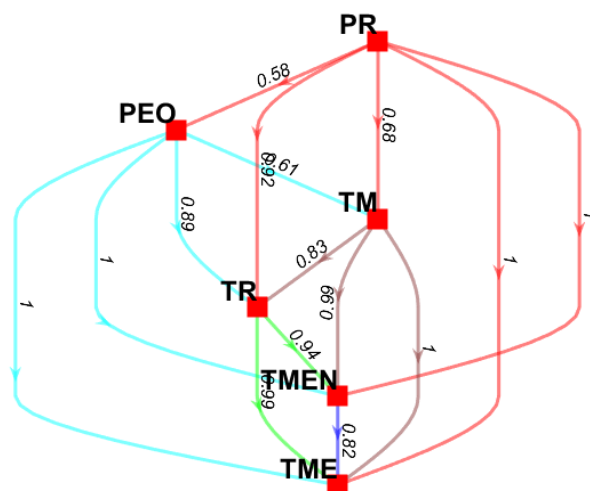


Figure 4. Credal Ranking of the organizational factors.

On the other hand, Security commands the technological factors with a weight of 0.1360, followed by Results Observability and Governance at 0.1263 and 0.1218, respectively.

Lastly, the Environment category is a balanced category overall, with the first six factors weight-wise separated by a mere 0.0305. Customers’ Influence leads the way with a weight of 0.1523, followed by Trading Partners’ Readiness, Competitive Pressure, and Regulatory Status with weights of 0.1483, 0.1403, and 0.1308, respectively.

Table 3. Weights of categories and factors.

Category	Factor	Category Weights	Local Weights	Global Weights
Technology	Cost	0.3058	0.1146	0.0350
	Governance		0.1218	0.0372
	Perceived Compatibility		0.0893	0.0273
	Perceived Ease of Use		0.0940	0.0287
	Perceived Usefulness		0.1166	0.0357
	Privacy		0.1161	0.0355
	Results Observability		0.1263	0.0386
	Security		0.1360	0.0416
Organization	People’s Readiness	0.4263	0.1967	0.0839
	Process Readiness		0.2022	0.0862
	Technology Readiness		0.1660	0.0708
	Top Management Enthusiasm		0.1322	0.0564
	Top Management Expertise		0.1133	0.0483
	Top Management Support		0.1896	0.0808
Environment	Competitive Pressure	0.2679	0.1403	0.0376
	Customers’ Influence		0.1523	0.0408
	Cooperation with ICT Providers		0.1236	0.0331
	Environmental Impact		0.1000	0.0268
	Government Support		0.0827	0.0222
	Regulatory Status		0.1308	0.0350
	Reputation		0.1218	0.0326
	Trading Partners’ Readiness		0.1483	0.0397

5.2. Global Weights

The global weights of the factors influencing the intention to adopt blockchain technology by SMEs with a logistics operation are shown in the last column of Table 3 (Global Weights).

Predictably, the factor with the highest weight (Process Readiness) belongs to the Organization category, which is relatively more important than both Technology and Environment, as discussed above. Due to the latter, all six factors from the Organization category have higher weights than any other non-organizational factor. Conversely, if the organizational determinants are omitted, Security is the factor with the highest weight among the technological and environmental factors, standing at 0.0416 and closely followed by Customers' Influence at 0.0408.

On the other hand, Government Support and Trialability are the factors with the lowest weights, standing at 0.0233 and 0.0261, respectively.

5.3. Controls

As two significant clusters were noticed while analyzing the demographics of the respondents (Italian and Dutch corporations), Mann-Whitney U tests ($p < 0.05$) were conducted to compare the local weights yielded by the two sub-samples and to account for confounding effects. The results revealed several weight differences spanning the Technology, Organization, and Environment categories. In particular, the respondents employed by Dutch SMEs put more emphasis on Security and Privacy among the Technological factors, Top Management Expertise among the Organizational factors, and Reputation and Regulatory Status among the Environmental factors. On the other hand, the respondents working at Italian SMEs put more value on Trialability, People's Readiness, Customers' Influence, Cooperation with ICT Providers, and Environmental Impact than the respondents at Dutch SMEs.

