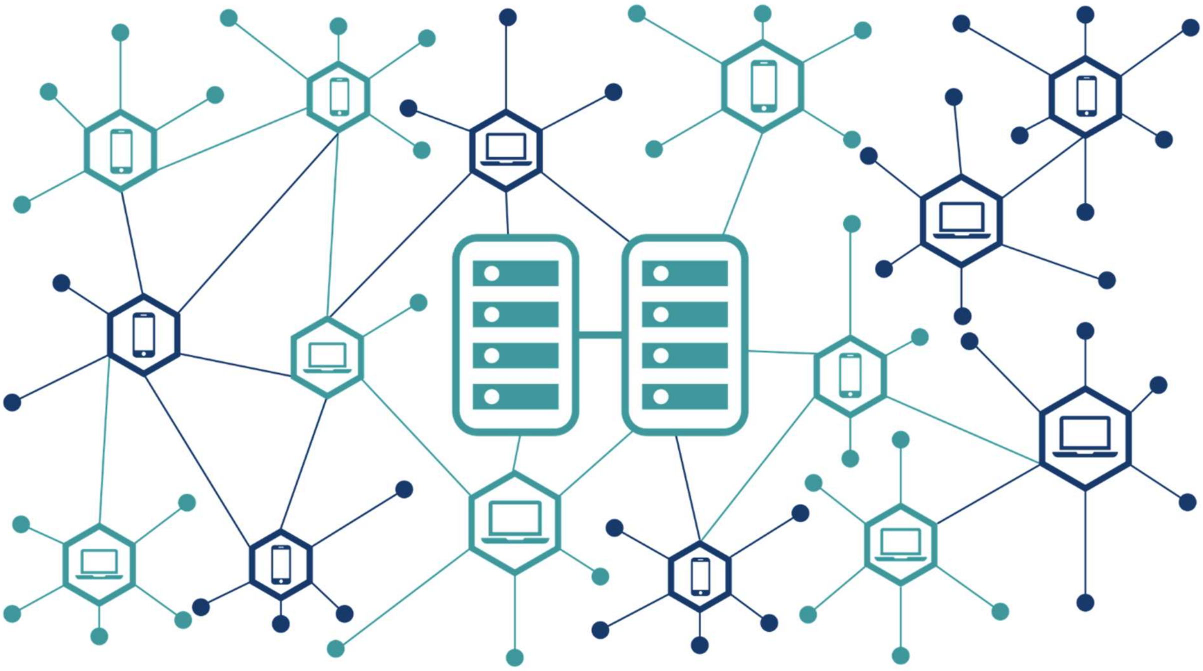

BLOCKCHAIN IN SUPPLY CHAIN MANAGEMENT:

AN EMPIRICAL STUDY INTO THE KEY FACTORS INFLUENCING THE INTENTION TO ADOPT BLOCKCHAIN BY SMES

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Blockchain in Supply Chain Management:

An Empirical Study into the Key Factors influencing the Intention to Adopt Blockchain by SMES

By

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PREFACE AND ACKNOWLEDGMENTS

This section sets the stage for my master thesis, which was conducted in partial fulfilment of the requirements for the degree of MSc in Management of Technology (MoT) at TU Delft. In this document, an exploratory study was conducted to identify the factors that influence blockchain adoption intention by SMEs with a logistics operation, rank them based on their importance, and provide suggestions on how SMEs can be supported in the adoption of blockchain based on the obtained results.

This master thesis has been an inspiring journey from the start, thanks to the people I met along the way.

First, I would like to express my gratitude towards my "supervision team" at TU Delft. I would like to sincerely thank my first supervisor J. Ubacht, who supported and guided me from the start of this project. Without her timely suggestions, patience, and continuous feedback, this master thesis wouldn't have come to fruition. Moreover, I am grateful for the contribution of my second supervisor, J. Rezaei, who has provided me with inspiring ideas for the quantitative section of my study, and constructive criticisms that have helped me stay on course. Lastly, I would like to thank G. P. van Wee, who joined my Graduation Committee at a late stage, but was still able to positively impact my master thesis with his insightful comments.

As far as TNO and the Spark! Living Lab are concerned, I have to sincerely thank all the people that made my experience unforgettable, despite the unprecedented circumstances. First, I am grateful to J. de Greeff, my external supervisor, for warmly welcoming me at TNO and supporting me throughout this project. He constantly provided me with valuable remarks, and he leveraged his network to help me distributing the questionnaire. Moreover, I would like to thank W. Hofman, who aided me in developing a concrete research proposal at the beginning of the project, and provided me with his expert feedback to refine the theoretical framework. Also, I appreciated the suggestions of M. Burghoorn, who not only translated the questionnaire into Dutch (for which I also have to thank A. Stuivenwold) but also contributed to making my questionnaire more understandable and visually attractive. Furthermore, I would like to express my gratitude to L. Gelsomino from Windesheim University for providing me with inspiration and invaluable suggestions for crafting my research proposal and improving my questionnaire. V. van der Hulst, the manager of the Spark! Living Lab, also reviewed my survey with a critical eye and went to great lengths for helping me with its distribution (shout out to M. Benes as well), and I am sincerely grateful for it. I also would like to thank S. Heeringa, who, despite the hectic Covid-19 situation, shared my questionnaire with a pool of a hundred interested companies from the network of evofenedex. Lastly, but not least, I would like to thank the group of interns that shared this experience with me, and all the people from TNO's Data Science department who shared a moment, a laugh, a meditation session, or a foosball game with me and that welcomed me on board from day one. Unfortunately, my days at New Babylon didn't last long, but I really enjoyed it!

Finally, I would like to sincerely thank my family, who showed nothing but support in the past five months, despite all the ups and downs. I would like to express my gratitude to my friends of many years from Italy, who made me feel less lonely during the long weekend nights during the lockdown and constantly supported me. Also, I am grateful for having met a wonderful group of friends in the Netherlands that made my two-year experience abroad special. An honorable mention goes to "The Italians", the whole MoT crew, the "Marrakech Express" group, and Willem, my roommate for one-and-a-half years. Thank you all!

SUMMARY

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 the members of a supply network would greatly benefit from the visibility of the flow of goods, money, and information enabled by blockchain. Nonetheless, despite its promise to revolutionize SCM, several barriers (technological, organizational, and operational) stand in the way of blockchain's large scale adoption. These impediments are especially hard on small-to-medium-sized-enterprises (SMEs), which often lack the ICT infrastructure and capabilities to join a blockchain-based network. However, SMEs occupy a prominent role in the European Economy, and the all-encompassing participation requirement of distributed ledger technology implies that blockchain has to be made accessible to them as well to impact the performance of entire supply chains. It is with this aim that the Spark! Living Lab was launched. The Spark! Living Lab is a consortium that involves several partners (including TNO and TU Delft) that have come together to support stakeholders in developing use-cases with blockchain in Supply Chain and Logistics. This research was commissioned as one of TNO's initiatives within the consortium.

Furthermore, the systematic literature review conducted as the starting point for this study revealed a severe knowledge gap on the integration of blockchain for Supply Chain Management from the standpoint of SMEs. Moreover, the aforementioned integration has seldom been investigated with empirical approaches, with only one study of this sort being found during the course of the literature review. Hence, in light of this gap, and the practical problem that TNO and the Spark! Living Lab aim to tackle, the following Main Research Question (MRQ) has been formulated: "How can SMEs with a logistics operation be supported in the adoption of blockchain for Supply Chain Management?". To answer the Main Research Question, a mixed approach, comprising both qualitative and quantitative methods, was chosen. In particular, qualitative methods were employed in the initial exploratory stages of the project to develop a conceptual model. Then, once a theoretical background was formed,

quantitative methods were employed to collect and extract information from empirical data. To assist the researcher in addressing the MRQ, five sub-research questions have been articulated.

The first sub-research question "Which frameworks are available in the literature that investigate the factors that influence the intention to adopt blockchain for Supply Chain Management by SMEs?" was answered by conducting a systematic literature review that yielded a conceptual model based on the Technology, Organization, and Environment (TOE) framework. The latter was chosen because of its flexibility and empirical validity. According to the TOE, the identified factors were classified under the three headings of Technology, Organization, and Environment, and subsequently revised in consultation with the thesis supervision team and experts from TNO. The final list of factors comprised twenty-three determinants.

The next chapter in the manuscript was entirely dedicated to explaining the methods' choices for the analytical portion of this study, which corresponds to the second sub-research question "How can the relative importance of each of the factors that are influencing the intention to adopt blockchain by SMEs with a logistics operation be determined?". The Bayesian Best-Worst-Method (BWM) was the selected technique for computing the weights of the identified factors, and, thus, sorting them in descending order of importance. The Bayesian BWM is a Multi-Criteria Decision Making (MCDM) method that can be used to calculate the weights of a set of criteria based on the preferences of one or more decision-makers. Compared to other MCDM methods, the BWM is easy to use and it generates more reliable results. To collect the empirical data necessary as input of the Bayesian BWM, an online questionnaire was the tool of choice, mainly due to its superiority in terms of time, which was a constraint in this research. The survey was designed with the Qualtrics Survey Software and later shared through the network of the Spark! Living Lab and the thesis supervision team.

After twenty responses were collected from the target population, the Bayesian BWM's MATLAB implementation was used to compute the local and global weights of the identified factors and categories, hence, answering the third sub-research question "What is the relative importance of the factors that are influencing the intention to adopt blockchain by SMEs with a logistics operation?". Notably, the Organization category was, by far, the relatively more important category based on the obtained results, followed by Technology, and Environment. As a consequence, the global weight-wise factors' ranking was dominated by organizational factors, which occupied the first six positions overall. Moreover, Security (from the

Technology category) and Customers' Influence (from the Environment one) rounded up the top eight.

While examining the characteristics of the respondents, two significant clusters were noticed: Italian and Dutch corporations. The latter accounted for 18 of the 20 participants (10 and 8 respectively), which triggered the execution of a comparative analysis of the two samples with a non-parametric statistical test (Mann-Whitney U). This was also driven by the strong interest of the Spark! Living Lab for Dutch SMEs. The results of the statistical tests revealed several weight differences spanning the Technology, Organization, and Environment category. In particular, the participants employed at Dutch corporations 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 participants working at Italian firms value more highly Trialability, People's Readiness, Customers' Influence, Cooperation with ICT Providers, and Environmental Impact.

The results of the Bayesian BWM and the findings from the Mann-Whitney U tests were then employed to provide actionable recommendations to TNO and the Spark! Living Lab, which accounts for the fourth, and final, sub-research question "Which factors should the consortium focus on when supporting SMEs in their blockchain journey based on the results of the present study?". Since the Spark! Living Lab mainly operates in The Netherlands, the recommendations' focal point was placed on Dutch SMEs. First, due to the leading position of Process Readiness, People's Readiness and Top Management Support in the global weight-wise factors' ranking, the consortium was suggested to emphasize the visible connection between blockchain and the state-of-the-art processes it enables, to leverage and advertise its training facilities, and to gain the support of the interested companies' senior executives. Furthermore, the Spark! Living Lab was advised to focus, technology-wise, on providing a blockchain platform that is confidential and reliable. Indeed, Security was the first non-organizational factor to appear on the standing, and the results of the Mann-Whitney U tests run on the technological factors showed that Security and Privacy are highly valued by Dutch SMEs. Lastly, the Spark! Living Lab was advised to put more emphasis on its role as a catalyst for legislators and enforcement authorities, as the Mann-Whitney U tests' results have also revealed a substantial difference in the relative importance placed on Regulatory Status, which is vital to Dutch SMEs.

In conclusion, this study has yielded a pioneering set of factors that influence blockchain adoption intention by SMEs with a logistics operation in Europe. This result contributes towards bridging the existing knowledge gap on blockchain and supply chain integration from the standpoint of SMEs, which is a relatively unexplored research field. Moreover, this research represents a contribution to the TOE domain, as the aforementioned framework has seldom been applied to study blockchain adoption. Lastly, this 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, Chuang, et al., 2020; Yang, Lo, et al., 2020). The obtained findings were then used to provide recommendations to the Spark! Living Lab with the aim to support SMEs with a logistics operation in the adoption of blockchain for Supply Chain Management. Moreover, suggestions for scholars that may want to take on similar research in the future were provided. First, it was advised to repeat this study with a larger sample size, which would legitimate this research's outcome. Secondly, it was suggested to look for an explanation for the weight differences between the Italian and Dutch samples in the dataset, perhaps by conducting the analysis with a larger sample, and by interviewing the respondents. Thirdly, it was recommended to investigate the interrelationships among the identified determinants, which was out of the scope of the present study but might yield interesting findings. Lastly, it was proposed to validate the developed conceptual model for blockchain adoption in other sectors or industries.

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1. PROBLEM EXPLORATION

Since its inception in 2008, when the Peer-to-Peer Electronic Cash System known as Bitcoin was first launched, several scientists had foreseen the transformative potential of blockchain (Aste et al., 2017). The distributed ledger, which was initially limited to the financial world, as a decentralized register for monetary transactions, now sees a broad range of possible applications (Hughes et al., 2019). Within the latter, Supply Chain Management (SCM) and Logistics have gained traction as fertile grounds for blockchain applications (Y. Wang et al., 2019). In particular, product traceability, supply chain digitalization and disintermediation, and improved data security for information sharing represent the areas where blockchain provides the most value for SCM (Y. Wang et al., 2019). To exploit the expected advantages of the distributed ledger, several pilot cases and studies have been launched. However, a substantial gap in blockchain-supply chain integration literature has been highlighted by multiple authors (Queiroz et al., 2019). Above all, according to Wamba & Queiroz (2020), the application of empirical approaches to study the aforementioned integration is lacking. For this reason, this research work is aimed at advancing thinking and practice by conducting an empirical study that will shed light on the factors that are influencing the intention to adopt blockchain by SMEs with a logistics operation. This study also contributes to the literature on blockchain adoption by SMEs, which often have insufficient resources to devote to acquiring new technologies and yet, they share the same need to be effective and efficient as large firms (Wong et al., 2019).

1.1 ISSUES WITH SUPPLY CHAIN MANAGEMENT

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, p.13). A simplified version of such a network is provided in Figure 1. These multi-actor systems are increasingly complex due to the globalization of supply, which requires additional effort 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 philosophy 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, p. 7). To act upon this theory, firms must establish a set of collaborative practices. The latter include mutually sharing information, integrating processes, and partnering to build and maintain long-term relationships (Mentzer et al., 2001). However, to harness the cooperation between multiple actors in a complex system, trust and commitment between the parties are needed (Morgan & Hunt, 1994).

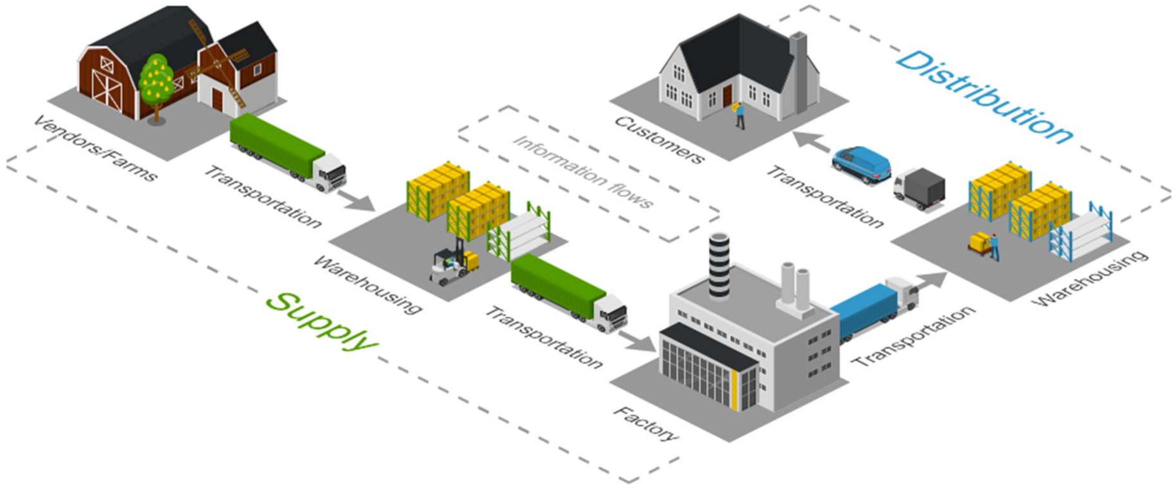


Figure 1:Simplified version of a supply chain, copied from Icograms (2020)

In particular, transparency and visibility of operations are critical to trust development (Akyuz & Gursoy, 2020).

1.2 SUPPLY CHAN VISIBILITY

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 are 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 may 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 & 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). The impact of the latter will be twofold. First, it could be possible to timely respond to supply-demand mismatches and 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 & Gursoy, 2020; X. Wang & Disney, 2016, p.691). Secondly, *synchro modal planning* may become a viable option. Synchro modal planning is a "form of multimodal planning in which the best possible combination of transport modes is selected for every transport order", as shown in Figure 2 (Mes & Iacob, 2015, p. 23). Mes & Iacob (2015) have claimed that this form of logistics has the potential to cut the CO_2 consumption associated with logistics by 15%, due to a more rational use of the available transport capacity. Furthermore, intermodality enables a better use for railways, inland waterways and transport by sea, which cannot individually act as standalone door-to-door services (European Union, 2005).

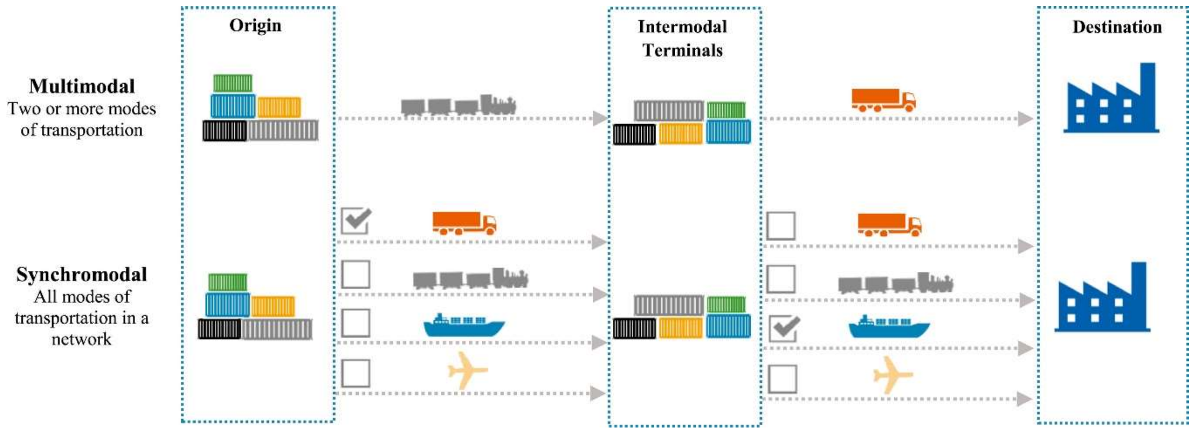


Figure 2:The difference between Multimodal and Synchromodal Planning, copied from Farahani et al., 2018)

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 very much a cumbersome process (Vyas et al., 2019). Indeed, despite technological advances and the coming age of logistics information brokers, it is often the case that the data shared is redundant and inaccurate with many organizations managing the same order (Vyas et al., 2019). However, a paradigm shift may be possible thanks to a breakthrough technology known as blockchain (Akyuz & Gursoy, 2020).

1.3 BLOCKCHAIN TECHNOLOGY

Blockchain is "a distributed ledger, or database, shared across a public or private computing network" (Carson et al., 2018, p.2). This concept was first introduced in 2008 when the article "Bitcoin: A Peer-to-Peer Electronic Cash System" (Nakamoto, 2008) came to fruition. In this article, Nakamoto (2008) argues the value of blockchain as the underlying technology for two parties to transact with each other without the need for a trusted third party, e.g. a bank. A blockchain, as the name would suggest, is a chain of blocks. Each block can hold a fixed amount of transaction data. Each transaction recorded on a block (with the value/asset being exchanged and the participants in the transaction) has a timestamp, as the transactions are registered in chronological order, and it is *cryptographically signed*[1], which guarantees the integrity of the data. Then, when a block has reached its "maximum capacity", all the nodes in the network try to solve a complex and irreversible computational problem, which takes the transaction data stored on the block and the *has*h of the previous block as an input to generate the hash of the current block, as shown in Figure 3.

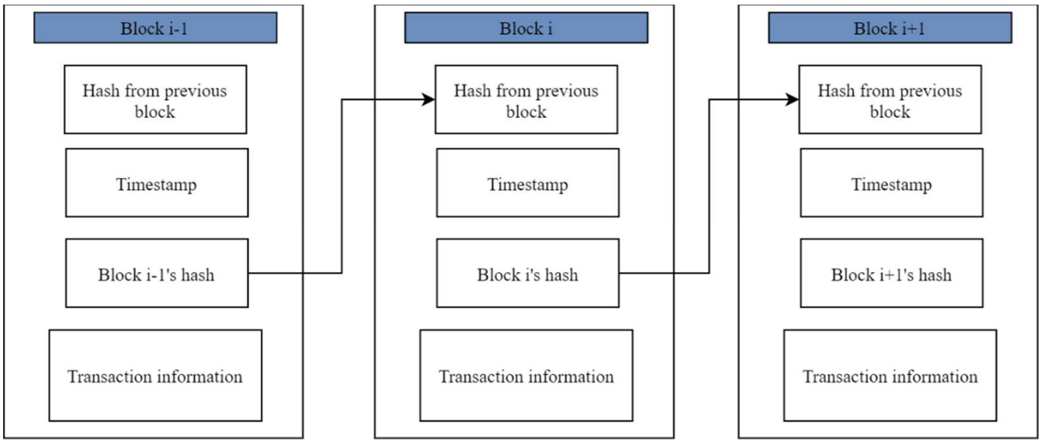


Figure 3: The process of validating a block on the chain, based on Nakamoto(2008)

[1] The idea of digital signature was first introduced by Diffie et al.(1976) who proposed that each user would have a pair of keys, one public and one private, which is only known to its owner. A private key signature guarantees the authenticity of a document, while encrypting a document with either one of the key pairs(usually the public one) guarantees that only the owner of the other key in the pair will be able to access it(integrity).

A “hash” is generally defined as a function that takes as input objects and 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. Once consensus is reached, the block is finally added to the chain. To motivate the participants, or nodes, in the network to use their computational power to validate transactions, and thus make the peer-to-peer model commercially viable, a compensation for their contribution is offered with “tokens” (application-specific assets) (Carson et al., 2018). The previously described consensus mechanism represents the underlying idea of the Proof of Work (PoW) consensus mechanism that regulates Nakamoto (2008)’s blockchain, but different algorithms have been introduced to cope with its inherent shortcomings, such as the slow speed of transaction verification (Mingxiao et al., 2017). The latter has been set by design by Nakamoto (2008), as each block has a limited size (one MegaByte) and is validated every ten minutes on average, with the complexity of the computational problem changing based on how fast the nodes (or “miners”) find its solution (Mingxiao et al., 2017). For instance, Hazari & Mahmoud (2019) proposed a parallel PoW in which no more than two miners work on the same block, obtaining an estimated 34% improvement in scalability. On the other hand, a group of miners and developers envisioned that increasing the size of each block, and lowering the amount of data that needs to be stored, can result in a faster transaction verification process (Kwon et al., 2019).

The characteristics of blockchain offer key advantages if compared to a centralized database, namely decentralization, cryptographic security, transparency, and immutability (Carson et al., 2018; Aste et al.,2017). Since all the participants in the network hold a copy of the ledger, there is no single point of failure (Carson et al., 2018). Furthermore, cryptographic security ensures the integrity of the data, as each transaction requires a digital signature with the private key of the sending node, which is only in his possession. On the other hand, the public key of each participant in the network is visible to everyone as transactions are announced publicly in the blockchain. Nevertheless, privacy is maintained by keeping these public keys anonymous (Nakamoto, 2008). Finally, the immutability of the ledger, which can be hardly tampered with, stems from cryptographic hashing (Landerreche & Stevens, 2018). A cryptographic hash function features three crucial properties: 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 & Chen, 2015). From these properties, it follows that if a malicious user tampers with a block in the chain, the block's hash will certainly 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 & Stevens, 2018).

Despite being initially developed to favor the exchange of financial assets without the need of a trusted third party (Nakamoto, 2008), any hard or soft assets may be transacted with a system like blockchain (Swan, 2015). For instance, a 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).

Furthermore, several authors have recognized the potential of blockchain to reconfigure all aspects of society and its operations (Iansiti & Lakhani, 2017; Swan, 2015), with "smart contracts" being perhaps the most transformative application (Iansiti & Lakhani, 2017). Smart contracts are "blockchain transactions that go beyond simple buy/sell transactions, and may have more extensive instructions embedded into them" (Swan, 2015, p.16). These contracts are automated and enforced by the code as the negotiated conditions are met (Iansiti & Lakhani, 2017). However, notwithstanding its fascinating possibilities, blockchain may still be decades away from reaching its full potential (Iansiti & Lakhani, 2017). According to Iansiti & Lakhani (2017), the trajectory of blockchain may resemble the one followed by another highly disruptive technology, the TCP/IP protocol, which took more than thirty years to reshape the economy. Nonetheless, firms may already benefit from localized applications, which are high in novelty but require a limited number of users to create immediate value (Iansiti & Lakhani, 2017). The latter is also known as a "private and permissioned" architecture, which is presumably going to be the design of choice for most commercial blockchain applications (Carson et al., 2018). As can be seen in Figure 4, four options are available for designing a distributed ledger. In particular, a decision has to be made on the ownership of the data infrastructure (public or private), and the permissions granted to the participants (e.g. read, write or commit) (Carson et al., 2018). A public blockchain (e.g. Bitcoin) is hosted on public servers and anyone can join and read (Carson et al., 2018). On the other hand, a private blockchain is hosted on private servers and the owner of the infrastructure decides who can read, join and change the information recorded (Carson et al., 2018; Mingxiao et al., 2017). Once the ownership of the infrastructure is settled, the permissions granted to the participants are allocated, with a high-level distinction between permissionless and permissioned architectures (Carson et al., 2018). In a permissionless architecture, anyone can write and commit, whereas, in a permissioned one, only the participants authorized by the network owner can add new information to the ledger (Carson et al., 2018).

As mentioned earlier, *private and permissioned blockchains (*right bottom corner of Figure 4*)* will be the favored solution to extract commercial value from blockchain implementations (Carson et al., 2018). Indeed, private and permissioned architectures enable the dominant players in the network to maintain their controlling position while collaborating with the other industry players to capture and share value (Carson et al., 2018; Iansiti & Lakhani, 2017).

	Permissionless	Permissioned
Public	• Anyone can join, read, write, and commit • Hosted on public servers • Anonymous, highly resilient • Low scalability	• Anyone can join and read • Only authorized and known participants can write and commit • Medium scalability
Private	• Only authorized participants can join, read, and write • Hosted on private servers • High scalability	• Only authorized participants can join and read • Only the network operator can write and commit • Very high scalability

Figure 4: Available blockchain architectures, based on Carson et al. (2018)

1.4 BLOCKCHAIN TECHNOLOGY FOR SUPPLY CHAIN MANAGEMENT

Within the SCM context, blockchain is seen as a potential solution for traceability purposes and for generating closer and trustworthy relationships (Fosso Wamba & Queiroz, 2020). Indeed, Akyuz & Gursoy (2020) argue that a number of blockchain properties positively match the needs of the SCM domain.

1.4.1 TRANSPARENCY, VISIBILITY AND TRACEABILITY

In a blockchain-based network, all the stakeholders hold a single-version-of-truth-copy of all transactions and the immutability of the ledger assures that the record is not modified in any way (Akyuz & Gursoy, 2020). Moreover, the cryptographic security layer enables the supply chain actors to comfortably share data even if it contains highly sensitive commercial information (Akyuz & Gursoy, 2020). Indeed, the shared data is encrypted with the public key of the receiver first, and then with the private key of the sender (which is only known to him/her), as shown in Figure 5. The latter guarantees that the data has been generated by the sender, as only his/her public key will be able to decipher it. Furthermore, the first encryption assures that the information will only be accessible to the receiver, as only his/her private key can decrypt the inner message (Diffie et al., 1976). Besides, sensible data can be replaced with a non-sensitive equivalent symbol, or token, that enables the creation of a digital identity for goods in transactions (Olsen et al., 2018).

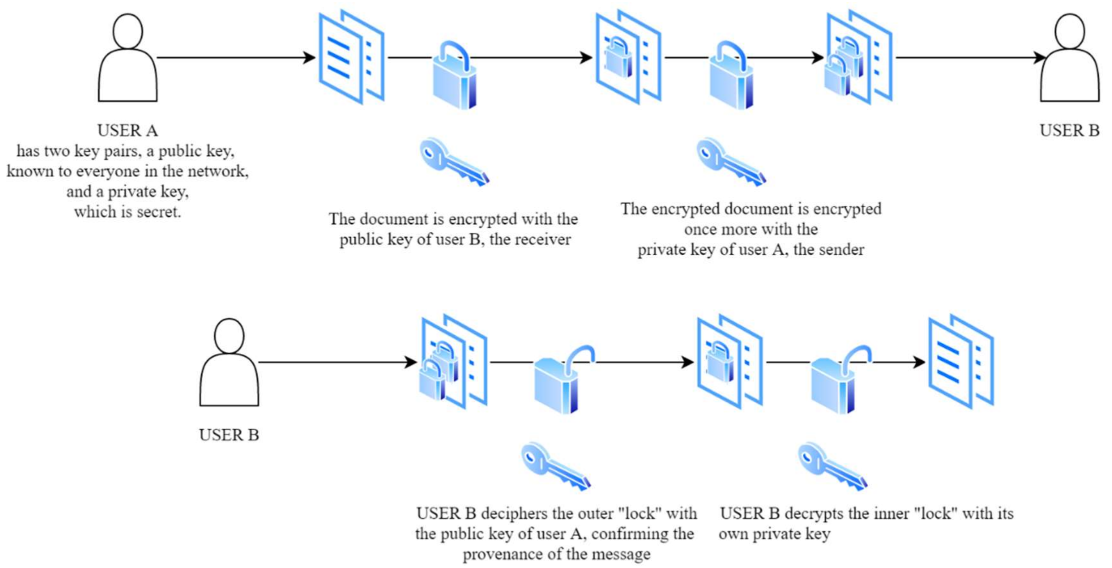


Figure 5:The cryptographic security layer guarantees the provenance and the integrity of the documents exchange between two users (own figure)

This provides "a trusted transactional database for the network for providing real-time, accurate and visible transactions among partners" (Akyuz & Gursoy, 2020, p.162). 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 & 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 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, privacy concerns and fears that the shared information (e.g. inventory levels) could be used by competing firms to undermine one's competitive advantage are lessened by cryptographic security (van Engelenburg et al., 2018). Indeed, the anonymity can be guaranteed through asymmetric cryptography, as all the parties are assigned a keypair that cannot be, in any way, traced back to its owner, and is frequently updated (van Engelenburg et al., 2018). Furthermore, the rights of the participants can be assigned preventively during the architecture's design phase, so that only selected parties (e.g. only the actors that are in the same supply chain) can be a node and have reading privileges (van Engelenburg et al., 2018).

1.4.2 FASTER AND LEANER GLOBAL TRADE

As mentioned in the previous paragraph, the immutability of the distributed ledger guarantees the integrity and authenticity of the recorded transactions (Akyuz & Gursoy, 2020). Hence, 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, p. 22; Takahashi, 2016). According to DHL (2018), using blockchain to replace the bill of lading documentation alone would lead to millions of dollars of cost savings across the supply chain. Moreover, blockchain can be used to automate the manual and inefficient customs-related processes, which are prone to error and cost up to one-fifth of the actual physical transportation cost (IBM, 2017). 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 dependable information source to assess the credit risk of the actors involved, which can in turn speed up the payment process and guarantee an easier access to funds, even for small businesses (Olsen et al., 2018).

1.4.3 AUTOMATED CONTROLS WITH SMART CONTRACTS

As digitized documents and real-time shipment information become simultaneously available to all the players in the supply chain, this information can be used to enable smart contracts (Segers et al., 2019). As mentioned in section 1.3, smart contracts are "blockchain transactions that go beyond simple buy/sell transactions, and may have more extensive instructions embedded into them" (Swan, 2015, p.16). Smart contracts have the potential to diminish the need for trust between parties, as they are defined by the code and automatically executed as the negotiated conditions are met (Swan, 2015). According to Ivanov et al. (2019), this mechanism is particularly useful for accelerating regulatory processes and increasing confidence in documentation across all stakeholders, which can, in turn, enhance collaboration.

Quantities, lot sizes, and special conditions can be translated into logical rules and monitored at all times during logistics and monetary transactions (Akyuz & Gursoy, 2020). Furthermore, if blockchain is combined with Internet of Things (IoT)[2], "smarter" logistics contracts can be created (Tsang et al., 2019). Indeed, if the goods being delivered are constantly monitored with an IoT device (e.g. wireless sensors), the blockchain-based system can automatically verify the delivery (based on the real-time location of the goods), and whether the goods have been delivered as per agreed conditions (DHL, 2018). Then, if the contract obligations have been accomplished, the payment to the appropriate parties is seamlessly released, as shown in Figure 6 (DHL, 2018).

[2] The term IoT defines "the next chapter in the evolution of the Internet where computing devices embedded in everyday objects are able to send and receive data themselves"(Berte, 2018, p.1)

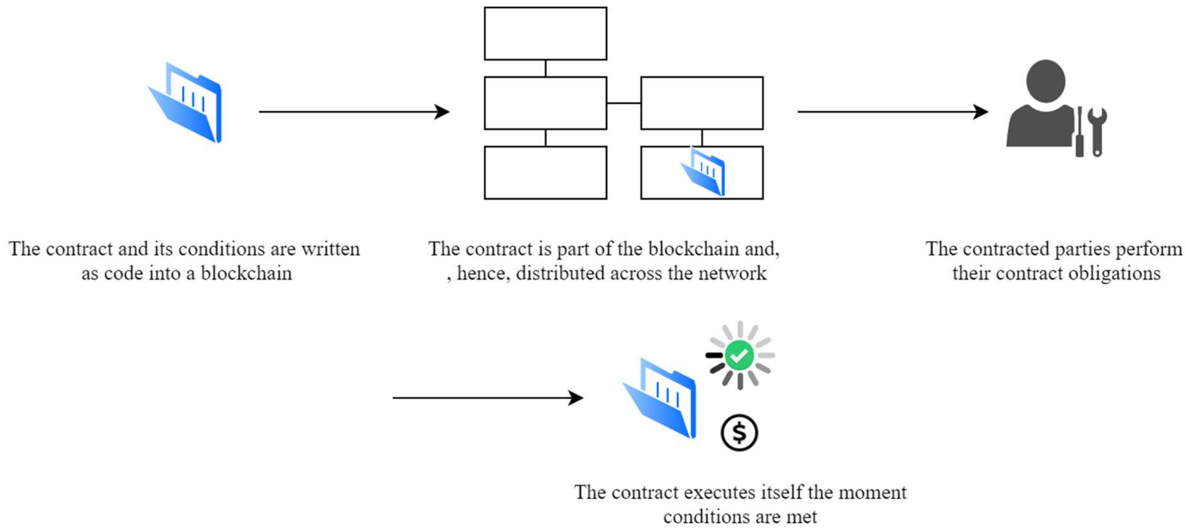


Figure 6:How smart contracts could work, based on DHL (2018)

1.5 RESEARCH PROBLEM

Despite its potential to create efficiencies throughout the whole supply chain, the challenges about how stakeholders can ensure that blockchain fulfills its promise are still unresolved (Fosso Wamba & Queiroz, 2020).

According to Iansiti & Lakhani (2017), two dimensions affect how technology and its business use cases evolve: novelty and complexity. The former represents "the degree to which an application is new to the world", whereas the latter consists of the "number and diversity of parties that need to work together to produce value with the technology" (Iansiti & Lakhani, 2017, p.119).

A foundational technology, such as blockchain, generally undergoes four stages of development (Iansiti & Lakhani, 2017), as shown in Figure 7. In particular, applications characterized by low novelty and low complexity are developed first, to deliver better, less costly, and highly focused solutions (Iansiti & Lakhani, 2017). One example of such applications is Bitcoin, which offered instant value to the people who used it as an alternative payment method (Iansiti & Lakhani, 2017). Next, innovations build on single-use applications to create local private networks that link multiple organizations (e.g. the Interbank Information Network that connects JP Morgan, the Royal Bank of Canada, and ANZ to facilitate cross-border settlements) (Iansiti & Lakhani, 2017; JP Morgan, 2020). Finally, substitutes and transformative implementations (third and fourth quadrant in Figure 7, respectively) that require increasing coordination are introduced (Iansiti & Lakhani, 2017). For instance, cryptocurrencies as a whole can be considered a substitute as they represent a fully formed currency system that require all the parties that do monetary transactions to adopt it, and governments and regulatory agencies to acknowledge it (Iansiti & Lakhani, 2017).

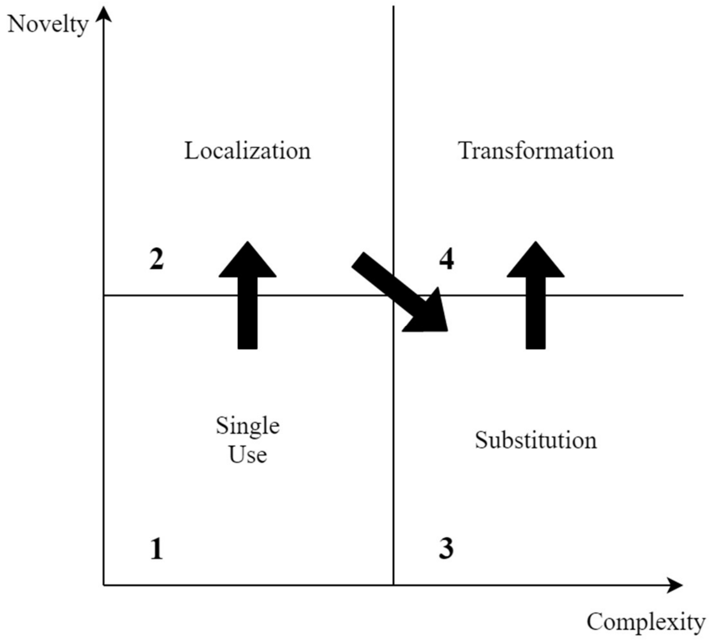


Figure 7:Framework for technology adoption, based on Iansiti & Lakhani (2017)

Based on the framework in Figure 7, Supply Chain Visibility applications powered by blockchain can be assigned to the second quadrant, which identifies highly novel applications but that do not require a substantial user base to generate value (Iansiti & Lakhani, 2017). Indeed, a Supply Chain Visibility ledger is normally shared with a selected number of trusted counterparties in a private and permissioned architecture, where the dominant players maintain a controlling position (Carson et al., 2018; Iansiti & Lakhani, 2017).

Nonetheless, several barriers, which Wang et al. (2019) have categorized as Organizational, Technological and Operational challenges, are hindering the diffusion of blockchain in the SCM domain, which is currently limited to a handful of pilot cases launched by large multinational companies (e.g. the pilot started by Walmart and IBM to trace food provenance in 2016) (Y. Wang et al., 2019).

From an organizational standpoint, the complexity of blockchain makes it difficult for users to comprehend, accept, and have trust in the technology (Y. Wang et al., 2019). Moreover, the integration with the existing IT systems remains an issue and the stringent participation requirement, which necessitates all the members of the supply chain to get on board, may be a problem for the upstream stages, which are often the least digitized (Beyer et al., 2019; Y. Wang et al., 2019).

SMEs (firms with less than 250 employees, a more extensive definition is provided in section 2.2.3) need special attention in this context. Indeed, despite possibly being the main beneficiaries of Distributed Ledger Technology, SMEs often have limited ICT capabilities to join a blockchain-based network, and, hence, face a concrete risk of being left behind in this transformative journey (Blockstart, 2020; Olsen et al., 2018; Y. Wang et al., 2019). SMEs would particularly benefit from the transparency of the blockchain ledger as an enabler of real-time tracking and a faster and leaner global trade, as it is explained below.

Real-time tracking of products is often referred to as the "Holy Grail" of the logistics industry (Blockstart, 2020). As mentioned in section 1.2, having a holistic view of the supply chain enhances trust between stakeholders, and facilitates accurate forecasting and timely interventions based on real-time and reliable information (Vyas et al., 2019). Moreover, the existence of a single source of truth greatly reduces the need for manual reconciliation of documents in the supply chain, which can, in turn, diminish the time required for export by 44% according to the UNECE[3] (Olsen et al., 2018). Although a Supply Chain Visibility ledger is typically initiated by large firms, the efficiency gains it produces permeate to the whole supply network, including SMEs (Blockstart, 2020).

As mentioned earlier, blockchain can also have a transformative impact in enabling trade and Supply Chain Finance (SCF) for small-to-medium-sized businesses (Gao et al., 2019; Kim et al., 2019; Olsen et al., 2018). Trade finance consists of the set of products that are employed by companies to reduce transaction risk and working capital requirements, and hence facilitate international trade (Olsen et al., 2018). These products include letters of credit, which are issued by the buyer's bank to assure the supplier that the payment will be made upon the receipt of shipping/delivery confirmation of the goods (e.g. a bill of lading) (Olsen et al., 2018). On the other hand, SCF is the process by which the buyer extends its accounts payable, and the supplier sells its accounts receivable, plus a small fee, to receive an in-advance payment from a third-party (e.g. a financial institution) (Olsen et al., 2018). The latter is then paid back by the buyer at the end of the accounts payable's maturity period (Olsen et al., 2018). SCF represents a win-win situation for both buyer and seller, as the buyer can delay its payment without compromising its relationship with the supplier, and the supplier can have access to funds

[3] The UNECE is the United Nations Economic Commission for Europe. It was set up in 1947, and It has the aim to promote pan-European economic integration (UNECE, 2020).

earlier and at an advantageous rate, as the repayment risk is entirely borne by the (larger) buyer (Olsen et al., 2018).

According to a report from the World Bank (2017), credit institutions refuse more than fifty percent of the SMEs' requests for financing, compared to a ten percent rejection rate for multinational corporations. The same discrepancy has been found in a survey conducted by Kim et al. (2019), who have highlighted a forty-five percent rejection rate for SMEs' trade finance proposals. As a consequence, a global trade finance gap of roughly 1,5 trillion currently exists (Kim et al., 2019), stemming mainly from small-to-medium-sized businesses. The two main reasons for this high rejection rate are the typically weaker financial position of SMEs compared to larger firms, and the collateral requirements that many SMEs cannot fulfill (Kim et al., 2019). A collateral is an asset that is offered as a security for a loan's repayment, and that will be handed over to the lender in case of default (Sikarwar, 2017). Furthermore, even when a small business meets the pledge's prerequisite, it is extremely costly for banks to monitor the pledge risk on an ongoing basis (Gao et al., 2019). The latter is the risk that stems from the value fluctuation of the collateral, which may be subject to devaluation during the credit period (Gao et al., 2019).

Theoretically, SCF could bypass these issues and contribute to close the trade financing gap of SMEs. Indeed, (small-to-medium-sized) suppliers can rely on the repayment promise of a (larger) buyer to have access to a third-party's funds at an advantageous rate (Olsen et al., 2018). Nonetheless, most SCF still relies heavily on paper-based processes and involves a broad range of parties and intermediaries (i.e. the buyer, its bank, the supplier, and its bank, a third-party funder) (Olsen et al., 2018). Hence, submitting the required documents (e.g. letter of credit and bill-of-lading) entails a substantial administrative burden for financial institutions, with the operational expenses nearing 50-60% of the total income (before covering the costs of risk and liquidity), which makes small-ticket transactions particularly unattractive (Olsen et al., 2018).

According to Gao et al. (2019), Kim et al. (2019) and Olsen et al. (2018), blockchain can help to close the trade financing gap for SMEs by providing a single-source-of-truth, immutable database that makes faster credit risk assessment possible (from the immutable, and hence, reliable transaction history), minimizes human error in document checks, and automatizes the execution of repetitive workflow steps through smart contracts. If distributed ledger technology is adopted by all participants in the supply chain ecosystem, it could decrease trade finance operating cost by 50-70% (Baxter et al., 2018).

To summarize, the integration of blockchain and Supply Chain Management is still at an embryonic stage, and limited to a few pilots launched by large multinational companies, with several barriers (technological, organizational and operational) hindering large scale adoption (Queiroz & Fosso Wamba, 2019; Y. Wang et al., 2019). The path to digitalization can be especially arduous for SMEs, for which these challenges can become insurmountable mountains (Blockstart, 2020). SMEs would greatly benefit from the adoption of distributed ledger technology, as it would enable real-time tracking of products, which brings about unparalleled efficiency gain for the whole supply chain, and easier access to financing, the lack of which is the cause for over 30% of SMEs' demises (Baxter et al., 2018; Olsen et al., 2018). Besides, SMEs occupy a prominent role in the European Economy and logistics in particular (Velthuijsen et al., 2018), which means that distributed ledger technology has to be made accessible to them as well to impact the performance of entire supply chains.

It is with this aim that the Spark! Living Lab (SLL) has been launched. The project involves several stakeholders, including 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, which have offered to mobilize their physical infrastructure. The ultimate goal of the SLL is to support stakeholders in developing use-cases with blockchain in SCL, with the selection of those that directly involve SMEs, and promote rapid community development. Furthermore, through the SLL, a repository knowledge hub for parties, especially SMEs that want to experiment, will be built.

Within the SLL, this research is aimed at conducting an empirical study to identify the factors that are influencing the intention to adopt blockchain by SMEs with a logistics operation. The latter identifies not only logistics service providers, but also small-to-medium-sized businesses that manufacture or buy physical goods and are part of an extended supply chain.

1.6 RESEARCH DESIGN

1.6.1 RESEARCH QUESTIONS

Based on the previously delineated research problem, the following main research question is developed:

How can SMEs with a logistics operation be supported in the adoption of blockchain for Supply Chain Management?

Given the nature of the main research question, which reflects the ultimate goal of the study, this thesis work can be categorized as an Exploratory Research. Indeed, an exploratory study attempts to investigate an issue that has seldom been explored in the past and for which no solution is currently available (Sekaran & Bougie, 2016).

The approach that is taken in this study is inductive, as theory and recommendations on how SMEs with a logistics operation can be supported in the adoption of blockchain for Supply Chain Management are developed as a result of data analysis. Furthermore, both qualitative and quantitative methods are employed in this study. First, a qualitative approach is adopted during the initial exploratory stage of the project, which lays the ground for developing a conceptual model. Then, once a theoretical background has been formed, a quantitative approach is adopted to collect and analyze the data. The division between the two sections (qualitative and quantitative) is shown in the Research Flow Diagram (RFD) in Figure 8.

The following sub-research questions will help answer the main research question:

1.6.1.2 Sub-Question 1

Which frameworks are available in the literature that investigate the factors that influence the intention to adopt blockchain for Supply Chain Management by SMEs?

Concerning the first sub-research question, a systematic literature review has been the chosen method to identify a broad set of explanatory factors for blockchain adoption intention. The examined articles have been located by using multiple bibliographic databases containing peer-reviewed literature (Scopus and Web of Science) to make the literature search more rigorous. The identified factors have then been categorized according to a theoretical framework (the TOE[4]) that has been selected throughout the literature review. In addition, experts from TNO,

[4] The Technology-Organization-Environment Framework is "an organizational level theory that explains that three different elements of a firm's context influence adoption decisions(Baker, 2011, p.2).

and the thesis supervision team have been consulted to perfect the *Factors Identification* (the second block in the RFD in Figure 8).

1.6.1.4 Sub-Question 2

How can the relative importance of each of the factors that are influencing the intention to adopt blockchain by SMEs with a logistics operation be determined?

After having identified a set of explanatory factors, the relative importance of each of the identified factors had to be determined empirically. To accomplish this, the Best Worst Method (BWM) was chosen. The BWM is a Multi-criteria decision making (MCDM)[5] method that can be used to infer the weights of the decision criteria based on the preferences of the decision-maker (DM) (Mohammadi & Rezaei, 2019). To collect the preferences of the decision-maker(s) within SMEs, an online questionnaire (which can be found in its entirety in appendix 8.A) has been designed with the Qualtrics Survey Software provided by TU Delft, and by following the BWM's guidelines. Then, the survey has been distributed through the network of TNO and its partners in the Spark! Living Lab, and, once enough responses were collected, the Data Analysis phase is carried out.

Further details on the methodology and the sampling process are provided in the third chapter of this manuscript.

1.6.1.5 Sub-Question 3

What is the relative importance of the factors that are influencing the intention to adopt blockchain by SMEs with a logistics operation?

The data analysis has been carried out by employing the MATLAB implementation developed by Mohammadi & Rezaei (2019), which yielded a ranking of the identified factors. Before the respondents' preferences could be used as inputs in the MATLAB implementation, a Python script has been developed to transform the Qualtrics' output (an Excel sheet with all the responses) into the matrix format compatible with MATLAB's syntax.

The results of the analysis are presented in detail in the fourth chapter of this master thesis, whereas the Python script can be found in Appendix B.1.

[5] MCDM is often used interchangeably with Multi-attribute decision-making (MADM), which is the branch of decision-making theory that deals with problems that have a discrete solution space and are evaluated based on a handful number of criteria (Rezaei, 2015).

1.6.1.6 Sub-Question 4

Which factors should the SLL consortium focus on when supporting SMEs in their blockchain journey based on the results of the present study?