In this section, we presented the category, local, and global weights obtained with the Bayesian BWM in Table 3. The obtained results reveal several weight differences spanning the Technology, Organization, and Environment category. In particular, organizational factors (i.e., Process Readiness, People's Readiness, and Top Management Support) appear to be the most influential factors when it comes to blockchain adoption decisions by SMEs with a logistic operation. This outcome was justified by the higher weight of the Organization category (0.4263) over Technology and Environment (0.3058 and 0.2679 respectively). Also, the existence of two major groups in the respondents (Dutch and Italian firms) prompted a comparative analysis of the two sub-samples, which yielded several significant weight differences encompassing the three categories. These findings are discussed more extensively in the next section, in which we formulate their ramifications and the limitations of our analyses.

6. Discussion

In this section, we discuss the findings from our BWM study by comparing them to the extant academic literature. We then formulate the practical implications of our findings and reflect on the limitations of our study.

6.1. Comparison to Extant Literature

The analyses of our BWM approach show that organizational factors play a predominant role in the adoption of blockchain-based applications by SMEs in the domain of SCM. This result contradicts the outcomes obtained by Awa and Ojiabo (2016), Dinca et al. (2019), Kühn et al. (2019), and Queiroz and Fosso Wamba (2019), who all concluded that technology adoption is more heavily influenced by technological factors rather than by organizational and environmental ones. This discrepancy with previous research may be partially explained by the different time frames and environment in which this study has taken place and the technology under investigation. Indeed, the works of Awa and Ojiabo (2016) and Dinca et al. (2019) are focused on the adoption of ERP Software in Nigeria and on the adoption of Cloud Computing in Romania, respectively. Furthermore, Queiroz and Fosso Wamba (2019) studied the factors for blockchain adoption by SMEs in India and the USA, whereas Kühn et al. (2019) investigated blockchain adoption by SMEs in Germany alone.

Furthermore, compared to our literature review, which referred to Perceived Usefulness (PU) (Anjum 2019, Awa and Ojiabo 2016, Kühn et al. 2019, Queiroz et al. 2019, Wong et al. 2019) and Costs (C) (Dinca et al. 2019,

Kühn et al. 2019, van Hoek 2019, Wang et al. 2019, Wong et al. 2019) as two of the most crucial factors influencing technology adoption among SMEs, in our study PU and C are ranked as the fourth and sixth technological factors respectively, as shown in Table 3. On the other hand, the inclusion of Governance (G) proved to be a rightful addition, as G was selected four times as most important and is the third factor weight-wise, standing at 0.1263.

Moreover, Technology Readiness, which was deemed as a significant predictor of adoption intention by five authors (AL-Shboul 2019, Awa and Ojiabo 2016, Dinca et al. 2019, Kühn et al. 2019, Queiroz and Fosso Wamba 2019), only ranks as the fourth organizational determinant in our study.

Lastly, the weight-wise ranking of the Environmental factors appears to be in line with the reviewed literature, with the exception of Customers' Influence (CUS). Indeed, the relevance of the latter was downplayed by Kühn et al. (2019) and van Hoek (2019), who stated that CUS seems to be low in the contexts they examined (i.e., German SMEs and US firms, respectively).

6.2. Practical Implications

The ranking of the factors that are considered by SMEs in a technology adoption decision can aid blockchain consortia in determining which elements they should put more emphasis on when supporting SMEs in their blockchain journeys. It also contributes to comprehending which aspects of distributed ledger technologies ICT service providers can explain more to potential customers when presenting their services. The reflections that are provided below are based on the global weight-wise factors ranking obtained with the Bayesian BWM (as presented in Table 3) and are focused on those factors that the members of a consortium can directly or indirectly influence with their actions.