Based on the output of the data analysis, a final ranking of the identified factors has been provided to the Spark! Living Lab consortium so that potential users can be targeted more effectively, as explained in section 1.9.

Finally, the Main Research Question is answered in Chapter 6.

1.7 RESEARCH FLOW DIAGRAM

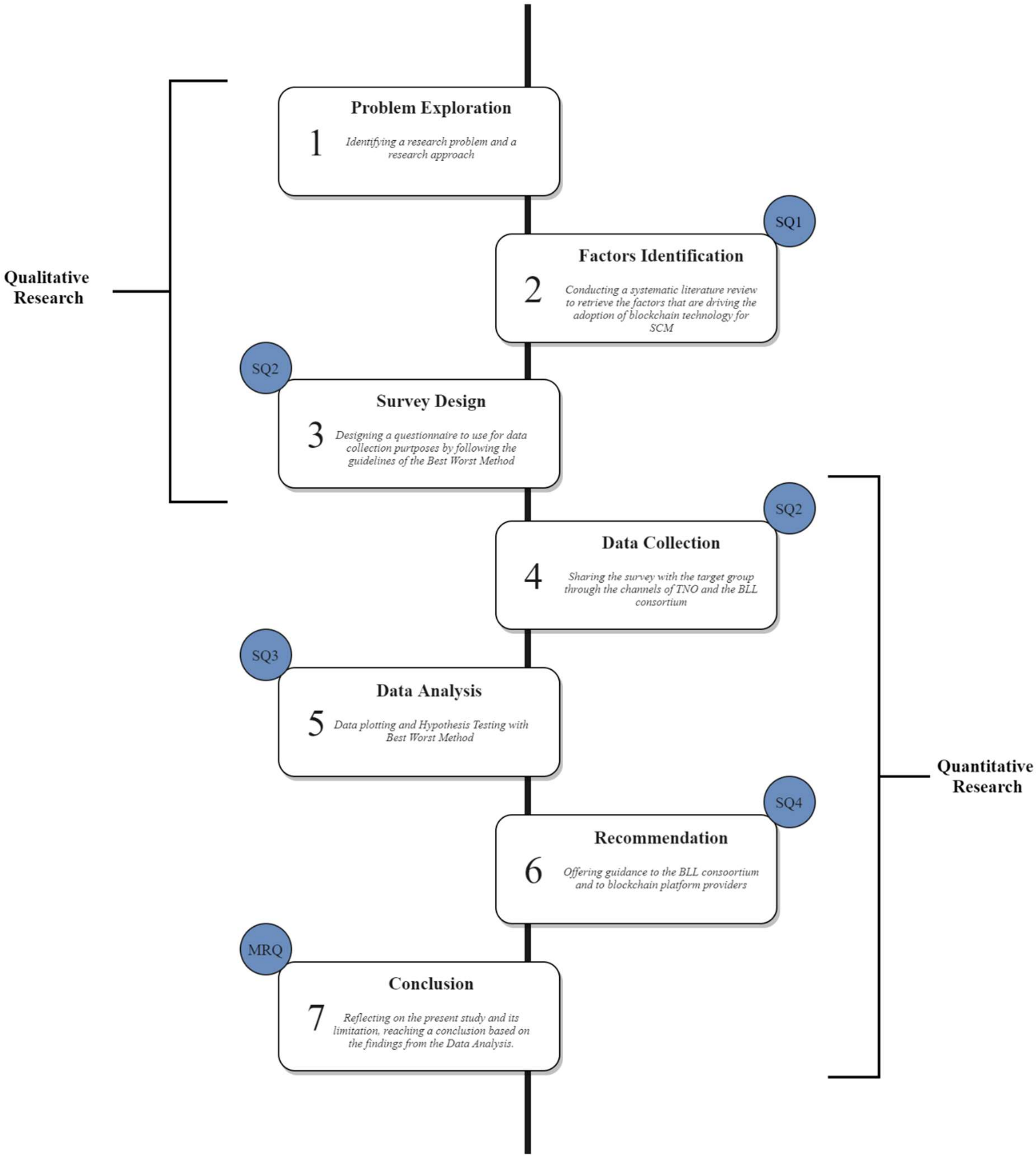


Figure 8: Research Flow Diagram

1.8 SCIENTIFIC RELEVANCE

This study locates itself in a scientific landscape where, according to (Kshetri, 2018), "scholars have barely begun to systematically assess the effects of blockchain technology on various organizational activities" (p. 80), with the study of its interplay with supply chain still being at an embryonic stage. Furthermore, Fosso Wamba & Queiroz (2020) and Wong et al. (2019) have both emphasized the need to further investigate the adoption challenges with distributed ledger technology as only a marginal percentage of studies have reported on blockchain with empirical approaches. This statement finds confirmation in the literature review conducted in the Chapter 2 of this research work, with only a handful of articles returned by Scopus and Web-of-Science on the topic. Remarkably, only one article, by Wong et al. (2019), has been located when restricting the search scope to small-to-medium-sized businesses applications, showing the novelty of the topic.

The empirical research conducted by Wong et al. (2019) offers an invaluable comparison for this Master thesis, as the authors have administered a survey to more than 200 SMEs in Malaysia to identify the factors driving the intention to adopt blockchain for Supply Chain Management. However, the outcome of the present study might be dramatically different as it will be conducted in a dissimilar setting if compared to Malaysia, and it will employ a different method for designing the survey.

1.9 SOCIETAL RELEVANCE

The societal and practical contribution of this study is threefold. First, the factors identified are used to provide guidance to the SLL consortium. By using the methods explained in Chapter 3, the weights of the identified factors are computed, and a ranking based on them is established. The ordering of the issues that are considered by SMEs in a technology adoption decision can then help the SLL consortium in determining which elements they should put more emphasis on when supporting SMEs in their blockchain journeys. Secondly, shedding light upon these determinants may assist the SLL, but also blockchain platform providers, in comprehending which aspects of distributed ledger technology they should better explain to potential customers when advertising their services. Lastly, the factors' weights may aid SMEs themselves in their blockchain adoption decisions as this research work will highlight the factors that their peers are considering when making such a critical commitment. On a higher level, this study will contribute to promote the SLL consortium to a larger audience, as the questionnaire has been shared through various wide-reaching channels, as explained in section 3.4.3.

2. FACTORS IDENTIFICATION

In the present chapter, the first sub-research question "Which frameworks are available in the literature that investigate the factors that influence the intention to adopt blockchain for Supply Chain Management by SMEs with a logistics operation?" is answered by conducting a systematic literature review. The latter has resulted in the identification of a theoretical framework and a set of explanatory factors that have been reviewed in consultation with experts from TNO, and the thesis supervision team. As the present study is explorative, and it aims to identify a pioneering set of factors influencing blockchain adoption intention and provide a rough estimate of their relative importance (or weights), the interrelationships (e.g. mediation and moderation) between the factors have been omitted from the model. An in-depth investigation of these effects, however, makes for an interesting follow-up to this research.

2.1 REVIEW PROTOCOL

To answer the first sub-research question, a systematic literature review has been the chosen research method. A systematic literature review is preceded by the definition of a review protocol, which specifies the research question that the review is intended to answer and delineates a strategy to detect as much of the relevant literature as possible (Kitchenham & Charters, 2007). This is aimed at enhancing the completeness and repeatability of the process, even though it is almost impossible to replicate searches of digital libraries (Kitchenham & Charters, 2007).

This review will be performed with the funnel method of structuring a literature review, which starts from looking at works that are relevant to the investigation but do not specifically contribute to answering the formulated research question and then moves towards studies that relate more closely to the topic of interest (Hofstee, 2006).

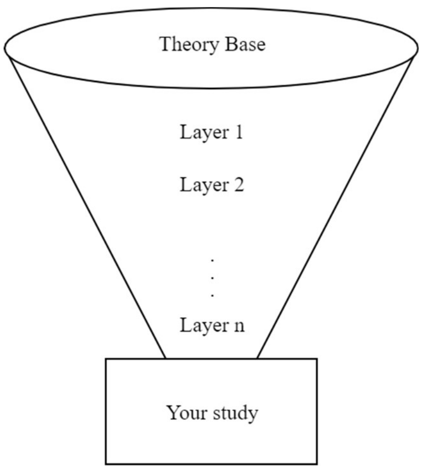


Figure 9: The funnel method of structuring a literature review, based on Hofstee (2006)

The terms that will be searched at each layer of the funnel are presented in Table 1, along with their synonyms, generated with powerthesaurus.org. As it can be noticed from Table 1, only the fifth layer's research question belongs to the sub-research questions identified in section 1.8. Indeed, the first four rows' inquiries have been developed, in accordance with Hofstee (2006), to lead up to the utmost point of the funnel and give the reader a mostly quantitative overview of the research that has been conducted so far on SMEs. Furthermore, the results from the fourth and fifth row have been combined after careful consideration due to the overall scarcity of sources on the topic, and a substantial overlapping in the research output. Only the results from these two rows will be analyzed in full to produce the desired deliverables and answer the first two sub-research questions.

Table 1:Layers in the funnel and search term

Layer	Search Term(s)
1-What exactly are SMEs?	SMEs OR "Small and medium sized enterprises" OR "Small and medium sized businesses" OR "Small enterprises" OR "Small businesses" OR "Small firms" AND ("Definition" OR "What are" OR "What is")
2-What is an Small-to-Medium Sized Business's role in the Supply Chain?	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")
3-How would SMEs benefit from Blockchain and Supply Chain Integration?	Search terms from above cell AND ("Blockchain" OR "Block chain" OR "Distributed ledger") AND ("Benefits" OR "Advantages" OR "Opportunities" OR ''Positive'' OR ''Impact'')
4- What is in the literature available on the adoption of blockchain by SMEs?	Search terms from above cell AND ("Adoption" OR "Appropriation"). If the results are not satisfying add OR "ict" OR ''information technology'' to the previous query.
5-Which frameworks are in the literature available that investigate the factors that influence the intention to adopt blockchain for Supply Chain Management by SMEs?	("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 main literature repository that will be used for this systematic review is Scopus, the largest abstract and citation database of peer-reviewed literature. Nonetheless, the search results of the bottom two rows of Table 1 will be compared and complemented with the results from Web-of-Science (WoS), to make the review more rigorous.

Only the studies accessible in full-text will be selected for the literature review. A constraint will also be placed on the publication type (only peer-reviewed journal articles and conference proceedings) although it may be needed to recur to grey literature if the scientific literature is lacking in the final stages. Also, a constraint will be put on the language of the sources (which have to be written in English), the year (after 2015), and obviously on the topic. A limit on the publication year has been imposed due to the novelty of the topic, as the majority of the publications released before 2015 were solely related to Bitcoin applications. In the first three layers, only the most relevant works will be chosen based on the filtering tools from Scopus, while the studies identified in the conclusive two and most important layers will be thoroughly examined by looking first at the abstract and then to the full article when in doubt.

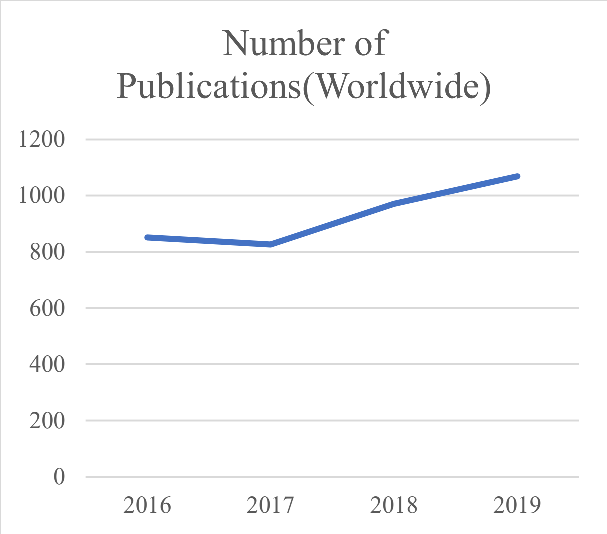
2.2 WHAT EXACTLY ARE SMEs?

2.2.1 LITERATURE SELECTION

Based on the delineated research strategy and the above selection criteria, 3889 results were returned by Scopus. Due to the abundance of the results, a "country" filter (The Netherlands) has been applied, resulting in a drop in the number of search results to 98. The "country" filter limits the search output to studies that have either taken place in The Netherlands or carried out by researchers at Dutch universities. After sorting the obtained literature based on "Relevance"[6], the article "Governing and accelerating transformative entrepreneurship: exploring the potential for small business innovation on urban sustainability transitions" was selected. Nonetheless, after reading through the abstract, it was clear that this paper would not have answered this layer's research question. Indeed, this article focuses on the role of SMEs in the sustainable transition of urban spaces, which is out of the scope of this review. Thus, the second article on the list has been picked instead. Nevertheless, before diving into the article from Chong et al. (2019), an overview of the results will be presented.

[6] A query's results on Scopus can be sorted based on the relevance index, which is higher as the articles match more closely the search words that have been entered (Burnham, 2006).

2.2.2 RESULTS OVERVIEW



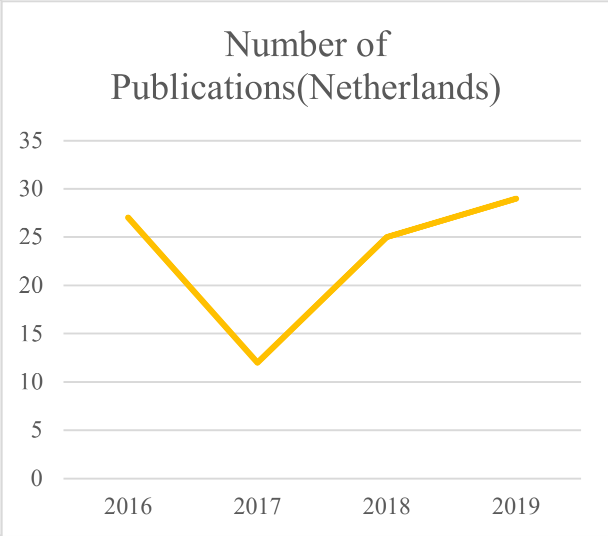


Figure 10:Number of Publications on SMEs, Worldwide and in the Netherlands

As can be seen in Figure 10, both worldwide and in The Netherlands, the number of publications on SMEs decreased in 2017. Although, the number of publications dropped significantly more in The Netherlands, plateauing at 12, after standing at 27 the year before. Then, both graphs show a change of tendency in 2018 and 2019, with the number of documents surpassing the 1000 mark worldwide and signaling an increasing interest in small and medium scaled businesses. Despite the recent increase in the number of publications in the Netherlands, the country remains far behind the leader in publications (the United Kingdom, with roughly 600 documents) standing at the 15th place worldwide, as shown in Figure 11.

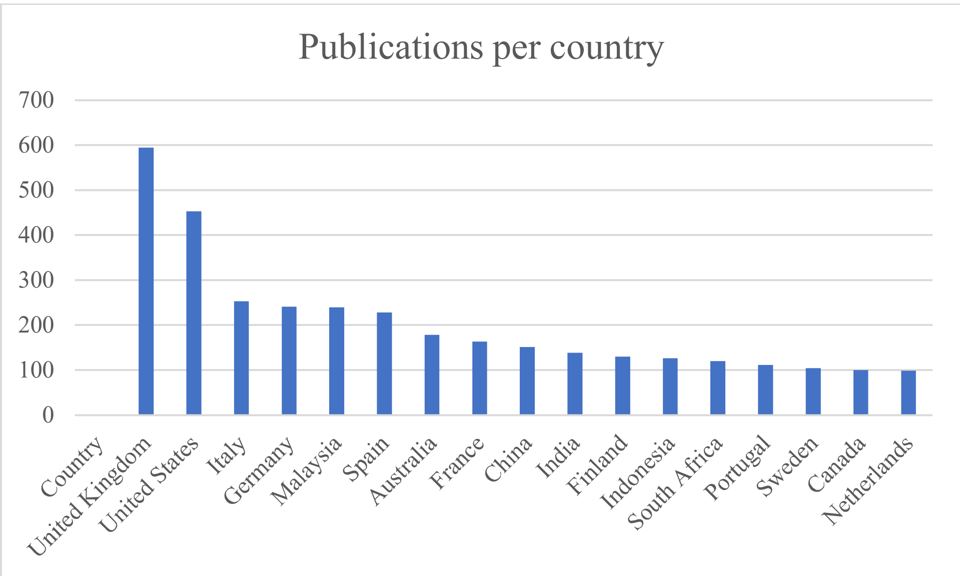


Figure 11:Number of publications per country on SMEs between 2016 and 2020

2.2.3 ANSWERING SR1.1

According to Chong et al. (2019), the definition of SMEs should go beyond the "traditional" statistical delineation that classifies all of the enterprises with less than 250 employees as small-to-medium sized companies. A more appropriate definition classifies enterprise as Small-to-Medium "only if the highest national aggregate level (the enterprise group), have less than 250 employees and should not be a subsidiary of a foreign multinational enterprise" (Chong et al., 2019, p.3). This characterization is how SMEs will be defined for the remainder of this paper.

2.3 WHAT IS A SMALL-TO-MEDIUM SIZED BUSINESS' ROLE IN THE SUPPLY CHAIN?

2.3.1 LITERATURE SELECTION

By implementing the research strategy explained above, the second layer's query (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") returned 1088 documents, of which only 246 had Open Access. Due to the abundance of sources available, an attempt was made to filter the results based on the country of provenance. However, because of the shortage of documents for the "Netherlands" (25), the constraint was removed. The query's output was again sorted according to the Scopus' relevance index. By considering both the order and the compatibility of the article's titles (and abstracts when in doubt) with the research question for this second layer (What is a Small-to-Medium Sized Business's role in the Supply Chain?), the document from Thoo et al. (2017) was selected.

2.3.2 RESULTS OVERVIEW

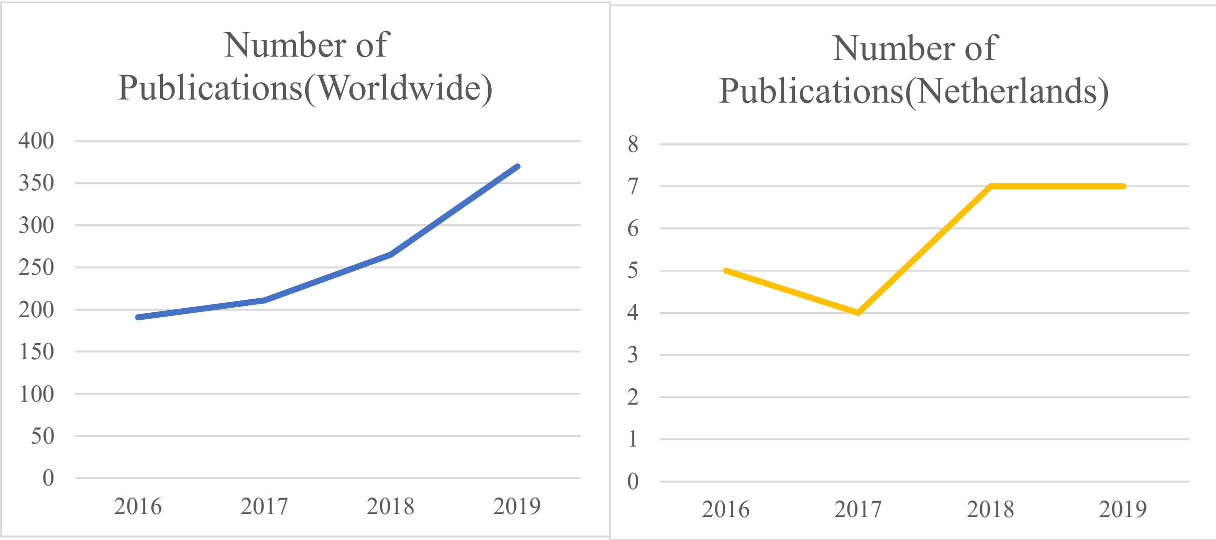


Figure 12:Number of publications on SCM for SMEs, worldwide and in The Netherlands

The two graphs in Figure 12 confirm the increasing attention paid by the scientific community to SMEs' research in recent years. Furthermore, it can be seen from the graph on the left-hand of Figure 12 that the rise in publications has been steeper within the SMEs and SCM niche than in the SMEs' space as a whole (Figure 10). By looking at the number of publications in the graph on the right hand of Figure 12, it can also be noticed a sharp increase from 2017, the lowest point, to 2019, with the number of publications almost doubling from 4 to 7. Nonetheless, due to the very limited number of articles overall, the increase in popularity of SCM and SMEs' research in The Netherlands has to be taken with a grain of salt.

By looking at Figure 13, which reflects the number of publications per country, it can be observed the dramatic rise of China, which holds the first place in this particular niche. The United Kingdom maintains a prominent role, with over 100 publications, while the Netherlands remains in the 12-15 range, with 25 publications.

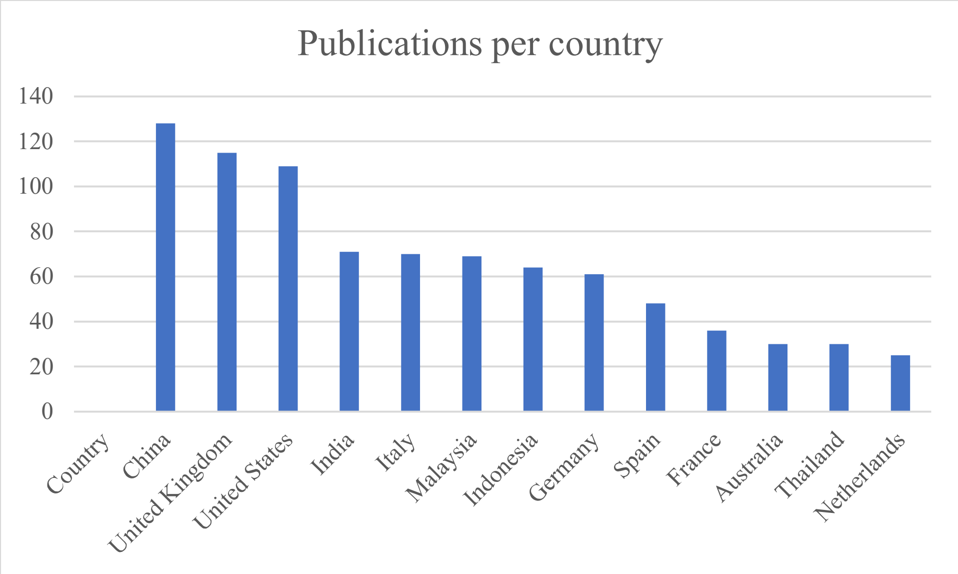


Figure 13:Number of publications per country on SCM for SMEs between 2016 and 2020

2.3.3 ANSWERING SR1.2

According to Chong et al. (2019), the total value added by SMEs in The Netherlands is comparable to the total value added by large enterprises. In particular, SMEs have a leading role in sectors such as agriculture, transport, and services, and are more often suppliers to other enterprises than suppliers to final consumers (Chong et al., 2019). SMEs are often independently owned and operated, with a strong cultural influence and a small management team (Thoo et al., 2017). This makes SMEs more flexible to changes, and thus potentially fertile ground for disruptive innovations (Chong et al., 2019). Nonetheless, Thoo et al. (2017) argue for the financial constraints of small-to-medium-sized businesses and the difficulty of SMEs to get access to credit, which represents a threat to their survival in the current competitive environment.

2.4 HOW WOULD SMEs BENEFIT FROM BLOCKCHAIN AND SUPPLY CHAIN INTEGRATION?

2.4.1 LITERATURE SELECTION

When searching for the keywords from the third row of Table 3 on Scopus ((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 "Block chain" OR "Distributed ledger") AND ("Benefits" OR "Advantages" OR "Opportunities" OR ''Positive'' OR ''Impact'')), and excluding the word SMEs (and synonyms) from the query, 298 documents are returned by the literature repository. Although, if the SMEs (and synonyms) are included, only 5 documents are shown in the results. This outcome illustrates the shortage of literature considering the integration of blockchain and supply chain from the perspective of small-to-medium-sized businesses. Of the 5 results displayed, three articles are focused on the applications of blockchain for Supply Chain Financing, and only two out of five are accessible in full text. Thus, a Google search has been performed to look for grey literature (e.g. company reports) that may complement the literature search. The keywords that have been looked up on Google are "SMEs & Supply Chain Management & Blockchain". Within the results, the research on Blockchain Innovation for SMEs conducted by Mittal (2019) of Enrst & Young has been deemed as useful for this layer. Furthermore, the research previously conducted by Windesheim University of Applied Sciences (the leading institution in the Spark! Living Lab) in the context of the EU-funded Blockstart project (Blockstart, 2020), has been taken into account to answer SR1.3.

2.4.2 RESULTS OVERVIEW

To present an overview of the search results, the output of the first query (without SMEs or synonyms) has been used due to the scarcity of the output of the complete search.

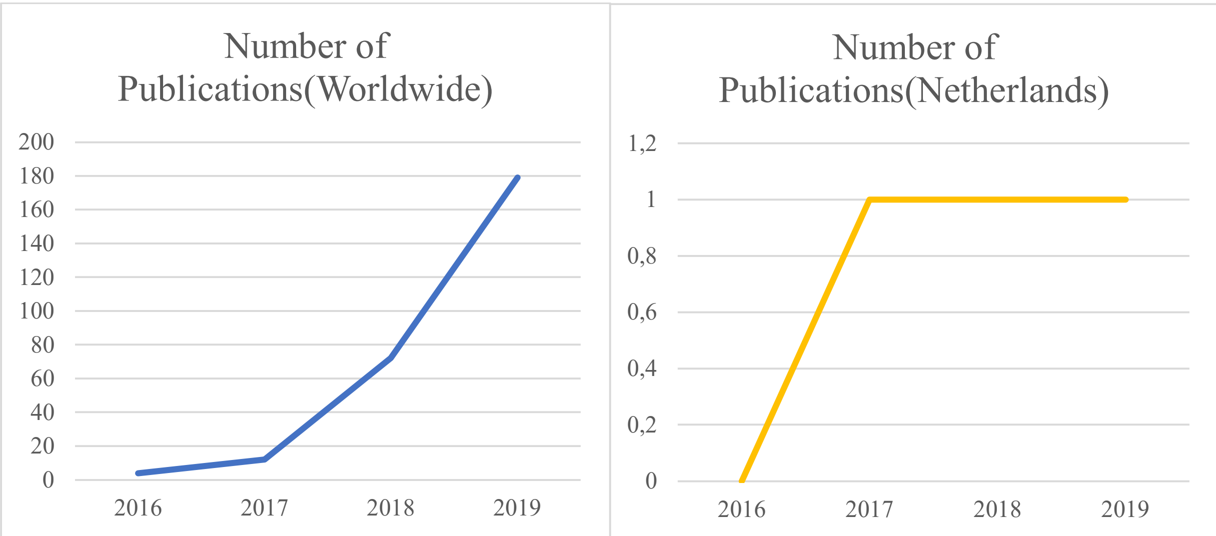


Figure 14:Number of publications on the use of BT for SCM by SMEs, worldwide and in The Netherlands

As can be seen from the above graph on the left, the number of publications on the benefits of blockchain and supply chain integration skyrocketed in the past four years, increasing from a mere four publications in 2016 to 179 in 2019. On the other hand, the rising popularity of the topic did not seem to affect The Netherlands, which recorded only three publications from 2016, standing at the 33rd place worldwide.

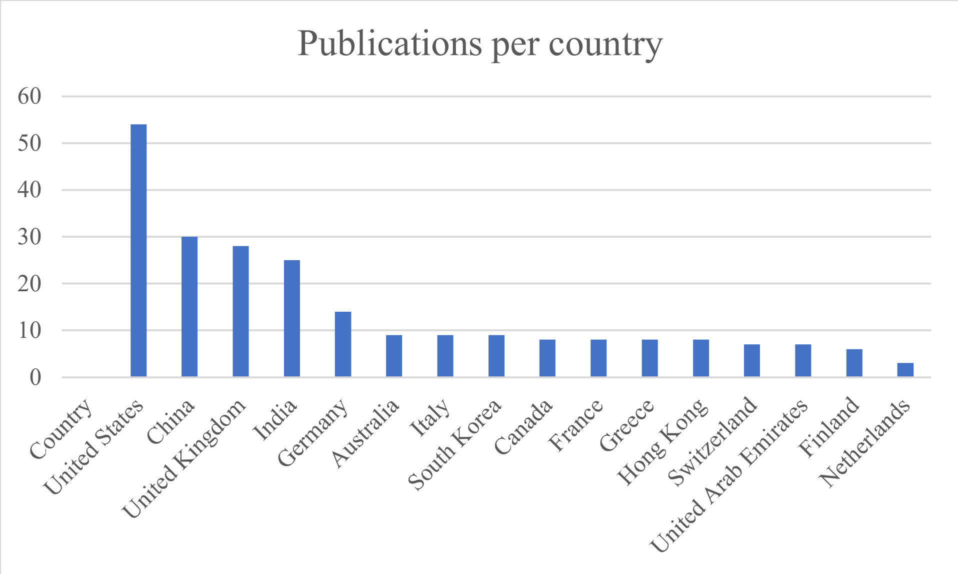


Figure 15:Number of publications per country on the use of BT for SCM by SMEs between 2016 and 2020

2.4.3 ANSWERING SR1.3

According to Gao et al. (2019), Supply Chain Financing is often precluded to small-to-medium-sized enterprises. Banks are reluctant to accept loan applications from SMEs due to the potential loss the bank will undertake if the principal of the loan is not paid back. In particular, financing item risk is considered one of the main risk sources (Gao et al., 2019). Financing item risk "refers to the risk brought about by account receivables and pledge risk'' (Gao et al., 2019, p. 1). A pledge is an asset that is given as collateral by a debt issuer to increase its chances of getting its request accepted by a financial institution. If an asset is used as a pledge and the borrower defaults on its promise to repay the principal, the financial institution will take the ownership of the pledged asset. The latter may, however, be subject to devaluation during the credit period (pledge risk), which forces banks to invest plenty of manpower and financial resources to frequently reevaluate the current value of the pledge (Gao et al., 2019). Nonetheless, this costly process may be avoided with blockchain technology (Gao et al., 2019). Indeed, the distributed ledger can be used by the bank to collect the real-time price of the pledge (a process named "real-time staring" by the author) and evaluate its present value compared to the initial one (Gao et al., 2019). If the latter is higher than the present value of the pledge, a replenishment by the borrower is required. The financial institution can have complete trust in the reliability of the collected data, as the immutability property of blockchain guarantees that the owner of the pledged asset has not tampered with the information (Gao et al., 2019). This makes the manual auditing process carried out by the banks' employees redundant, and, hence, avoidable, saving plenty of financial resources (Gao et al., 2019).

Gao et al. (2019) have tested the effectiveness of this strategy with three numerical experiments, which have shown the potential of real-time staring enabled by blockchain technology to eliminate most losses brought about by the price fluctuations of the pledge. According to the authors, this application of blockchain may give SMEs access to online Supply Chain Financing, which is of great significance to small-to-medium-sized businesses.

Mittal (2019) and Blockstart (2020) also argue for the suitability of blockchain for SMEs that are facing trade financing challenges in the area of Supply Chain. These challenges include trust and communication issues, low visibility as input are localized in companies' internal databases, and unnecessary and duplicated procedures (Mittal, 2019). As it has been explained in paragraph 2.3, blockchain enables the creation of a trusted transaction system and smart contracts for the transfer of value. Hence, it may be used to establish an immutable trail of all trade and financing transactions, which could give financial institutions reliable information to assess short-term credit standing (Mittal, 2019; Blockstart, 2020). Furthermore, sealing a disintermediated one-on-one digital contract between parties, which is undisputable and self-executing, would set in stone the seller's performance targets and eliminate concerns on buyer's repayment risk (Mittal, 2019).

Lastly, Blockstart (2020) and Wong et al. (2019) both insist on the disruptive impact that blockchain-empowered Supply Chain Visibility might have on the industry. Blockstart (2020) claims that creating a single-version-of-truth for all parties in the supply chain would facilitate accurate forecasting and timely interventions based on real-time and reliable information. Although Supply Chain Visibility has an impact on all the members of the supply chain, including SMEs, it will be typically initiated by larger firms (Blockstart, 2020). On the other hand, Wong et al. (2019) argue that the elimination of costly third parties might perhaps be the most significant benefit brought about by blockchain and supply chain integration for SMEs.

2.5 TAKEAWAYS FROM THE FIRST THREE LAYERS

In this paragraph, a brief overview of the previous three sections is provided.

The output of the first two layers of the funnel (1-What exactly are SMEs?, 2-What is a Small-to-Medium Sized Business's role in the Supply Chain?) has demonstrated an increasing interest of the scientific community in SMEs and their role in supply chains, with the latter having a more pronounced increase in publications than the SMEs' universe as a whole. Nonetheless, the third layer's query (3-How would SMEs benefit from blockchain and supply chain integration?) only returned five articles on the topic of blockchain and supply chain integration for SMEs, which locates this study in a relatively unexplored field.

In the first layer, an unequivocal definition of a small-to-medium-sized business was provided by Chong et al. (2019), who classified SMEs as firms with "less than 250 employees and that are not a subsidiary of a foreign multinational enterprise" (p. 3). Moreover, Chong et al. (2019) and Thoo et al. (2017) advocated for the importance of small-to-medium-sized-enterprises in sectors such as transport and services in the second layer. Based on their study, Chong et al. (2019) asserted that SMEs are more often "B2B" businesses and they are generally independently owned and operated. As a consequence, they are more flexible to change, and, hence, a fertile ground for disruptive innovations (Chong et al., 2019). Nonetheless, Thoo et al. (2017) warned, SMEs face serious difficulties in getting access to credit, and their attempts to innovate are often stifled by these financial constraints. Lastly, three of the five articles identified in the third layer explore applications of blockchain for Supply Chain Financing. Gao et al. (2019) proposed a blockchain-based solution to monitor in near real-time the value of the collateral in a loan transaction. Whereas, Mittal (2019) and Blockstart (2020) advocated for the suitability of distributed ledger technology to create an immutable trail of all trades and transactions in a supply chain network, which could then be accessed by financial institutions to reliably assess a firm's short-term credit standing. The remaining sources discussed the role of blockchain as an enabler of Supply Chain Visibility, which can facilitate accurate forecasting and timely interventions when disruptions occur (Blockstart, 2020; Wong et al., 2019).

2.6 FACTORS IDENTIFICATION

In the present sub-chapter, the final two, and most crucial, phases of the literature review are carried out and the first sub-research question ("Which frameworks are available in the literature that investigate the factors that influence the intention to adopt blockchain for Supply Chain Management by SMEs?") is answered.

As mentioned in the review protocol in section 2.1, the results of the two conclusive layers, which are shown in Figure 16, are combined due to overlapping and a general scarcity of sources on the topic. Then, once the identified articles have been selected, a general overview of the search outputs is provided. Next, a framework to categorize the soon-to-be-identified factors is chosen based on the reviewed papers. Finally, the factors that have been found during the review are presented in Table 5, which is the main deliverable of the second chapter of this manuscript.

2.6.1 LITERATURE SELECTION

By searching for the keywords in the fourth row of Table 3 ((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 “Block chain” OR “Distributed ledger”) AND (“Benefits” OR “Advantages” OR “Opportunities” OR ‘’Positive’’ OR ‘’Impact’’) AND (“Adoption” OR “Appropriation”)) on Scopus and applying the previously delineated research strategy, only one result was displayed. Therefore, the words ‘’ict’’ and ‘’information technology’’ were added to the query, obtaining a more satisfactory 24 results. Of these 24 results, 13 were discarded based on the title alone, while another three were discarded as they were not freely accessible. Thus, only eight articles have been selected for this literature review. Remarkably, none of the articles, except the one from Wong et al. (2019), which was present in both these results and the ones from the previous query, investigates the adoption of blockchain by small-to-medium-sized businesses. Of the eight articles that have been kept, the papers from Mathu & Tlare (2017) and Rao & Kumar (2019) were rejected after reading the full text. Indeed, the former investigates the benefits of information technology adoption for the supply chain, rather than the adoption process in itself. While, the latter depicts the benefits of adopting agile practices, which do not fit the scope of the present literature review. As it has been previously stated, a parallel search has also been conducted on Web-of-Science. However, only one of the five results displayed on WoS was not present in the Scopus’ output and it was regarded as not suitable after reading the title and abstract.

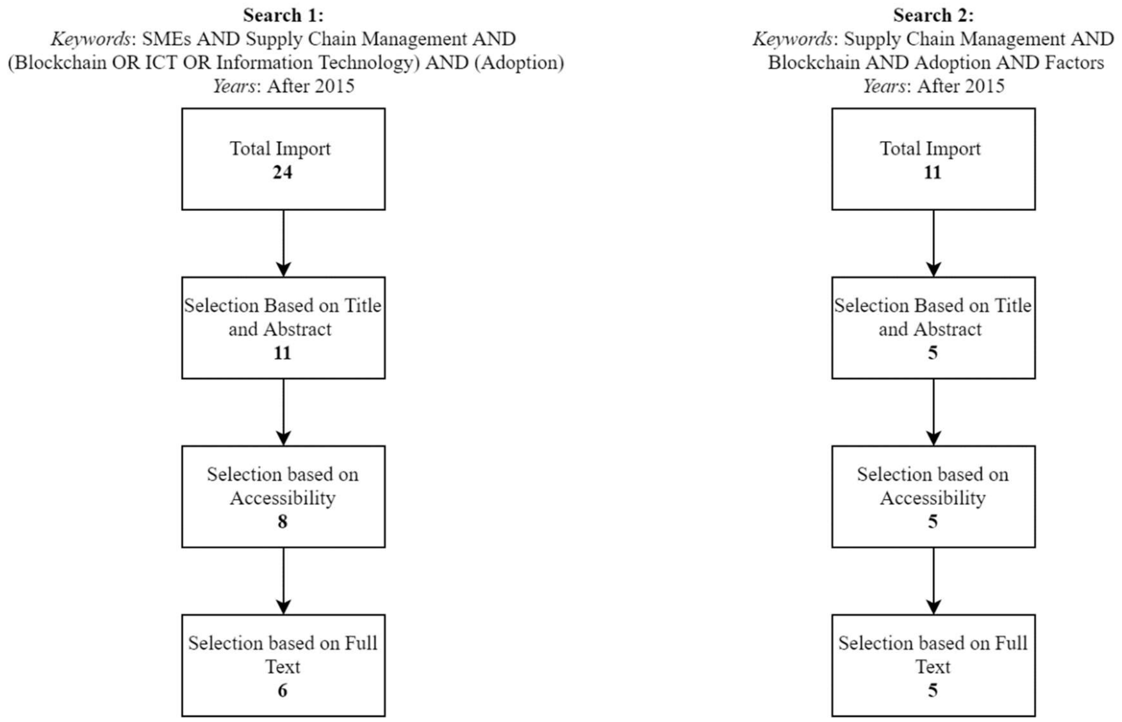


Figure 16: Schematic view of the queries from the last two layers of the literature review

Lastly, a decision was made to merge the results of the present search (Search 1 in Figure 15) with the results of the next, and final, funnel's layer (Search 2 in Figure 15), due to a significant overlapping in the search outputs and an overall scarcity of sources on this topic. Initially, the keywords that were used in Search 2 included the words from Search 1 plus "factors OR drivers OR determinants''. Nevertheless, the output only displayed the article from Wong et al. (2019), which had already been found in previous queries. Hence, the constraint on the SMEs' focus was removed at this time and the query shown in Figure 15's Search 2 was used instead. The output of the latter consisted of 11 documents, which have all been published in 2019, signaling once again the novelty of this topic. The paper from Wong et al. (2019) was discarded as it was already present in the previous inquiry. Moreover, one paper was rejected based on the title alone, whereas other 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.

By repeating the same search on WoS, four results were returned. However, all four articles were either overlapping with the results of previous queries (two of them), or not-suitable topic-wise.

Despite being presented together in the findings section, the results of the two searches, which are shown in Table 2, will be kept separate for clarity purposes. In particular, the numbers in

bold in the first column indicate that the articles can be traced back to the first search, with the opposite being true for the numbers in *Italic*.

Table 2:List of the papers included in the Systematic Literature Review

Article	Author	Year	Where Published	Where Conducted	Technology	Theoretical Framework
1	AL-Shboul	2019	Business Process Management Journal	Developing Economies	ERP Software	DOI and TOE
2	Anjum	2019	Humanities and Social Sciences Review	India	ICT	TOE
3	Awa & Ojiabo	2016	Journal Information Technology and People	Nigeria	ERP Software	TOE
4	Dinca et al.	2019	Journal of Business Economics and Management	Romania	Cloud Computing	DOI and TOE
5	Kühn et al.	2019	Hamburg International Conference of Logistics	Germany	Blockchain	TOE
6	Surjandy et al.	2019	ICIC Express Letters	/	Blockchain	PPTF
7	Queiroz & Fosso Wamba	2019	International Journal of Information Management	India & USA	Blockchain	TAM
8	van Hoek	2019	Supply Chain Management Journal	USA	Blockchain	/
9	Walker et al.	2016	Journal of Internet Commerce	Slovakia	e-commerce	TAM, DOI, TOE
10	Wang et al.	2019	Supply Chain Management Journal	/	Blockchain	/
11	Wong et al.	2019	International Journal of Information Management	Malaysia	Blockchain	TOE

2.6.2 RESULTS OVERVIEW – ANSWERING SR1.4

In the present section, a brief overview of the search outputs of the final two stages of the literature review is provided, and, hence, the fourth layer's research question (4-What is in the literature available on the adoption of blockchain by SMEs?) is answered.

By looking at the year column in Table 2, it can be noticed that only two of the reviewed papers were published in 2016, while the remaining articles were all released in 2019, signaling the novelty of the topic. The ''Where published'' column of Table 2 also displays the dominance of a single category. Indeed, ten of the eleven reviewed papers are journal articles and they have been published in periodicals of different nature, with only two journals appearing more than once (the International Journal of Information Management and the Supply Chain Management Journal, both two times). The "Where Conducted'' column shows a pronounced focus on developing economies rather than developed ones when it comes to ICT/blockchain adoption, which is reasonable considering the increased difficulty of innovating in an environment characterized by presumably worse business and governance conditions. However, this should not suggest that research on innovation adoption is not desirable for developed economies, which share the same need to be competitive in the global marketplace.

The information and communication technologies that have been investigated are ERP Software, Cloud Computing, e-commerce, and Blockchain, with two, one, one, and six articles respectively. Nonetheless, if only the first SMEs' focused query is considered (bold-numbered rows in Table 2, Search 1 in Figure 15), blockchain adoption has only been explored once, by Wong et al. (2019), indicating a shortage of literature on the topic.

Concerning the theoretical frameworks that have been used by the analyzed authors, the Technology, Organization and Environment Framework seems to be the most popular choice to conduct an empirical study on innovation adoption, as it has been employed, alone or in combination with other frameworks, in seven out of nine articles that used a theoretical framework. The models that have been referred to include the Technology Acceptance Model (TAM), which is an information systems theory to illustrate how users come to accept and use a technology (Davis et al., 1989), and the Diffusion of Innovation Theory (DOI), which Rogers (1962) developed to explain how an idea or product gains momentum and diffuses over time within a specific population. The TAM has been used by Queiroz & Fosso Wamba (2019) to study blockchain adoption in India and the USA, while the DOI model has been used in combination with the TOE by several authors.

2.6.3 FRAMEWORK SELECTION

As can be seen in Table 2, several frameworks have been employed in the study of ICT adoption. This has been confirmed by Baker (2011), who listed the most widely used theories for adoption research in his work. The list includes the above-mentioned models (TAM, DOI, and TOE) along with the United Theory of Acceptance and Use of Technology (UTAUT). The latter draws upon eight previous models of technology use to provide a unified theory for predicting behavioral intentions in the organizational context (Venkatesh et al., 2012).

While the DOI and the TOE both examine technology adoption at a company's level, the TAM and UTAUT focus on the adoption by individual users and have thus been excluded from this study. The Diffusion of Innovation Theory has demonstrated to be consistent with the Technology-Organization-Environment Framework (Baker, 2011). Indeed, the DOI adoption predictors "individual leader characteristics" and "internal characteristics of organizational structure" have been compared to the TOE's organizational context. Whereas, the "external characteristics of the organization" and Rogers (1962)'s 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 & 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, gaining empirical validity (Awa & Ojiabo, 2016; Baker, 2011) and demonstrating an explanatory power that encompasses sectors and nations (Baker, 2011). In particular, it 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 & Ojiabo, 2016; Baker, 2011; Wong et al., 2019). Due to its many advantages, the TOE has been chosen as the framework to categorize the identified factors in the following section. Although, the influence of DOI is evident, especially in the *technology context*, which comprises determinants (i.e. Perceived Compatibility, Complexity) introduced by Rogers (1962) in its model.

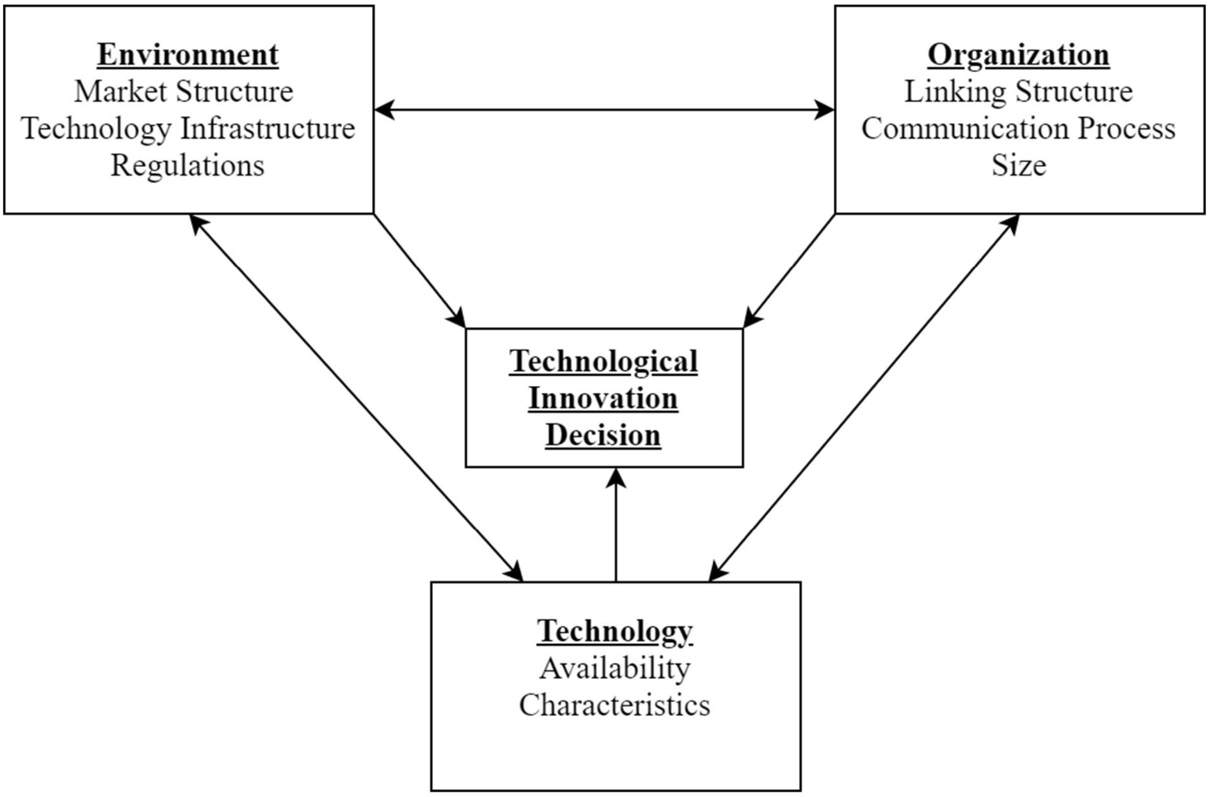


Figure 17: TOE Framework, based on DePietro et al. (1990)

As can be seen from Figure 17, 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, p. 154). The *Technology context* includes the technologies that are relevant to the firm, both internal and external, as well as their perceived characteristics (i.e. Perceived Usefulness) and availability (Awa & 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 business scope, and top management support (Anjum, 2019; Awa & Ojiabo, 2016). Lastly, the *Environment context* depicts the industry's structure, the presence of ICT providers, and the regulatory environment (Baker, 2011).

2.6.4 FACTORS IDENTIFICATION

In the current section, and following the Concept-Centric matrix described by Webster & Watson (2002), the factors retrieved from the articles in Table 2 are represented in Table 3, which, together with sections 2.6.2 and 2.6.3, answers the first sub-research question of this manuscript ("Which frameworks are in the literature available that investigate the factors that influence the intention to adopt blockchain for Supply Chain Management by SMEs?").