First, due to the leading position of Process Readiness, People's Readiness, and Top Management Support in the global weight-wise factors' ranking, it becomes apparent that blockchain consortia need to emphasize the visible connection between blockchain and the state-of-the-art processes it enables. Moreover, it is paramount that they leverage and advertise their training facilities (if available) and gain the support of the interested companies' senior executives. Furthermore, blockchain consortia can technology-wise focus on providing a blockchain platform that is confidential and reliable. Indeed, Security was the first non-organizational factor to appear on the standing. Lastly, blockchain consortia should attempt to take on the role of catalysts for legislators, as the firms surveyed (and Dutch SMEs in particular) place rather high importance on blockchain's regulatory issues among environmental factors (Regulatory Status).

6.3. Limitations

Considering the sheer size of this study's target population (European SMEs with a logistics operation), the number of responses collected (20) can be considered low. Nevertheless, gathering more responses has proven to be a particularly arduous task, despite having relied on trusted and well-respected partners for the survey distribution. This lack of responsiveness may have been due to the detrimental economic climate brought about by the Covid-19 pandemic, the complexity of the questionnaire, and the absence of a concrete gain for the participants, other than receiving this study's final report.

Moreover, it was not entirely possible to use blockchain-specific determinants in the conceptual model built in this study due to the scarcity of literature on the present topic. However, if analogous research is repeated in the future, it is more likely that scientific literature specifically focused on blockchain adoption for SCM by SMEs will be available. Furthermore, the comprehensiveness of the developed framework depends on the thoroughness of the research conducted by other scholars, which implies that it cannot be asserted with absolute certainty that all the relevant factors for blockchain adoption intention by SMEs with a logistics operation have been included. Thus, it is suggested to conduct additional interviews with experts from the field or with several representatives of the target population to lower the chance of overlooking one or more factors. Lastly, the results obtained with the conceptual model from Table 2 are context-dependent, and there is no guarantee that the answers of the participants would not change if the study was conducted in a different place or time. Especially an increase of blockchain-based applications will be instrumental in augmenting the knowledge amongst SMEs of the contribution to SCM.

7. Conclusion

In conclusion, this study has yielded a pioneering set of factors that influence blockchain adoption intentions by SMEs with a logistics operation in Europe. The obtained findings have practical implications for blockchain consortia or supply chain interest groups that aim to support SMEs in the adoption of blockchain for SCM. This study also contributes to the academic literature in bridging the existing knowledge gap on blockchain and supply chain integration from the perspective of SMEs, which is a relatively unexplored research perspective. Moreover, our study lends empirical validity to the novel Bayesian BWM, which has only been applied five times so far (Garousi Mokhtarzadeh et al. 2020, Guo et al. 2020, Li et al. 2020, Yang et al. 2020, Lo et al. 2020). This innovative technique leverages the ease-of-use and consistency yielded by the Best-Worst Method while avoiding the inherent shortcomings of weight-aggregation, which can be significant when dealing with a dispersed dataset (Mohammadi and Rezaei 2020, Rezaei 2015, 2016). Also, the Bayesian BWM's Credal Rankings were featured in this study, providing the confidence with which one can be sure of the superiority of one factor over another, which can further aid the DMs' decision (Mohammadi and Rezaei 2020). Nevertheless, future research needs to be conducted with a larger sample size, which would legitimate this research's outcome. Such a larger sample size can also be used to look for an explanation for the weight differences between the Italian and Dutch samples in the dataset. Interviews with SME stakeholders can shed further light on these differences. Furthermore, the interrelationships among the identified determinants can be investigated, which was out of the scope of this exploratory study. Lastly, we recommend using the conceptual model from this research as a starting point for investigating blockchain adoption by SMEs in other sectors or industries in order to uncover adoption factors that may hamper the take-up of blockchain-based applications that can contribute to improved business processes. These studies can inform blockchain consortia and supply chain stakeholders but also policymakers on how to incorporate the interests of SMEs into blockchain-based applications and how to use instruments to lower their adoption barriers. For the Spark! Living Lab, this study provided input for the development and selection of information and knowledge sharing concepts in order to demonstrate the added value of blockchain-based applications for SMEs and thus address their adoption barriers.

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