Table 3: Concept-Centric Matrix of Factors

Factors	**Authors**
Technology	
Cost	(Dinca et al., 2019); (Kühn et al., 2019); (Surjandy et al., 2019); (van Hoek, 2019); (Y. Wang et al., 2019); (Wong et al., 2019)
ICT Infrastructures	(Awa & Ojiabo, 2016); (Kühn et al., 2019); (Queiroz & Fosso Wamba, 2019)
Results Observability	(Anjum, 2019)
Perceived Compatibility	(AL-Shboul, 2019); (Anjum, 2019); (Awa & Ojiabo, 2016); (Dinca et al., 2019); (van Hoek, 2019); (Walker et al., 2016)
Perceived Ease-of-Use	(AL-Shboul, 2019); (Anjum, 2019); (Dinca et al., 2019); (van Hoek, 2019); (Walker et al., 2016); (Wong et al., 2019)
Perceived Usefulness	(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	(Dinca et al., 2019); (Surjandy et al., 2019); (van Hoek, 2019)
Security	(AL-Shboul, 2019); (Awa & Ojiabo, 2016); (Dinca et al., 2019); (Surjandy et al., 2019); (van Hoek, 2019)
Technical Know-How	(Awa & Ojiabo, 2016); (Dinca et al., 2019); (Kühn et al., 2019)
Technology Readiness	(AL-Shboul, 2019)
Trialability	(Anjum, 2019); (Dinca et al., 2019)
Organization	
Cross-functional Collaboration with the IT Department	(Dinca et al., 2019)
Top management Enthusiasm	(Walker et al., 2016)
Top management Expertise	(Anjum, 2019); (Dinca et al., 2019)
Top Management Support	(Anjum, 2019); (Walker et al., 2016); (Wong et al., 2019)
Environment	
Coercive Influence from Customers	(Kühn et al., 2019); (van Hoek, 2019); (Y. Wang et al., 2019);
Competitive Pressure	(Awa & Ojiabo, 2016); (Dinca et al., 2019); (van Hoek, 2019); (Walker et al., 2016); (Wong et al., 2019)
Cooperation with ICT Providers	(Dinca et al., 2019); (Kühn et al., 2019); (Walker et al., 2016)

Factors	Authors
Environmental Impact	(Anjum, 2019)
External Support	(Anjum, 2019); (Awa & Ojiabo, 2016); (Dinca et al., 2019); (Wong et al., 2019)
Regulatory Status	(Kühn et al., 2019)
Reputation	(Anjum, 2019); (Y. Wang et al., 2019)
Trading Partners' Readiness	(Awa & Ojiabo, 2016); (Kühn et al., 2019); (Y. Wang et al., 2019)

2.6.4.1 Technology

As it can be noticed from Table 3, the *Technology* factors occupy a prominent position in the adoption models that have been employed so far, accounting for 11 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 & Ojiabo, 2016) and several authors (Anjum, 2019; Awa & Ojiabo, 2016; Kühn et al., 2019; Queiroz & Fosso Wamba, 2019; van Hoek, 2019; Wong et al., 2019) have recognized 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), with van Hoek (2019) and Kühn et al. (2019) classifying it as a hinderer of blockchain adoption. The latter may be a result of the financial constraints of supply chain participants, especially SMEs (Y. Wang et al., 2019), and it could signal that firms may be moving beyond the hype and starting to take a harder look (van Hoek, 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, p. 5). Several authors (AL-Shboul, 2019; Awa & Ojiabo, 2016; Walker et al., 2016) have advocated for the importance of this variable for adoption intention, whereas Anjum (2019) has claimed that Perceived Ease-of-Use (PEU) exercises a greater influence on adoption decisions. PEU is defined as the degree to which a technology is perceived as simple to use and easy to understand (Davis et al., 1989). Despite the mixed judgment of the authors on the significance of PEU, with AL-Shboul (2019) and Dinca et al. (2019) classifying it as a non-relevant predictor and Anjum (2019) reckoning it as the most important one, it has been decided that the variable was worthy of consideration.

Additional factors are Security (S) and Privacy (P). Security has been described as one of the highest risks in ICT adoption (Awa & 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 & 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 a technology can guarantee to the user (Dinca et al., 2019). Both these determinants represent potential strengths of blockchain, and due to their similarity, they might be combined in one variable in a later stage. Awa & Ojiabo (2016) have included Security among the most influential predictors for ERP adoption, whereas Surjandy et al. (2019) have claimed that both S and P have been cited in over 57.5% of the studies on blockchain adoption as significant factors.

Awa & Ojiabo (2016) has further added that the presence of an ICT Infrastructure (INF) stands among the most significant determinants for technology adoption. "ICT Infrastructure" is defined as ''the access to network services to support web and internet technologies" (Awa & Ojiabo, 2016, p.907). INF has been deemed as a positive predictor for blockchain adoption by Queiroz & Fosso Wamba (2019), who have however specified that this proposition only holds for USA firms, while it stands as a hindered for adoption in emerging countries. Indeed, the latter often lack an adequate IT infrastructure and Internet speed, not to mention other impediments, such as Technical Know-How (K) (Queiroz & Fosso Wamba, 2019). K represents an organization's employees' knowledge about general IT, "especially in the field of interface control and blockchain infrastructure" (Dinca et al., 2019; Kühn et al., 2019, p. 398) and it has been included among the most significant predictors by Awa & Ojiabo (2016). Although, Technical Know-How may be developed through a collaboration with ICT providers (which will be further explained in chapter 2.6.4.3), who offer the possibility to experiment with the innovation on a limited basis (Anjum, 2019). The latter is known as Trialability and it has been featured in the TOE models created by Anjum (2019) and Dinca et al. (2019), who have however both asserted its insignificance as a predictor.

2.6.4.2 Organization

The *Organization* block of the TOE Framework only accounts for 4 out of the 23 identified factors, with three of them being related to the top management and its tendencies. This is reasonable, according to Anjum (2019), as 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, p. 379), has been recognized as a significant positive predictor by Walker et al. (2016). On the other hand, Anjum (2019) and Wong et al.

(2019) has advocated for its irrelevance based on their analysis. Nonetheless, the two authors admit that this result is inconsistent with previous studies (Anjum, 2019) and perhaps motivated by the upper management's lack of knowledge on the benefits of blockchain (Wong et al., 2019). As the last proposition would suggest, Top Management Expertise (TME) has also been considered as a critical adoption factor by several 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), a firm with an owner with IT experience may be keener to explore disruptive paradigms and to take risks to adopt new technology. This hypothesis has been confirmed by Dinca et al. (2019), who have deemed TME as a significant predictor based on their model. An influence on TMS may also be exercised by the Top Management Enthusiasm (TMEN) for an innovative technology, which has been included by Walker et al. (2016) as a component of ''Organizational Readiness'' in their explanatory framework.

Lastly, Dinca et al. (2019) have claimed that a firm in which the IT unit has a closer collaboration with other business units (CFC) may be more likely to adopt a pioneering ICT.

2.6.4.3 Environment

The *Environment* block depicts the setting in which an organization acts. In this study, 8 environmental factors have been retrieved from the literature review, the first one being the Customers' Influence (CUS). Wong et al. (2019) have claimed 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. Contrarily, both Kühn et al. (2019) and van Hoek (2019) state that CUS influence seems to be low, with only a few customers asking for blockchain-based solutions.

Several authors (Awa & 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). In particular, Awa & Ojiabo (2016) argues that modern technologies may induce a change in industry structure, thus making adoption a strategic necessity. 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 also aid SMEs in solving ICT related issues (Anjum, 2019; Awa & Ojiabo, 2016). Dinca et al. (2019) have defined GS as the manager's perception of government intervention on ICT policy. The government intervention may consist of tax incentives for ICT investments, subsidies for ICT training, financing, or the creation of legal frameworks (Dinca et al., 2019). The latter has also been considered as a separate predictor due to its utmost importance. Indeed, Kühn et al. (2019) have recognized that legal uncertainties, especially referred to the validity of smart contracts, are a serious impediment to blockchain adoption.

As mentioned in chapter 2.6.4.1 another obstacle for technology adoption is the Technical Know-How of an organization's employees. This is why Walker et al. (2016) argues that SMEs should provide training courses demonstrating the use of technology to enhance business processes. The latter may only be possible by cooperating with ICT providers, who can offer their technical assistance, customer service, and coaching (Dinca et al., 2019). In particular, Cooperation with ICT Providers (CICT) has been placed among the main components influencing technology adoption according to the analysis conducted by Dinca et al. (2019) and has been found to be a significant predictor by Walker et al. (2016).

Finally, a managers' awareness of the Environmental Impact (EI) brought about by a newer technology may also be positively associated with its adoption (Anjum, 2019). A technology's EI may impact a firm's Reputation (R) too, depending on the environmental awareness of its consumers. Within the supply chain context, a firm's reputation may suffer if fraudulent products are introduced in the chain, which may be avoided thanks to the real-time tracking properties of blockchain (Y. Wang et al., 2019). Furthermore, a firm's managers may exploit the adoption of an innovative technology as a source of differentiation to create a new and improved company image (Winter et al., 2010).

2.6.5 FACTORS SELECTION

In the present section, a decision is made on the factors that will be investigated later in the manuscript. This selection is carried out by joining the factors that are similar or overlapping, and by adding the ones that were missing in consultation with experts from TNO and the thesis supervision team. Then, once a definitive list of determinants is obtained, a theoretical framework is drawn up in accordance with the TOE in Figure 18. As stated at the beginning of section 2.6, this study is explorative, and, hence, no interrelationships (e.g. mediation and moderation) between the factors have been hypothesized in the model. Nevertheless, this makes for an interesting follow-up to this research, as suggested in section 6.3. Lastly, the factors' definitions that will be provided to the respondents in the data collection phase are shown in section 2.7.

As can be seen from Figure 18 below, the number of factors has been reduced from the original 24 to a set of 23 factors. The factors that have been removed present a strikethrough, whereas the factors that have been added are shown in Bold and Italic (combined). In particular, the determinants "Technical Know-How", "ICT infrastructures", "Technology Readiness" have been merged into "Technology Readiness", which was then moved from the Technology category to the Organization one. This was motivated by the evident similarity between the three constructs, which all describe the availability of technological infrastructure and of IT human resources that can provide the knowledge and the skills to implement the technology (AL-Shboul, 2019). Due to its vicinity to the latter, the factor "Cross-functional Collaboration with the IT Department" has also been deemed as a component of "Technology Readiness" and thus removed from the Organization category, as shown in Figure 18. The shift of "Technology Readiness" from the Technology to the Organization category was made in accordance with AL-Shboul (2019), who recognized "Technology Readiness" as organizational preparedness rather than an inherent characteristic of the technology. Nonetheless, in consultation with the thesis supervision team, three new determinants were added to the factors' cluster. As it can be noticed from Figure 18, People's Readiness and Process Readiness are now included in the Organization category despite being overlooked in all but one of the reviewed articles (Surjandy et al., 2019). Indeed, as Chen & Popovich (2003) reckoned, people, process, and technology are the essential aspects of the implementation of Business Intelligence. The latter finds confirmation in the so-called "Golden Triangle" or "People, Process and Technology Framework (PPTF)", which has been popularized by the work of Hammer & Champy (1993), but its creation presumably dates back to the mid-sixties, with the introduction of Leavitt's Diamond Model[7](Leavitt, 1965). According to the PPTF, Business Intelligence can be successfully implemented only if the three elements of the model are aligned. This means that technology alone will not drive the transformation of a business, which requires the organization's processes, or portfolio of tasks, to remain fit for the purpose (Goodhue & Thompson, 1995) and the final users' Buy-In[8]. Furthermore, "Governance" was added to the Technology category, which now features nine factors, as can be seen in Figure 18. Blockchain governance is a controversial topic, as the transparency enabled by the technology may give rise to unfair activities by malicious actors, who might exploit the

[7] The diamond model is made up of four elements: structure, task, people and technology(Leavitt, 1965). The framework was developed to highlight the factors that should be considered for creating change in an organization. Later on, structure and task were merged into a single element, process.

[8] Buy-In is an expression used to define the people's confidence and support for a (presumably innovative) idea.

information recorded on the chain to front-run competitors or manipulate prices (Janssen et al., 2020). It follows that, for blockchain to be adopted, appropriate governance frameworks should be put in place by the interested stakeholders, including rules to approve/reject authorized participants, a correction mechanism, and applicable laws in case of disputes (Janssen et al., 2020). The latter is defined by Ølnes et al. (2017) as governance *of* blockchain, which diverges from the governance *by* blockchain, which refers to the consensus mechanism that manages "block-to-block" operations and assures the validity of the transactions. According to Rikken et al. (2019), two stages make up the governance *of* blockchain and complete the blockchain governance cycle, namely the stages of *design* (which leads up to the *operate* stage, governed *by* blockchain) and *evolve*. The design stage concerns decisions such as "make or buy" (Rikken et al., 2019) and on control, data ownership, privacy, and access (Ølnes et al., 2017). If the "buy" option is chosen and thus the development and maintenance of the blockchain infrastructure are outsourced to a trusted third party, such as IBM[9], the confidence of the users in the technology may be increased (W.J.H., TNO[10]). Nevertheless, Rikken et al. (2019) have advocated for the higher importance of the *evolve* stage, which concerns the decision-making procedures and authorities for how governance can change over time. Despite being a cumbersome process, traditional approaches to governance (such as voting and stakeholder management practices) can be applied to private and permissioned blockchain as decentralization is limited and the participants are known (Rikken et al., 2019). The latter is presumably going to be the design of choice for the use of BT within a supply chain network, making (design and evolve) governance decisions a complex problem, but workable with conventional procedures.

[9]The International Business Machines Corporation(IBM) is an American multinational technology company which produces and sells computer hardware, middleware and software(IBM, 2020).
[10] Dr. Ir. Wout Hofman, senior research scientist at TNO. The reported statement has been the result of an informal consultation with Dr. Ir. Wout Hofman during the present thesis work.

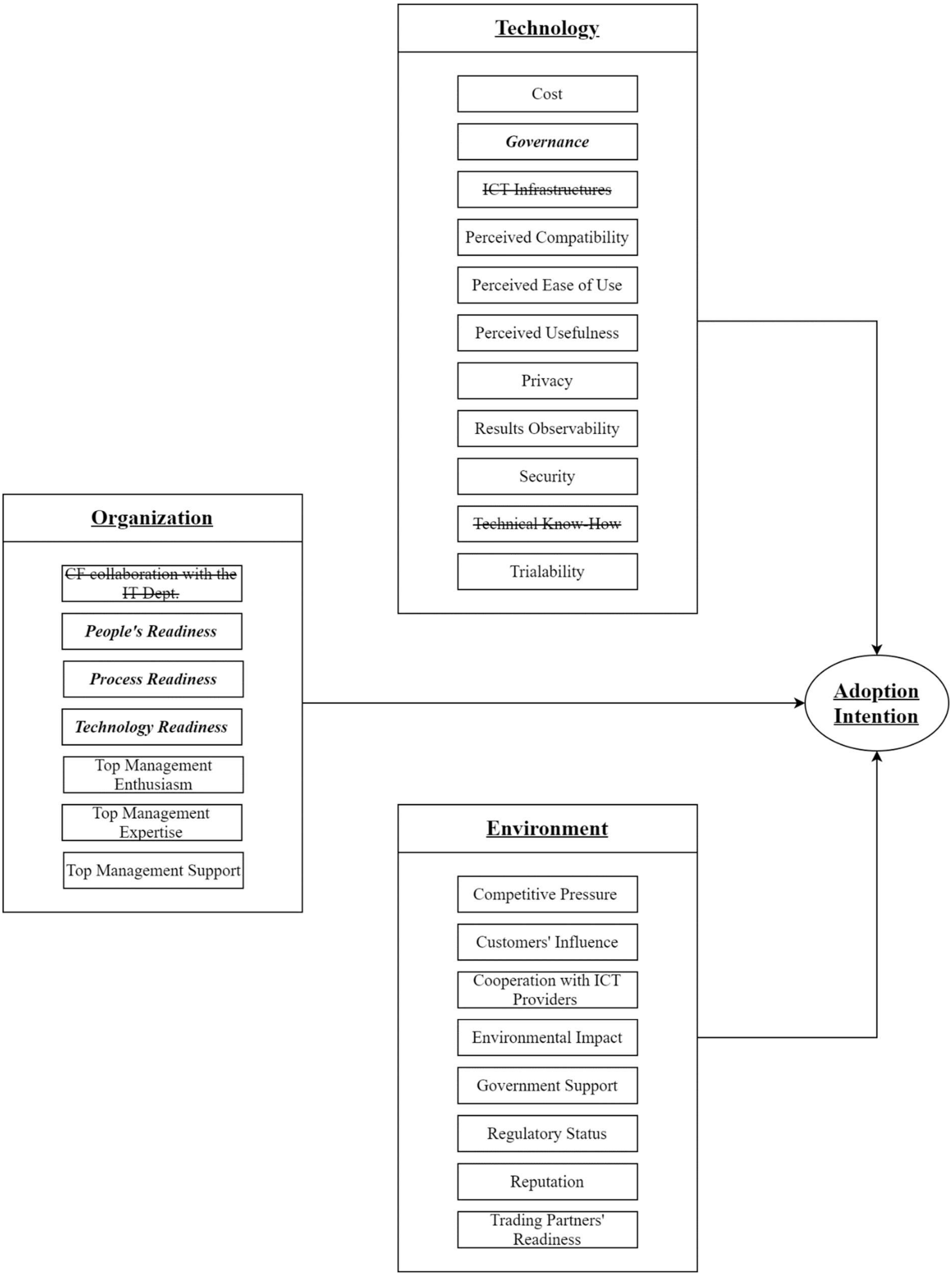


Figure 18:Schematic view of the developed TOE framework, including additions and deletions of factors

2.7 FACTORS' DEFINITION

Table 4:Factors' definitions

Factors	Definition
Technology	
Cost	Investment required to acquire the technology and implement it within the organization.
Governance	Rules that define who will be responsible to make decisions(e.g. who owns the data and who can access it, who participates in the decisions regarding the further development or modification of the blockchain) on behalf of the platform's users (Janssen et al., 2020).
Perceived Compatibility	Compatibility of the technology with existing work practices, prior experience, and values of the organization (Anjum, 2019).
Perceived Ease of Use	The degree to which a technology is perceived as simple to use and easy to understand (Davis et al., 1989).
Perceived Usefulness	Perception that the innovation has a relative advantage over the current practices (Anjum, 2019; Awa & Ojiabo, 2016).
Privacy	Level of anonymity that is guaranteed to the user(e.g. with the use of asymmetric cryptography) (Dinca et al., 2019).
Results Observability	The degree to which the results of an innovation are tangible(visible to the adopter) (Anjum, 2019).
Security	Level of trust in the integrity of the transactions' data and the availability of the platform (Awa & Ojiabo, 2016; van Hoek, 2019).
Trialability	The possibility to experiment with the technology on a limited basis, before making a 'buy' commitment (Anjum, 2019).
Organization	
People's Readiness	Acceptance of the technology by the organization's employees (also known as "Buy-In").
Process Readiness	The goodness of fit of the technology with the portfolio of tasks it supports (Goodhue & Thompson, 1995).
Technology Readiness	The capability of the organization to offer technological infrastructure and IT human resources that can provide the knowledge and skills to implement the technology (AL-Shboul, 2019).
Top management Enthusiasm	Top Management is thrilled by the technology.
Top management Expertise	Top Management is competent with different features of the technology and is aware of its advantages and deployment models (Dinca et al., 2019).
Top Management Support	Top Management understands the importance of the technology and is involved (Wong et al., 2019).

Factors	Definition
Environment	
Competitive Pressure	The degree to which the competition has adopted the technology.
Customers' Influence	Customers wish that the organization adopts the technology (e.g. they want to know the provenance of the food they eat) (Wong et al., 2019).
Cooperation with ICT Providers	The technical assistance, the customer service, and coaching offered by the technology provider (Dinca et al., 2019).
Environmental Impact	The amount of pollution that is generated/can be avoided by adopting new technology.
Government Support	Tangible government support that is given to technology-related issues (i.e. the creation of a public infrastructure, access to financing, and business consultancy services) (Dinca et al., 2019).
Regulatory Status	Government intervention on ICT policy, for instance with the creation of a regulatory framework (e.g. for Smart Contracts) (Dinca et al., 2019; Kühn et al., 2019).
Reputation	The degree to which a company's image is improved by adopting new technology.
Trading Partners' Readiness	The degree to which partners in the value chain are ready, and eager, to adopt new technology (Wong et al., 2019).

3. METHODOLOGY

In the present chapter, the methods that have been used to determine the relative importance of each factor (which correspond to the second sub-research question: “How can the relative importance of each of the factors that are influencing the intention to adopt blockchain by SMEs with a logistics operation be determined?”) are thoroughly described. First, the nature of the problem at hand is analyzed, and, based on its traits, a suitable technique is chosen for its resolution. Then, an appropriate instrument for data collection is selected and designed following the guidelines of the method chosen in the previous step. Finally, the sample population, to whom the data collection instrument is addressed, is defined, and the auxiliary tools that have been used to analyze the collected data are introduced.

3.1 MULTI-CRITERIA DECISION MAKING PROBLEM

Before deciding which is the most suitable method to answer the research question, it is crucial to understand to which class the problem at hand belongs to. Since the ultimate goal of this research is to “support SMEs with a logistics operation in the adoption of blockchain for SCM” it becomes apparent that the research objective of this study lies in computing the weights of a set of factors or criteria, which may then be used by members of the target group (SMEs with a logistics operation) to make informed technology adoption decisions. The latter may consist of a binary decision (affirmative or negative) or a discrete one if multiple technologies or designs are in play. In either case, the decision space can be classified as discrete, making this problem a Multi-Attribute Decision Making (MADM) one. A MADM problem is also commonly referred to as a Multi-Criteria Decision Making Problem (MCDM)[11], as the words “attributes” and “criteria” are often used interchangeably (Triantaphyllou et al., 1998). MADM methods can be further classified according to the number of decision-makers involved in the decision process as either *single* or *group* decision-making (Triantaphyllou et al., 1998). A technology adoption decision can hardly be classified as a single decision-making problem. Indeed, technology adoption in organizations has been compared by Ilori & Irefin (1997) to a “relay race” in which a set of players (e.g. the proponents of the technology and the senior management) with different aspirations and unbalanced influence is involved. Furthermore, the

[11] MCDM also identifies a wider class of decision-making problems, and a branch of Operations Research, that also includes Multi-Objective Decision Making(MODM) (Triantaphyllou et al., 1998). MODM identifies multi-criteria decision making problems with a continuous decision space.

present study aims to reach, and collect data from multiple decision-makers. Thus, the MADM method to use for data analysis will have to be suitable to combine several responses.

3.2 MCDM METHOD SELECTION

As it has been clarified in section 1.6, the objective of this study is to support SMEs in the adoption of blockchain for Supply Chain Management. To achieve this goal, this research aims to shed light upon the factors that are influencing the adoption intention of small-to-medium-sized businesses, compute the relative importance of these determinants, and provide suggestions to the Spark! Living Lab based on the obtained weight-wise ranking. Hence, a technique for weighting the identified factors has to be selected. Tzeng et al. (1998) have classified the models for determining the weights of criteria into subjective and objective methods. Objective methods do not need to ask for the preferences of decision-makers and generally employ mathematical inference to compute the criteria weights (Pamučar et al., 2018; Tzeng et al., 1998). For instance, the entropy method, which is considered one of the best objective weight-assessing methods, assigns a higher weight to the criteria with less uncertainty, which is calculated based on each criterion's possible outcomes (Tzeng et al., 1998). Nonetheless, considering the explorative nature of this research, it has been decided to utilize a subjective method. While the subjective judgment of DMs may be impaired by lack of experience, information, or capabilities (Alemi-ardakani et al., 2016), this study does not aim to calculate criteria weights that are undeniably correct and that can be instantaneously implemented in a technology adoption decision, but rather to understand the subjective perception of SMEs on the factors that are driving/hindering blockchain adoption.

Direct ranking is deemed as the simplest set of subjective methods available to elicit the criteria weights from DMs, as it entails no trade-offs and the respondents are simply asked to assign a numerical value to the different criteria (Németh et al., 2019). However, it is hardly imaginable that DMs can confidently assign precise numerical weights to all attributes, and reach an agreement on a set of exact weights (Roszkowska, 2013). On the other hand, rank-ordering weighting methods use mathematical formulas to compute the criteria weights based on rank ordering information (Roszkowska, 2013). Rank ordering weighting methods generally yield more reliable results than direct ranking techniques and are easier to implement and understand (Roszkowska, 2013). Indeed, ranking is usually simpler than weighting for both experts and non-experts, and it is to be realistically expected that a group of DMs can reach an agreement on a ranking of weights (Roszkowska, 2013). Of the rank ordering weighting methods, Rank-order Centroid (ROC) has often been deemed as the superior technique for accuracy and ease-of-use in a substantial number of studies (Barron & Barrett, 1996b, 1996a; Bottomley & Doyle, 2001; Jia et al., 1998; Srivastava et al., 1995; Sureeyatanapas, 2016). In the ROC approach, it is assumed that, provided the rank order of the criteria, "the weights are uniformly distributed on the simplex of rank-order weight $w_{r1} \geq w_{r2} \geq \ldots \geq w_{rn}$" (Roszkowska, 2013, p. 21), where $r_1, r_2, \ldots, r_n$ is the ranking position of each criterion. For instance, if n=2, $w_{r1} \geq w_{r2}$ entails that $0.5 \leq w_{r1} \leq 1$, and, based on the uniformity assumption, $E(w_{r1})=0.75$ (Roszkowska, 2013). This argument was generalized by Barron & Barrett (1996a), who developed the following formula to compute the expected value of the weights:

$$w_j(ROC) = \frac{1}{n}\sum_{k=j}^{n}\frac{1}{r_k}$$

Equation 1: ROC formula

Rank ordering weighting methods are praised for their immediacy and ease of use, but they present a fundamental flaw: they do not utilize the strength of a DM's preferences (Sureeyatanapas, 2016). Moreover, such methods do not conceive that two or more criteria may have equal importance in the eyes of a DM (Caballero & Go, 2010), even though this is likely going to occur if he/she is presented with a broad range of attributes. Hence, it was decided to narrow the method search to more sophisticated methods of pairwise comparisons, which require the DM(s) to compare each criterion to the others on an ordinal scale (Pamučar et al., 2018), capturing the strength of his/her preferences.

Several pairwise-comparisons methods exist to compute the weights of a set of attributes or criteria, including SMART (and its variations SMARTS and SMARTER), AHP, and the BWM (Best-Worst Method) (Rezaei, 2020a). AHP has historically been the most popular method according to the literature reviews conducted by Zavadskas et al. (2016) and Mardani et al. (2015). In particular, Mardani et al. (2015) have claimed that over 30% of the 393 reviewed papers (retrieved from Web of Science between 2000 and 2014) had employed AHP, with the second most frequently used tool (hybrid techniques) standing at roughly 16%.

AHP is easy to use, and it is scalable (Ceballos et al., 2016; Triantaphyllou et al., 1998). AHP makes use of pairwise comparisons (n(n-1) of them) to determine the weights of criteria and compare the alternatives. A set of pairwise comparisons is generally represented with a n x n matrix, where $a_{ij}>0$ (for every i,j=1,…,n) is the relative preference of a generic intangible stimulus (or criterion) i over a generic intangible stimuli j (Herman & Koczkodaj, 1996).

$$\begin{bmatrix} 1 & a_{12} & \cdots & a_{1n} \\ {}^{1}/_{a_{12}} & 1 & \cdots & a_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ {}^{1}/_{a_{1n}} & {}^{1}/_{a_{2n}} & \cdots & 1 \end{bmatrix}$$

Equation 2:Pairwise Comparison Matrix

Pairwise comparisons are used as a proxy for the quotients s_i/s_j, where s_i and s_j are the true (unknown) values or relative weights of the stimuli (or criterion) (Herman & Koczkodaj, 1996; Triantaphyllou et al., 1998). After having elicited the pairwise comparison values from the decision-makers, the relative weights of the stimuli (or criteria) are computed. Saaty (2008), the creator of AHP, has estimated the weights as the elements of the right principal eigenvector[12] of the pairwise comparisons' matrix. Nevertheless, alternative methods based on constrained optimization problems have been proposed to obtain the desired weight (Triantaphyllou et al., 1998). Once the weights of the stimuli (or criteria) have been extrapolated, and the scores of each alternative k with respect to each criterion i have been assessed by the decision-maker, the overall value of each alternative k is calculated, generally by using a simple additive weighted function ($\sum_{i=1}^{n} w_i p_{ik}$) (Rezaei, 2015), where w_i is the weight of criterion i and p_{ik} is the normalized score of alternative k on criterion i.

Compared to the AHP, both SMART (and its variations) and BWM require the DM(s) to carry out a lower number of pairwise comparisons. This makes both methods more data and time-efficient than the AHP, whose lengthy preference elicitation process might even contribute to the confusion and inconsistency of DMs (Rezaei, 2020a). In particular, the SMART technique is the most efficient one as it only requires the DM(s) to produce a single 1xn vector that contains the numerical score of each criterion, in ascending order from the least important one (Németh et al., 2019; Rezaei, 2020a). However, this "extreme" efficiency comes at a cost: "the consistency of the provided pairwise comparisons cannot be checked" (Rezaei, 2020a, p. 892). On the other hand, the BWM stands in the middle: it only requires the DM(s) to carry out 2n-3 pairwise comparisons (compared to the n(n-1) for the AHP) to produce two 1xn vectors, and it provides the possibility of monitoring the consistency of the submitted pairwise comparisons (Rezaei, 2020a). The BWM's pairwise comparisons are referred by Rezaei (2015) as "reference" comparisons, as the DM(s) is required to express his/her preference of the most

[12]If there is a vector X ϵ R^n such that AX=λX, where A is a k×k square matrix and λ is a scalar, λ is called the eigenvalue of A with corresponding right eigenvector X(Weisstein, 2020). Furthermore, "the eigenvector corresponding to the eigenvalue of largest magnitude is called the principal eigenvector" (Manning et al., 2009, p. 404).

important criterion over all the other criteria and the preferences of all the criteria over the least important criterion. The fact that the DM(s) is requested to identify the Best and Worst attributes at an early stage (before conducting the actual comparisons) leaves the DM(s) 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 DM(s) 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 (in AHP, the reciprocal of a_{ij}, a_{ji}, is given by $1/ a_{ij}$) (Rezaei, 2015).

For the aforementioned reasons, the BWM has been preferred to AHP and SMART (and its variations) in this study. The BWM has already been applied in the past to conduct empirical studies in areas as diverse as business and economics, education, agriculture, logistics, and technology selection (Rezaei, 2020). For instance, the BWM has been employed by Pamučar et al. (2018) to assist a logistics company in deciding which wagons were more suitable for the company's internal rail transport. Conversely, van de Kaa et al. (2017) and Kheybari et al. (2019) have used BWM to assess the relative importance of decision-making criteria in the selection of biomass thermochemical conversion technology and biofuel production technology respectively. Furthermore, in a similar fashion to the present study, Gupta & Barua (2016) have attempted to identify the enablers of technological innovation for Indian MSMEs with BWM.

3.3 BAYESIAN BEST WORST METHOD

Since the preferences of several respondents (or decision-makers) will have to be incorporated to obtain a unique set of weights, the Bayesian BWM (BBWM) has been chosen over the linear BWM. The two methods are equivalent until the fifth step in the process, where the linear BWM employs a constrained optimization problem (shown in Equation 2) to determine the factors' weights for each decision-maker and then combines them with an aggregation method such as the arithmetic mean (Mohammadi & Rezaei, 2019; Rezaei, 2016).

$$min_W \; max_j \left\{ \left| \frac{w_B}{w_j} - a_{Bj} \right|, \left| \frac{w_j}{w_W} - a_{jW} \right| \right\}$$

$$s.t. \quad \sum_{j=1}^{n} w_j = 1, \quad w_j \geq 0 \;\; \forall j = 1,2,\dots,n$$

Equation 3:Step 5 in the linear BWM (Rezaei, 2016)

Nonetheless, much information may be lost due to aggregation, as averages are sensitive to outliers and they are not appropriate for highly dispersed datasets. 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 & Rezaei, 2019). The BBWM 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 & Rezaei, 2019, p.2), which can significantly improve the DM's decisions.

The first four steps in the BBWM, which are shared by all methods based on BWM, are provided below. Conversely, the final step in the process will be explained on its own in the next three sections, due to its complexity.

According to Mohammadi & Rezaei (2019), the four opening steps of the original BWM are as follows:

Step 1: The DM needs to provide a set of decision criteria C={c_1, c_2, …, c_n}.

Step 2: The 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: The 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: The DM conducts the pairwise comparison between the worst (c_w) and the other criteria from C.

Similarly 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

$A_w=(a_{1w}, a_{2w,\dots}, a_{nw})$

where a_{jw} represents the preference of the criterion $c_j \in C$.

3.3.1 THE PROBABILISTIC INTERPRETATION OF THE BAYESIAN BWM

As mentioned in section 3.3, the Bayesian BWM models the inputs and outputs of the problem as probability distributions. In particular, the criteria are seen as random events, with their weights as their occurrence likelihood (Mohammadi & Rezaei, 2019). This interpretation is, mathematically speaking, in line with the MCDM, since $w_j \geq 0$ and $\sum w_j=1$ according to the probability theory as well (Mohammadi & Rezaei, 2019).

According to Mohammadi & Rezaei (2019), 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 5 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) (Mohammadi & Rezaei, 2019).

$$\mathrm{P}(A_w|w) = \frac{\left(\sum_{j=1}^{n} a_{jw}\right)!}{\prod_{j=1}^{n} a_{jw}!} \prod_{j=1}^{n} w_j^{a_{jw}}$$

Equation 4:Probability Mass Function of the Multinomial Distribution

The multinomial distribution, despite being completely different from what is expected for the BWM, fulfill its underlying idea (Mohammadi & Rezaei, 2019). Based on the multinomial distribution, the probability of the event j is proportionate to the number of occurrence of the event to the total number of trials, i.e.,

$$w_j \propto \frac{a_{jw}}{\sum_{i=1}^{n} a_{iw}} \quad \forall j = 1, \dots, n$$

Equation 5:Probability of event j based on the multinomial distribution

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

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

Equation 6:Probability (or weight) of the worst event (or criterion) based on the multinomial distribution

By using the prior two equations, one obtains

$$\frac{w_j}{w_W} \propto a_{jW} \; \forall j = 1, \dots, n$$

Equation 7:Ratio of the probability (or weight) of event (or criterion) j and the probability of event w (worst) based on the multinomial distribution

which is the relation that is sought after in the constrained optimization problem (Equation 2) of the linear BWM.

Likewise, A_B can also be modeled using the multinomial distribution (Mohammadi & Rezaei, 2019). 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.,

$$A_B \sim \text{multinomial}\left({}^{1}/_{w}\right)$$

Equation 8:Probabilistic interpretation of the Best-to-Others' vector

Identical to the worst criterion, one can write

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

Equation 9:Demonstration of the equivalence of the relationship between the multinomial's probabilities and the number of occurrences and the BWM's weights and Best-to-Others vector

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 & Rezaei, 2019). Thus, the Dirichlet distribution has been chosen as an appropriate distribution to model the weights.

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

Equation 10:Dirichlet distribution

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 $\sum w_j = 1$), as it is a probability distribution.

3.3.2 STATISTICAL INFERENCE AND THE BAYESIAN HIERARCHICAL MODEL

Modeling the inputs and outputs of the problem as probability distribution makes statistical inference techniques suitable to determine the optimal weights (Mohammadi & Rezaei, 2019).

One widely accepted inference technique is the Bayesian estimation (Mohammadi & Rezaei, 2019). Bayesian estimation is based on the Bayes' rule, which given f(x/α), and the prior distribution f(α), finds the posterior distribution f(α/x).

$$f(\alpha/x) = f(x/\alpha)f(\alpha)/f(x)$$

Equation 11: Bayes' rule

The chosen f(x/α) in the Bayesian BWM is the multinomial distribution, with the Dirichlet as the prior and posterior distribution (Mohammadi & Rezaei, 2019). According to Randolph (1969), the Dirichlet distribution is thus defined as a conjugate prior for the multinomial distribution, as it appears in both the prior and posterior distribution (with different parameters than those of the prior). Since the prior should be uninformative so that its impact on the posterior is minimal, the *uniform* Dirichlet (α=1) is chosen (Mohammadi & Rezaei, 2019; Randolph, 1969). Conversely, the posterior is a Dirichlet with the posterior parameter $\alpha_{post}=\alpha+A_w$ (assuming, for a moment, that there is only A_w in the BWM) (Mohammadi & Rezaei, 2019).

Nonetheless, the latter assumption is not acceptable, as both A_B and Aw must be included in the optimization problem. This stringent constraint greatly increases the complexity of the problem, which is compounded by the presence of multiple decision-makers (Mohammadi & Rezaei, 2019).

To solve the aforementioned issues, Mohammadi & Rezaei (2019) have proposed a hierarchical model, shown in Figure 19. w^{agg} represents the overall optimal weights, w^k identifies the optimal weights of the k^{th} DM, and $A^k{}_W$ and $A^k{}_B$ depict the k^{th} Others-to-Worst and Best-to-Others vectors (Mohammadi & Rezaei, 2019). Furthermore, the superscript $^{1:k}$ will be used to indicate the total of all vectors in the base.

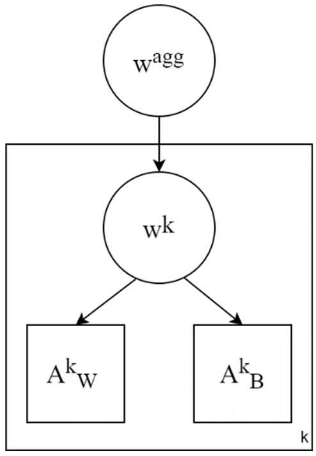


Figure 19:The probabilistic graphical model of the Bayesian BWM, based on Mohammadi & Rezaei (2019)

In the hierarchical model, the rectangles represent the observed variables, which are the inputs to the original BWM (Mohammadi & Rezaei, 2019). 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 (Mohammadi & Rezaei, 2019). Lastly, the plate that surrounds all variables except w^{agg} signals that the corresponding variables are iterated for all DMs (Mohammadi & Rezaei, 2019).

Based on the above, the independence and conditional independence between the variables of interest become apparent. Nonetheless, before applying the Bayes' rule and exploiting the identified relationships, it is necessary to write the joint probability distributions[13] of all random variables given the available data (Mohammadi & Rezaei, 2019).

Once the joint probability distributions have been computed, the Bayes' rule can be applied, obtaining the following

$$P(w^{agg}, w^{1:k} | A_B^{1:K},\ A_W^{1:K}) \propto P(A_B^{1:K},\ A_W^{1:K} | w^{agg}, w^{1:k}) P(w^{agg}, w^{1:k})$$

Equation 12:Bayes' rule applied in the Bayesian BWM

Then, considering the probability chain rule, all independence among different variables (per the hierarchical model in Figure 19), and the fact that each DM provides his/her preference independently (Mohammadi & Rezaei, 2019), it follows that

$$P(w^{agg}, w^{1:k} | A_B^{1:K},\ A_W^{1:K}) \propto P(A_B^{1:K},\ A_W^{1:K} | w^{agg}, w^{1:k}) P(w^{agg}, w^{1:k})$$

[13] A joint probability distribution is a probability distribution for two (or more) variables. In the context of the Bayesian BWM, Mohammadi & Rezaei(2019) are referring 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.

$$= P(w^{agg}) \prod_{k=1}^{K} P(A_W^k | w^k) P(A_B^k | w^k) P(w^k | w^{agg})$$

Equation 13:Simplified Bayes'rule

Now, the distribution of every element in Equation 12 will be specified according to the probabilistic interpretation illustrated in section 3.3.1, i.e.

$$A_B^k | w^k \sim multinomial(1/w^k), \forall k = 1, \dots, K$$

$$A_W^k | w^k \sim multinomial(w^k), \forall k = 1, \dots, K$$

$$w^{agg} \sim Dir(\alpha), \alpha = 1$$

$$w^k | w^{agg} \sim Dir(\gamma \times w^{agg}), \forall k = 1, \dots, K$$

Equation 14: Probability distribution of Eq.7's components

Looking at Equation 13, it can be noticed that w^{agg} and $w^k | w^{agg}$ have both been modeled with a Dirichlet distribution. In particular, w^{agg} (the so-called prior distribution) has been supplied with an uninformative Dirichlet distribution with a parameter α=1 (Mohammadi & Rezaei, 2019). On the other hand, $w^k | w^{agg}$'s distribution has been re-parameterized with respect to its mean and concentration parameter (Mohammadi & Rezaei, 2019). This was made with the assumption that, given w^{agg}, the weight vector w^k associated with each DM should be in its proximity (Mohammadi & Rezaei, 2019). The closedness of each w^k is governed by a non-negative concentration parameter, which is modeled with a gamma distribution with shape parameters a and b, i.e.,

$$\gamma \sim gamma(a, b)$$

Equation 15:Probability distribution of the concentration parameter γ

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, was 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 & Rezaei, 2019).

3.3.3 CREDAL RANKING

To provide more information on the confidence of the relation (> or <) between each pair of criteria, Mohammadi & Rezaei (2019) developed the notion of *credal ranking*, which is the real added value of the BBWM, especially in group decision-making.

Mohammadi & Rezaei (2019) first define the *credal ordering*, which is the building block of credal ranking.

For a pair of criteria c_i and c_j, the credal ordering O is defined as

$$O = (c_i, c_j, R, d)$$

where

- R is the relation between the criteria c_i and c_j, i.e., <, >, or =;
- d ϵ [0,1] represents the confidence of the relation

After having defined the credal ordering, Mohammadi & Rezaei (2019) present the credal ranking.

For a set of criteria C=(c_1, c_2, ..., c_n), the credal ranking is a set of credal orderings which includes all pairs (c_i,c_j), for all c_i, c_j ϵ C.

The confidence of each credal ordering (c_i, c_j) is determined with a new Bayesian test developed by Mohammadi & Rezaei (2019), i.e.,

$$P(c_i > c_j) = \int I_{\left(w_i^{agg} > w_j^{agg}\right)} P(w^{agg})$$

Equation 16: Bayesian test to determine the confidence of each credal ordering

where P (w^{agg}) is the posterior distribution of w^{agg} and I is one if the condition in the subscript holds, and zero otherwise.

The integration is approximated, once again, by the samples obtained via the MCMC (Mohammadi & Rezaei, 2019). In particular, having Q samples from the posterior distribution, the confidence can be computed as

$$P(c_i > c_j) = \frac{1}{Q} \sum_{q=1}^{Q} I_{\left(w_i^{aggq} > w_j^{aggq}\right)}$$

$$P(c_j > c_i) = \frac{1}{Q} \sum_{q=1}^{Q} I_{\left(w_j^{aggq} > w_i^{aggq}\right)}$$

Equation 17: Bayesian test's MCMC approximation

Where $q^{agg}{}_q$ is the q^{th} sample of w^{agg} from the MCMC samples.

If the DM(s) wants to obtain a traditional ranking of criteria, as in the linear BWM, that is obtainable by applying a threshold of 0.5 to the credal ranking.

3.4 DATA COLLECTION METHOD

3.4.1 METHOD SELECTION

As mentioned in section 3.3, the input of the Bayesian BWM, which has been chosen as the technique to determine the relative importance of the factors selected in section 2.6.5, is a set of k vectors A_B and A_w. To elicit the preferences of a group of DM(s) and, thus, obtain the desired input data, two main classes of methods are available: interviews and questionnaires.

Although interviews offer several advantages in terms of flexibility (e.g. the questions asked can be progressively adjusted as the researcher proceeds with the study), a questionnaire is a superior method in terms of cost, energy, and time (Sekaran & Bougie, 2016). Furthermore, a questionnaire is particularly suited as an efficient data collection method "when the researcher knows exactly what is required and how to measure the variables of interest" (Sekaran, 1992, p. 200).

Based on the characteristics of interviews and questionnaires and of the present study, an online questionnaire has been selected as the method for data collection. Indeed, cost, energy, and time are crucial due to the relatively short timeframe of this research. Moreover, the desired input data is well known (A_B and A_w) and Rezaei (2015) has already outlined a procedure to elicit preferences from DM(s).

3.4.2 QUESTIONNAIRE DESIGN

According to Sekaran & Bougie (2016), sound questionnaire design should focus on three areas: the wording of the questions, the planning of issues regarding how the variables will be categorized, scaled and coded, and the general appearance of the questionnaire.

The wording of the questions was based on the principles laid out by (Sekaran & Bougie, 2016). Thus, the questions were phrased in a way that could be understood by the target group (SMEs with a logistics operation), both in English and Dutch. In particular, the Dutch translation of the question-text (which had originally been written in English) was performed with the help of the thesis supervision team and TNO's marketing and communication department. Furthermore, the question-text has undergone several iterative modifications, as a result of constructive discussions with the thesis supervision team and the partners of TNO in the Spark! Living Lab. Due to the very specific information required (the pairwise comparison vectors A_B and A_w), closed questions have been used. Nonetheless, an open-ended question has been placed at the end of the survey, so that interested participants can voice their concerns and initiate a dialogue with the researcher. Also, an attempt has been made to prevent the bias brought about by double-barreled[14], ambiguous, leading[15] , and socially desirable[16] questions. Besides, lengthy question-texts have been avoided where possible, and it has been 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 & Bougie, 2016). The so-called "personal information" collected in the questionnaire is limited to the respondents' age, sex, role in the organization, years of experience, and email, which can be voluntarily provided to receive the outcome of the research. This data has not been considered threatening for the privacy of the participants of the study, as it will be shown in aggregate form only to describe the sample's characteristics. Moreover, the email address will only be used for communicating with the interested respondents within the context of this study.

The survey has been designed with Qualtrics Survey Software, of which TU Delft conveniently provided the license. Qualtrics Survey Software is consistently featured among the best survey tools on the market and has won the Applied Technology category in the 2020 Edison Awards (Edison Awards, 2020).

The questionnaire has been opened with an introductory statement (shown in section 1 of the appendix 8.A) to make clear for the participants the objective of the present study, disclose the identity of the researcher, and assure that the respondents' information will be handled with the maximum confidentiality, in accordance with the principles set out by the TU Delft Ethics Committee.

Next, a brief video-introduction to blockchain for SCM (Blockchain Council, 2018) has been provided so that even the least experienced participants can familiarize themselves with the technology and its implications.

The questions that follow have been designed according to the guidelines provided by Rezaei (2015). First, the DM(s) have been presented with the problem of blockchain adoption. Then, a set of factors (or decision criteria), divided according to the TOE framework from section

[14] According to (Sekaran & Bougie, 2016), a double-barreled question is a question that lends itself to different possible responses to its subparts.
[15] Leading questions are questions "phrased in such a way that they lead the respondents to give the responses that the researcher would like them to give" (Sekaran & Bougie, 2016, p. 148)
[16] Socially desirable questions are questions worded in such a way "that they elicit socially desirable responses" (Sekaran & Bougie, 2016, p. 148).

2.6.5 (Figure 18), has been provided to the respondent(s), who are first asked to express their category preferences, as shown in Figure 20.

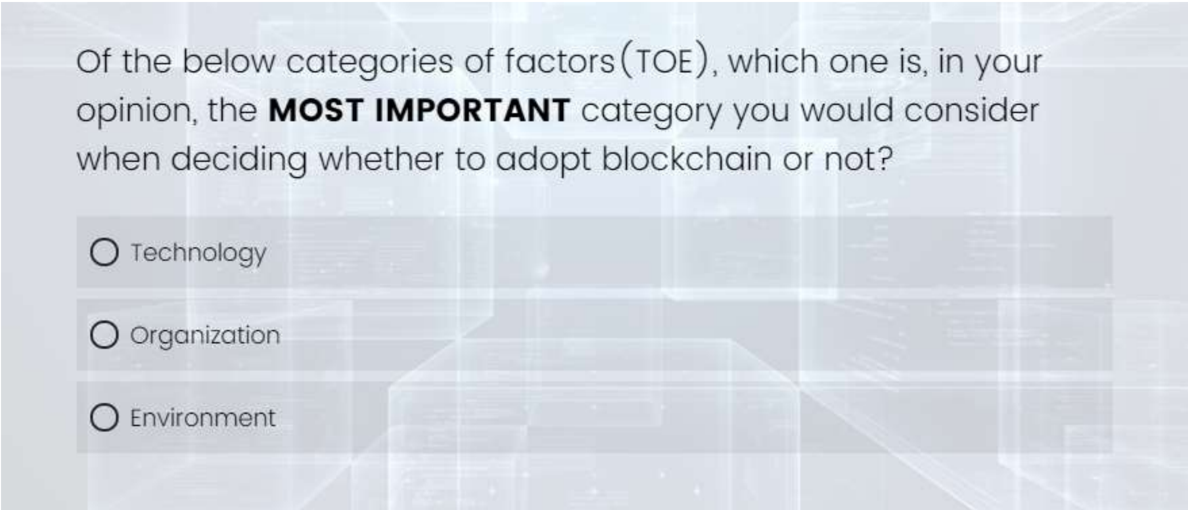


Figure 20:Eliciting the category preferences of the respondent(s)

Subsequently, the respondent(s) are asked to compare the best category to all the other categories, and all the other categories to the worst category. The comparison is elicited by using a scale ranging between 1 and 9, as in Rezaei (2015). However, following several negative remarks on the intermediate values in the scale, it was decided to only explain the meaning of the extreme values (1 and 9) to the reader. Moreover, the linguistic choice intended to represent the number 9 (*extremely more important*) was considered "unusual" by multiple reviewees and has, thus, been changed into *much more important*.

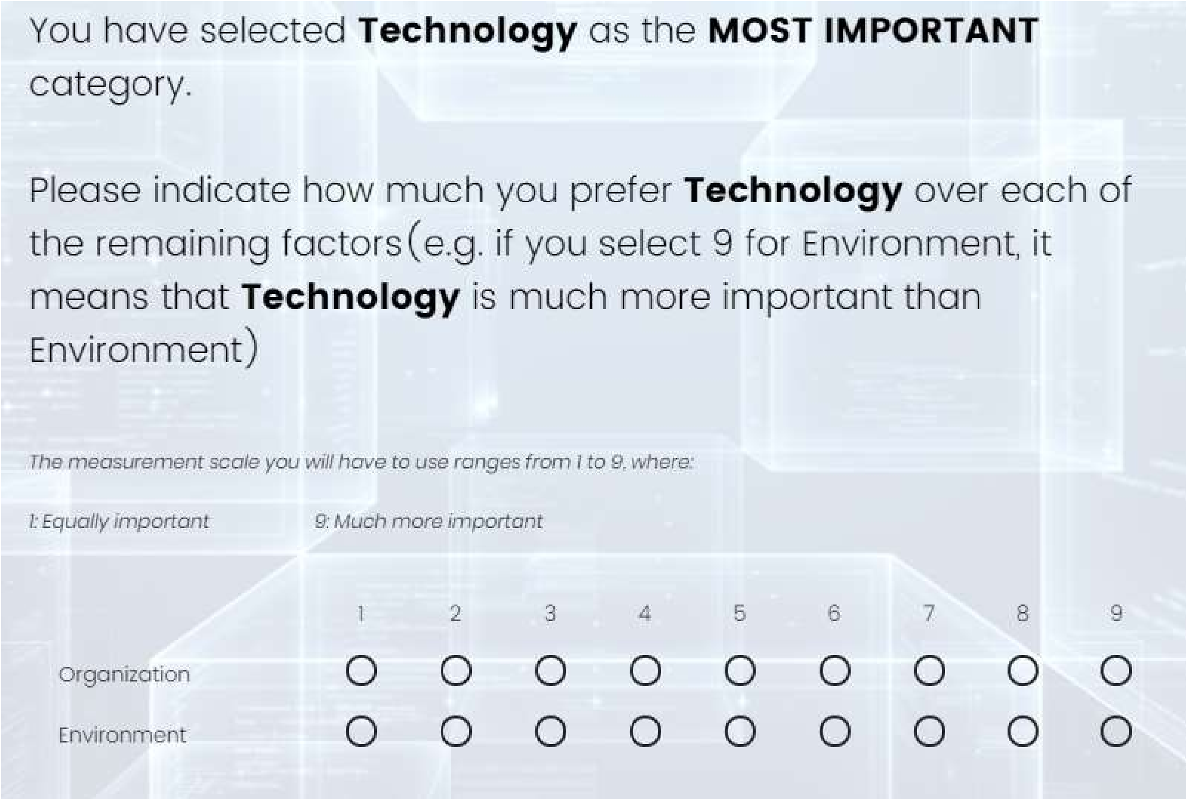


Figure 21:Eliciting the A_B vector for categories

The following pages of the survey have re-produced the same structure shown in Figures 20 and 21, eliciting separately the factors' preferences of the respondent(s) within each TOE category. Displayed in Figure 22 is an example of the Technology category.

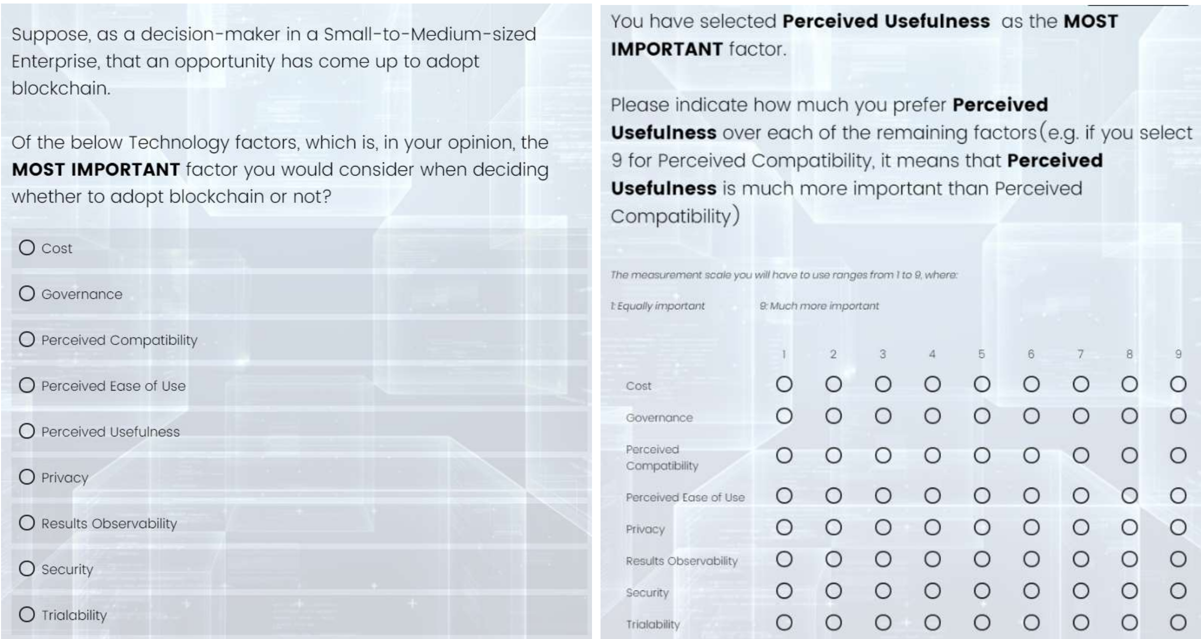


Figure 22: Eliciting the respondent(s) preferences within the Technology category

Due to the difficulty participants may have encountered in interpreting the meaning of the factors included in the study, a definition table is provided above each set of pairwise comparison questions. Furthermore, to make its appearance more elegant, the table can be visualized at the respondent(s)' discretion, by clicking the "read more" button, as shown below. This feature was suggested by Windesheim University's researcher Luca Gelsomino, who thought this would have improved the general appearance of the questionnaire.

The definitions provided in the online questionnaire can be found in section 2.8.

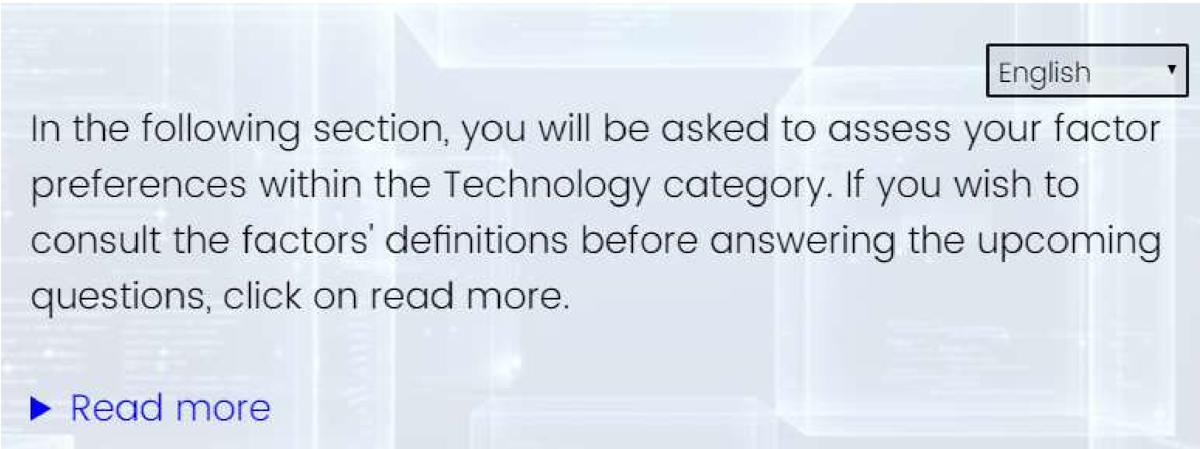


Figure 23:The "read more" button

Finally, the participants were asked twelve multiple-choice questions about themselves (their age, sex, job position, years of experience, and email), the company they are employed at (its size, age, location, and sector), and their interest in blockchain technology. As previously mentioned at the beginning of this section, a non-mandatory open-ended question is included. The latter focuses on the supply chain-related issues faced by the respondent(s), who are invited to initiate a dialogue with the researcher.

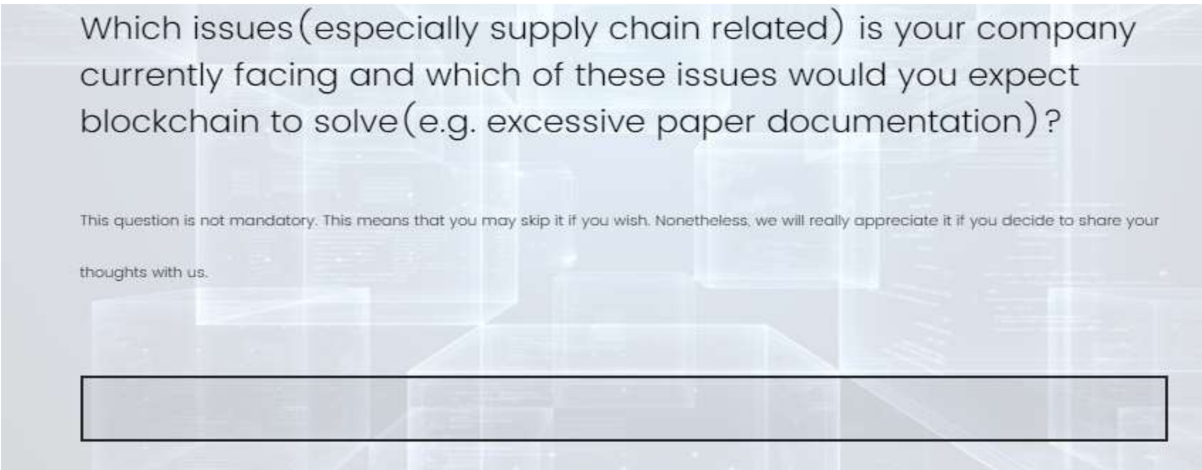


Figure 24:Open-ended question

After the respondents have completed the survey, a courteous "thank you" message will appear on the screen, as shown in Figure 25.

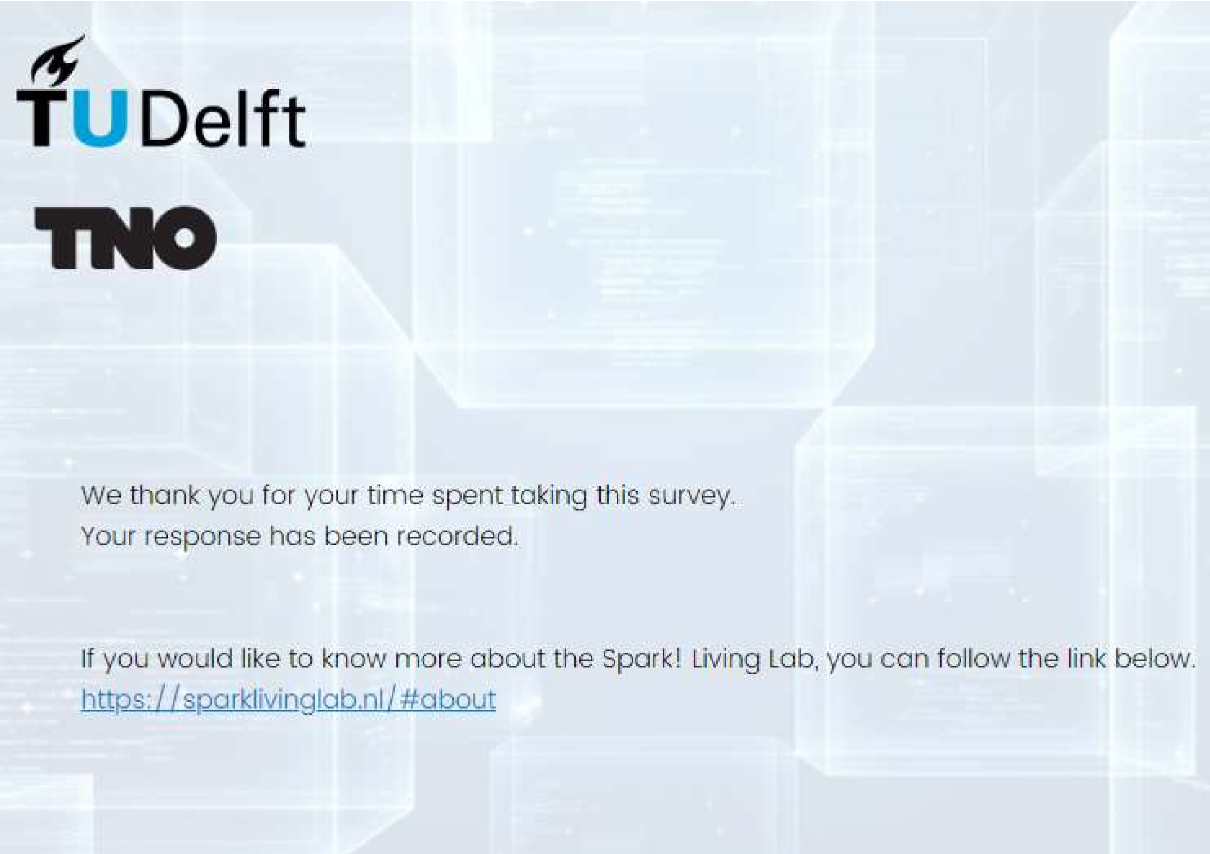


Figure 25:Survey termination message

3.4.3 SAMPLING

Sampling begins with the definition of the target population, which directly stems from the research objective and scope of the study (Sekaran & Bougie, 2016). As explained in the first chapter of this manuscript, this research is focused on SMEs with a logistics operation. Indeed, despite the intention of focusing entirely on Dutch SMEs, the scope of this research has been widened after the literature review (conducted in Chapter 2) revealed a shortage of literature on blockchain adoption coming from The Netherlands. Moreover, the survey is complex and takes roughly 20 minutes to be filled out properly, which is far higher than the ideal survey duration of 10 minutes suggested by Revilla & Ochoa (2017). Hence, considering the expected low response rate, this research will tap into a wider (but still European) audience.

Furthermore, for the study to yield reliable results, the respondents should possess a minimum-viable-knowledge or interest in blockchain technology. This implies that it is necessary to obtain information from a specific target group, which calls for a *purposive sampling* approach (Sekaran & Bougie, 2016). In particular, *judgment sampling* is a type of purposive sampling which "involves the choice of subjects who are most advantageously placed or in the best position to provide the information required" (Sekaran & Bougie, 2016, p. 248). This method has been chosen due to the narrow focus of this study, and its convenience in terms of time, which is a severe constraint.

The appropriateness of the responses will be assessed by looking at the personal and company-based section of the questionnaire, which, if compiled correctly, will enable the research team to filter the collected data according to the firms' size (≤250 employees) and expertise of the participants (at least interested in blockchain technology).

Practically, the online questionnaire will be distributed through several channels and made available from the 4th of May 2020. First, the survey will be shared by evofenedex and Blocklab, two of TNO's partners in the Spark! Living Lab. Evofenedex will directly email the survey to 98 companies pulled from their CRM[17]. These organizations have been selected by evofenedex due to their previously expressed interest in digital technologies, and blockchain in particular, and their availability for participating in research. Conversely, Blocklab has shared the present research on its website. Secondly, the survey will be directly sent to the attendees of the Spark! Living Lab's webinar (held on the 19th of May) that replaced the physical event. Lastly, the online questionnaire was published on Linkedin and shared via the Spark! Living Lab'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.

The minimum sample size has been set at 20 respondents, and, once this threshold is reached, the data collection will be interrupted and the data analysis will start. Despite being arguably a small sample size, the goal of this research is neither to yield generalizable findings nor to statistically test quantitative hypotheses, but rather to conduct an exploratory study in a relatively unexplored field. Moreover, previous empirical studies carried out with the BWM has involved as low as six respondents (experts) (Ren et al., 2017). Furthermore, the sample size's threshold has been progressively adjusted as the research went on, mainly due to timing constraints and a low response rate, whose causes are explored in section 6.3.1.

[17] Customer Relationship Management

3.5 DATA ANALYSIS METHOD

3.5.1 BAYESIAN BWM's MATLAB IMPLEMENTATION

The MATLAB implementation, provided by Mohammadi (2019) in its GitHub repository, will be used. The aforementioned implementation, given $A_B^{1:k}$ and $A_W^{1:k}$ as inputs, automatically executes the steps laid out in section 3.3.2, to simultaneously determine w^{agg} and $w^{1:k}$. Nonetheless, since the output from Qualtrics is cumbersome and is not in a format compatible with MATLAB, a short Python script (provided in the first section of appendix 8.B) has been developed to selectively import only the numerical columns in the survey's output and generate the matrices $A_B^{1:k}$ and $A_W^{1:k}$ for the categories and each set of factors. The latter are also provided in the second section of appendix 8.B.

3.5.2 MANN-WHITNEY U TEST

As will be explained in the upcoming chapter, the existence of two major groups in the respondents (Dutch and Italian firms), and the keen interest of the Spark! Living Lab for Dutch SMEs, have prompted the addition of section 4.2.6. In the latter, Mann-Whitney U tests are performed to assess the magnitude of the discrepancies among the two clusters in the survey sample. The Mann-Whitney U test is a non-parametric test that can be used to determine whether two independent groups of variables come from the same distribution (Nachar, 2008). This test can be employed for small samples of subjects, and it only needs three basic conditions to be met (Nachar, 2008). First, the investigated groups must be randomly drawn from the target population; secondly, each measurement must come from a different participant; finally, the data measurement scale has to be of ordinal or continuous type (Nachar, 2008).

The null hypothesis (H_0) of the Mann-Whitney U test specifies that the two investigated groups come from the same population (Nachar, 2008). Conversely, the alternative hypothesis (H_1) stipulates that the two groups' populations are different. Hence, since the relationship will be tested regardless of its direction (> or <), a two-tailed test will be used.

Practically, to perform a Mann-Whitney U test, the U statistic has to be calculated for each group (Nachar, 2008), i.e.,

$$U_x = n_x n_y + \frac{n_x(n_x + 1)}{2} - R_x$$

$$U_y = n_x n_y + \frac{n_x(n_x + 1)}{2} - R_y$$

Equation 18:Formulas for calculating the U statistic

where n_x and n_y represent the number of participants from the first and second group respectively, while R_x and R_y identify the sums of the ranks assigned to the two clusters. To compute R_x and R_y, all the observations from the two groups are placed in ascending order, and each observation is assigned a score based on its position in the "standing" (e.g. if observation A is the first observation, it will be awarded a score of 1) (Nachar, 2008). Then, once U_x and U_y have been calculated, the p-value corresponding to the smallest U is retrieved from the Mann and Whitney tables and compared with an a priori determined threshold or α, which is set, in the present study, at 0.05 (Nachar, 2008). 0.05 is the most commonly used α level in statistics and has been proposed by Fisher (1992).

To automate the execution of the test, a MATLAB implementation will be used, and both the inputs of the tests (the weights of the categories and the factors, for both Dutch and Italian firms) and the function that will be employed are provided in appendix 8.C.

4. DATA ANALYSIS

In the present chapter, the BWM is employed to determine the relative importance of the factors identified in the second section of this manuscript and answer the third sub-research question "What is the relative importance of the factors that are influencing the intention to adopt blockchain by SMEs with a logistics operation?". Nonetheless, before the results of data analysis are introduced, an overview of the sample's characteristics is presented to the reader. Then, the Mann-Whitney U Test is used to understand if different sub-samples (i.e. Italian and Dutch firms, which are the two most numerous clusters location-wise) have a statistically relevant difference in the weights.

4.1 RESPONDENTS OVERVIEW

In the present sub-section, an overview of the sample's characteristics is provided.

As mentioned in section 3.4.3, the online questionnaire has been distributed through several channels and it has been made available between May 4th and June 8th. First, the survey has been shared by evofenedex and Blocklab, two of TNO's partners in the Spark! Living Lab. Evofenedex has directly targeted 98 Dutch logistics or manufacturing companies that have expressed interest in blockchain in the past, while Blocklab has shared the present research on its website. Furthermore, the survey has been sent to the twenty firms that have participated in the consortium's webinar event on May 19th. Lastly, the online questionnaire has been published on Linkedin, and shared on the Spark! Living Lab'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.

Despite the wide reach of the channels used for the distribution of the survey, the response rate has been low[18], and only 36 total responses have been collected. Of these 36 responses, 16 had to be discarded, as they were either incomplete (14 of them) or because they did not fit the firm's profile of interest for this research (company with less than 250 employees, respondent at least interested in blockchain technology). This selection has been carried out by looking at the company and blockchain-related information provided by the respondents at the end of the questionnaire. An overview of the twenty responses that are analyzed in the next sub-sections is provided below.

[18] An exact figure for the response rate has not been calculated, as it would have been extremely difficult to compute the total number of people that came in contact with the survey. However, even if only the companies contacted by evofenedex and the consortium are considered (98+20=118), the computed response rate is 36/118≅30%.

4.1.1 PERSONAL INFORMATION

In this sub-section, a summary of the personal characteristics of the respondents is provided. The aforementioned personal characteristics are limited, due to privacy reasons, to the participants' gender, age, and role in their present organization.

Remarkably, as shown in Figure 26, one gender is largely more represented in the analyzed sample, with 19 out of 20 respondents being classified as "Male". On the other hand, the Respondents' Age, which is also shown in Figure 26 on the right, is more balanced, but still displays the dominance of a single category ("45-54") that groups 50% of the participants.

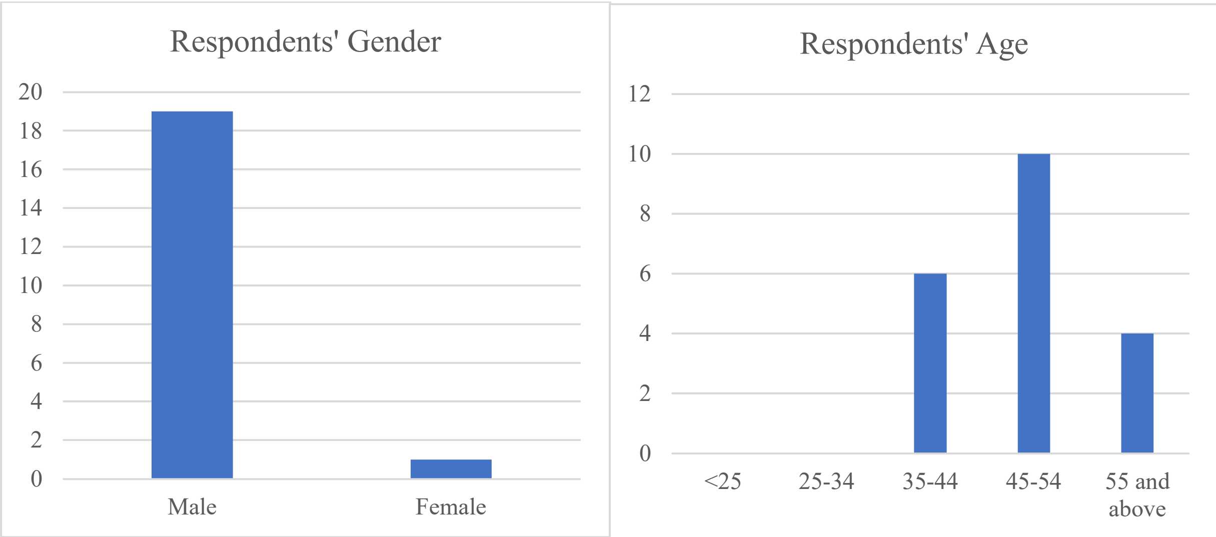


Figure 26:Respondents' Gender and Age

Moreover, eleven of the twenty survey respondents selected for the analysis identify themselves as "Senior Manager or Director", whereas seven occupy a Middle Management position, as exhibited in Figure 27 on the left. Also, the participants are mostly experienced professionals with a long tenure in their current organization, as shown in Figure 27 on the right.

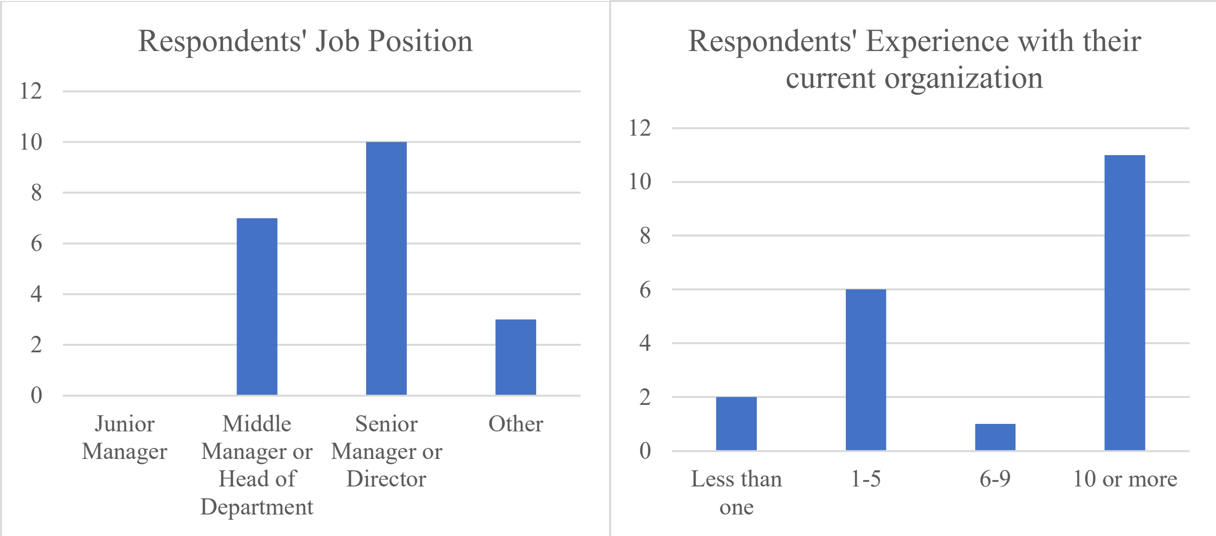


Figure 27:Respondents' job position and experience with their current organization

Lastly, as can be seen in Figure 28, the primary job scope of the respondents is highly diverse instead, with no category appearing more than four times (Administration).

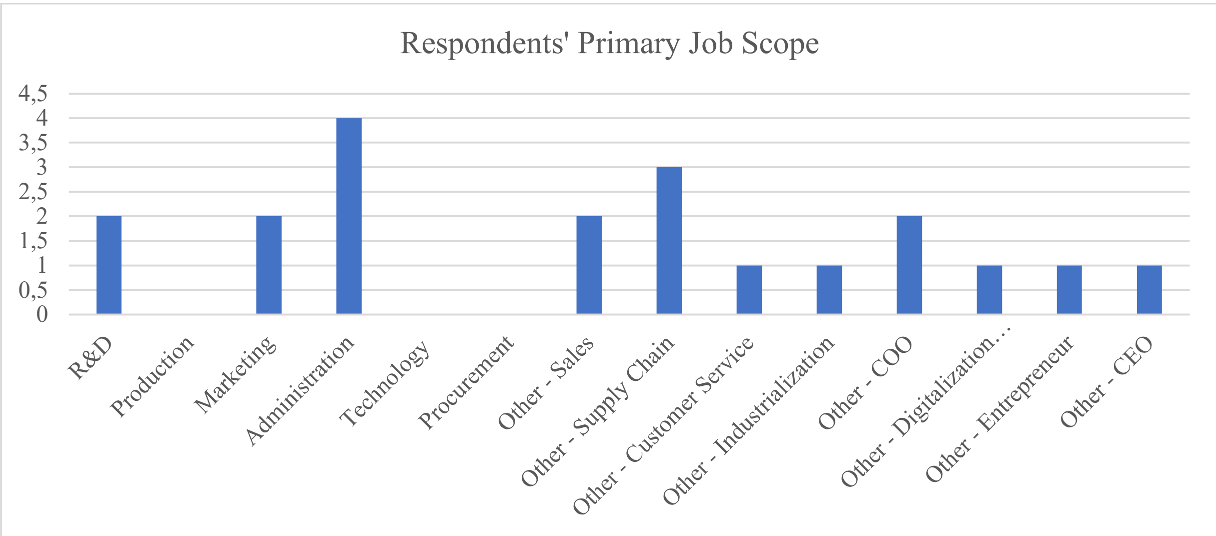


Figure 28:Respondents' Primary Job Scope

4.1.2 BLOCKCHAIN INFORMATION

In this sub-section, a summary of the respondents' perspective and remarks on blockchain is provided.

Three were the blockchain-related questions included in the questionnaire. First, the respondents were asked "Which of the following best describes your present level of understanding on Blockchain Technology?" (Wong et al., 2019, p. 6). Then, the participants were asked their expectations on blockchain technology, and, in particular, "Which application or functionality of blockchain do you consider more desirable?". Ultimately, an open question was inserted at the end of the survey so that the participants could voice their concerns, and, again, add valuable remarks on their expectations for the technology ("Which issues is your company currently facing and which of these issues would you expect blockchain to solve?").

As can be seen in Figure 29, four were the possible answers to the first blockchain-related question. Not-so-surprisingly, the most popular choice was "Interested in the technology", which was picked by 13 out of 20 respondents. This denotes once again the immaturity of blockchain, and the fact that the integration of blockchain and business practices is still at an embryonic stage (Akyuz & Gursoy, 2020). On a more positive note, 7 out of 20 respondents were already in the process of learning the technology (one respondent), testing the technology (two) or even implementing (two) and advising (two) on the technology.

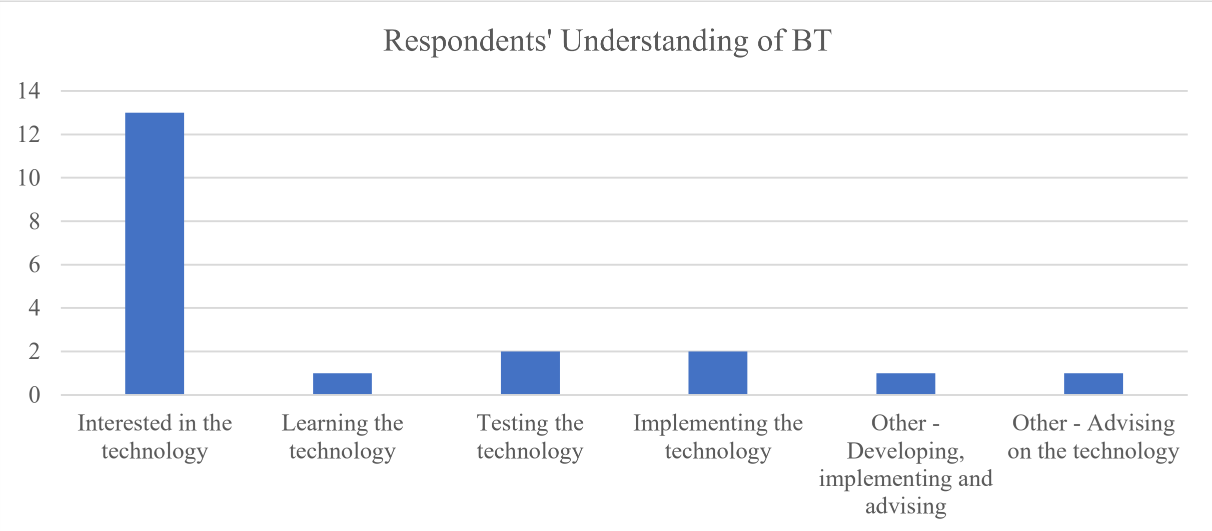


Figure 29:Respondents' Understanding of blockchain technology

Concerning the respondents' expectations for the technology, six participants consider "Paperless Transportation Documentation" as the most desirable application of blockchain. The latter is reasonable, as the manual and paper-based customs-related processes are costly (one fifth of the actual physical transportation cost) and prone to error (IBM, 2017). Conversely, "Disintermediation of Financial Transactions", "Real Time Tracking of Products" and "Smart Contracts" have been selected as the most desirable blockchain application by five, four, and four respondents respectively.

By looking at the answers provided by the participants to the open question at the end of the questionnaire (which has however been filled out by only five respondents), their reasoning can be better understood. In particular, two of the respondents (who coincidentally both selected "Disintermediation of Financial Transactions" in the previous question) stated that distributed ledger technology would be valuable to “constantly trace the goods and money between buyer and supplier” and that “financial transactions with the suppliers go through an excessive number of intermediaries”. Moreover, another participant (who picked “Paperless Transportation Documentation”) claimed that blockchain may be useful for “tracking” purposes and for “streamlining the existing processes”. Finally, the remaining two respondents (who chose “Smart Contracts” and “Other” in the previous inquiry) envision “internal process optimization” and “delivery time-reduction” enabled by blockchain technology, which however needs “a genius socio-technical ecosystem to really make a difference”.

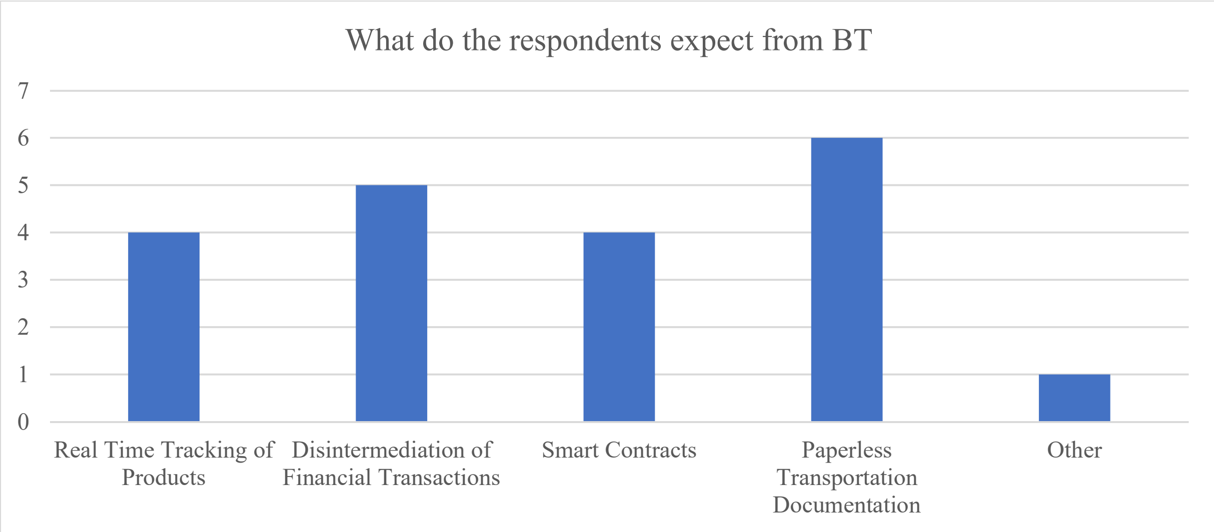


Figure 30:Expectations of the respondents from blockchain technology

The collected responses to the one, and only, open question in the survey can be found in appendix 8.D.

4.1.3 COMPANY INFORMATION

In this sub-section, a summary of the respondents’ company-related information is provided. The aforementioned information are limited, due to privacy reasons, to the firms’ age, size, country of origin, and sector.

As it can be noticed in Figure 31 on the left, 18 of the 20 surveyed companies have existed for 10 or more years, whereas the remaining two were founded 6 to 9 years ago. The organizations’ size is also skewed towards the right end of the spectrum, with 18 out of 20 companies employing between 100-250 workers, as shown in Figure 31.

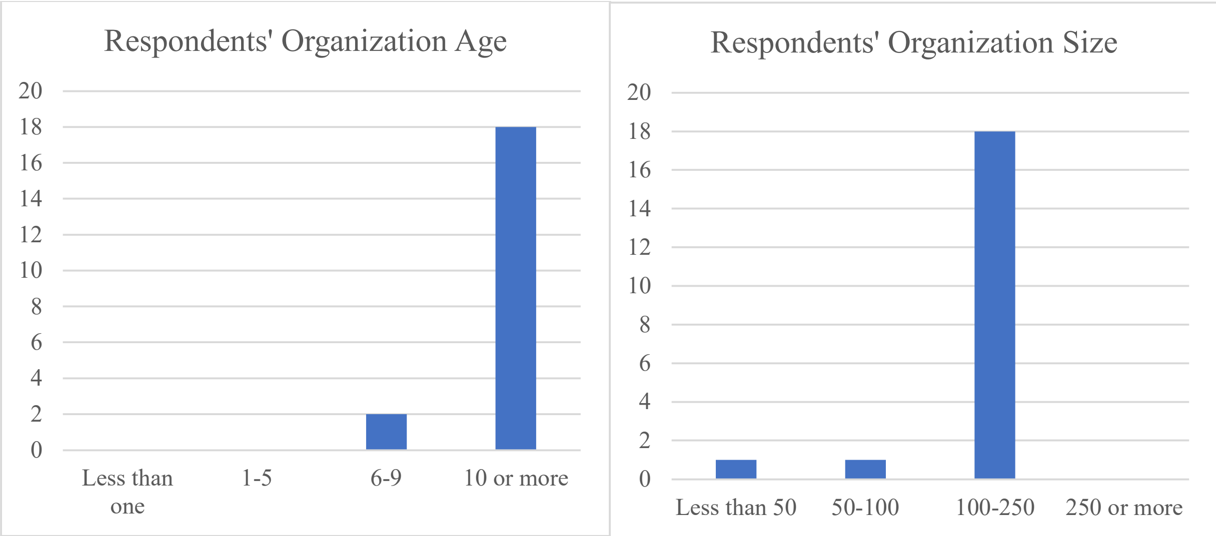


Figure 31:Respondents' Organization Age and Size

The country of origin of the respondents' employers, depicted in Figure 31 on the left, features four different countries with at least one participant. The latter are, from left to right, The Netherlands, Germany, Italy, and Denmark, with 8, 1, 10, and 1 respondents respectively. Obviously, since this research is addressed to the Spark! Living Lab, which has an international reach, but is mainly focused on Dutch SMEs, the results are later provided both globally and for The Netherlands alone. Moreover, since 90% of the surveyed firms come from either The Netherlands or Italy (which group 40% and 50% of the surveyed firms respectively), a comparative analysis of the two countries' respondents is provided in section 4.3 by using Mann-Whitney U tests.

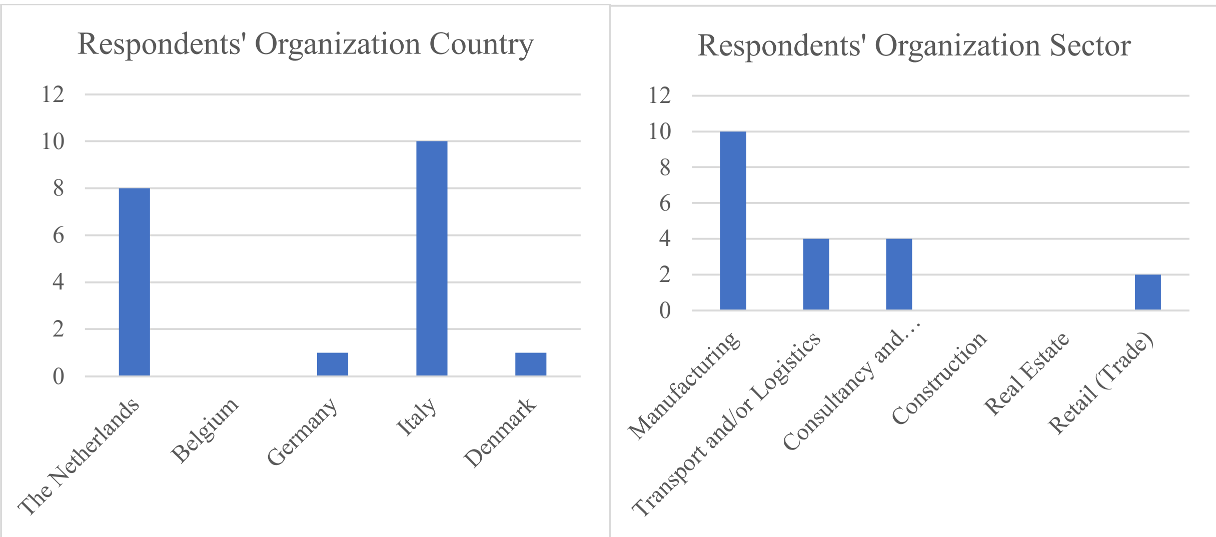


Figure 32:Respondents' Organization Country and Sector

Finally, as shown in Figure 32 on the right, the sector with the highest number of respondents is the manufacturing one, with a total of ten surveyed organizations, followed by "Consultancy and Management" and "Transport and/or Logistics", with four companies each.

4.2 RESULTS OF BWM

In the present sub-question, the results of the BWM are presented. First, the weights of the Technology, Organization, and Environment categories are computed. Then, the importance of the factors inside each category is revealed, and ultimately, the global weights of the factors are calculated by multiplying their "inner" weights by the weight of their matching category. Hence, the main deliverable of this chapter is obtained (the relative importance of the identified factors) and the fourth sub-research question ("What is the relative importance of the factors that are influencing the intention to adopt blockchain by SMEs with a logistics operation?") is answered.

4.2.1 CATEGORY WEIGHTS

As can be seen in Table 5, the technology category has been chosen three times as the most important category by the respondents. The latter is the lowest figure among the three classes, with Organization and Environment being selected 12 and 5 times respectively, as shown in Table 5.

Table 5:Frequency of categories selected most and least important in the questionnaire

Category	Selected as most important	Selected as least important
Technology	3	5
Organization	12	3
Environment	5	12

In Table 6, the weights computed with the Bayesian BWM's MATLAB implementation provided by Mohammadi & Rezaei (2019) are presented. As can be noticed from the "Weight" column, 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, while Environment comes in last with a weight of 0.2679.

Table 6:Weights of the categories generated with the Bayesian BWM

Category	Weight
Technology	0.3058
Organization	0.4263
Environment	0.2679

The ordering of the categories can also be visualized in Figure 33, which depicts the “Credal Ranking” of Technology, Organization, and Environment. The Credal Ranking, as explained in depth in section 3.3.3, has been introduced by Mohammadi & Rezaei (2019) to provide more information on the confidence of the relation (> or <) between each pair of criteria.

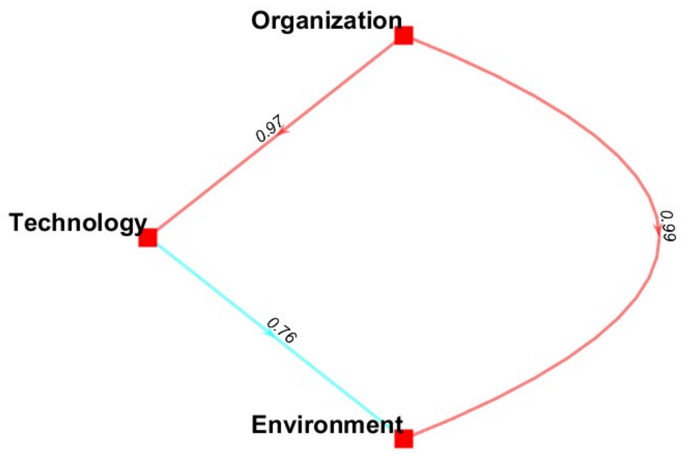


Figure 33:Categories' Credal Ranking

As it can be noticed in Figure 33, 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 doubts. Indeed, the confidence that the weight of Organization is higher than the weights of Technology and Environment is 97% and 99% respectively. This result contradicts the outcomes obtained by Awa & Ojiabo (2016), Dinca et al. (2019), Kühn et al. (2019), and Queiroz & 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 frame and environment in which this study has taken place, and technology under investigation. Indeed, the works of Awa & Ojiabo (2016) and Dinca et al. (2019) are focused on the adoption of ERP Softwares in Nigeria, and on the adoption of Cloud Computing in Romania respectively. Furthermore, Queiroz & 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.

4.2.2 TECHNOLOGY CATEGORY: LOCAL WEIGHTS

The frequency of technological factors selected most and least important in the questionnaire is shown in Table 7. As it can be noticed, "Perceived Usefulness" has been selected as the most important factor within the Technology category the highest number of times (6), followed by Governance and Results Observability (4 times each). On the other hand, Trialability leads the "least important" ranking, with seven selections.

Table 7:Frequency of technological factors selected most and least important in the questionnaire

Factor	Selected as most important	Selected as least important
Cost	2	0
Governance	4	1
Perceived Compatibility	1	3
Perceived Ease of Use	0	4
Perceived Usefulness	6	0
Privacy	1	4
Results Observability	4	1
Security	1	0
Trialability	1	7

Despite the "leading" position of PU in Table 7, its weight computed with the Bayesian BWM stands at 0.1166, behind Security, Results Observability and Governance, which have weights of 0.1360, 0.1263, and 0.1218 respectively, as shown in Table 8. This discrepancy in the factors' order can be imputed to inconsistencies in the responses of the participants, who have evidently assigned higher scores to determinants (e.g. Security) other than the "most important ones". Moreover, this "irregularity" has repeated itself continuously, as Security is, by far, the relatively more important technological factor, despite only being selected once as such by the respondents. A possible explanation lies in the abundance of determinants provided to the participants, who may have needed more time to make up their mind on the factors that were most/least important.

Table 8:Local weights of the technological factors, computed with the Bayesian BWM

Factor	Weight
Cost	0.1146
Governance	0.1218
Perceived Compatibility	0.0893
Perceived Ease of Use	0.0940
Perceived Usefulness	0.1166
Privacy	0.1161
Results Observability	0.1263
Security	0.1360
Trialability	0.0852

Compared to the reviewed literature, which referred to Perceived Usefulness (Anjum, 2019; Awa & Ojiabo, 2016; Kühn et al., 2019; Queiroz et al., 2019; Wong et al., 2019) and Cost (Dinca et al., 2019; Kühn et al., 2019; van Hoek, 2019; Y. Wang et al., 2019; Wong et al., 2019) as two of the most crucial factors influencing technology adoption among SMEs, PU and C are ranked as the fourth and sixth technological factors respectively, as shown in Table 8. On the other hand, the inclusion of Governance as a determinant, prompted by the thesis supervision team, 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.

4.2.3 ORGANIZATION CATEGORY: LOCAL WEIGHTS

The frequency of organizational factors selected most and least important in the questionnaire is shown in Table 9. As can be noticed from the latter, Technology Readiness has been chosen seven times as the most important factor, followed by Top Management Support and Process Readiness, with five and four selections respectively. On the other hand, Top Management Expertise has been deemed as the least important factor by nine respondents, trailed by Top Management Enthusiasm at five.

Table 9:Frequency of organizational factors selected most and least important in the questionnaire

Factor	Chosen as most important	Chosen as least important
People's Readiness	3	2
Process Readiness	4	2
Technology Readiness	7	1
Top Management Enthusiasm	0	5
Top Management Expertise	1	9
Top Management Support	5	1

Nevertheless, the factors' ranking based on Table 9 alone is not entirely reflected in Table 10, which shows the local weights of the determinants within the Organization category. Indeed, by looking at Table 10, it can be seen that Process Readiness leads the way with a weight of 0.2015, with People's Readiness and Top Management Support 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.

Table 10:Local weights of the organizational factors, computed with the Bayesian BWM

Factor	Weight
People's Readiness	0.1961
Process Readiness	0.2015
Technology Readiness	0.1660
Top Management Enthusiasm	0.1321
Top Management Expertise	0.1152
Top Management Support	0.1891

The Credal Ranking in Figure 34 confirms the closedness 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).

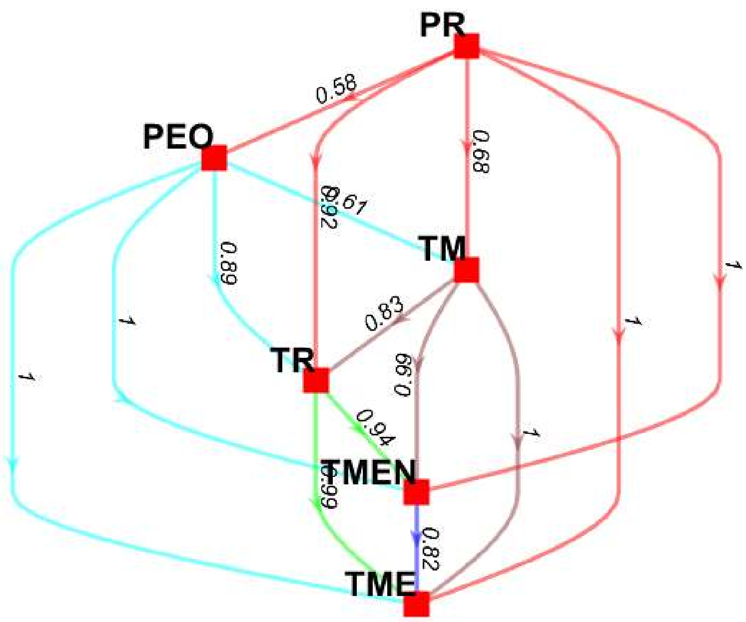


Figure 34:Credal Ranking of the organizational factors

Hence, it can be asserted that the inclusion of the remaining two elements of the "Golden Triangle" for organizational change was legitimate based on the obtained findings, which show PR and PEO as the two relatively more important factors in the Organization category. On the other hand, the third element in the triangle (Technology Readiness), which was deemed as a significant predictor of adoption intention by five authors (AL-Shboul, 2019; Awa & Ojiabo, 2016; Dinca et al., 2019; Kühn et al., 2019; Queiroz & Fosso Wamba, 2019) only ranks as the fourth determinant weight-wise.

4.2.4 ENVIRONMENT CATEGORY: LOCAL WEIGHTS

The frequency of environmental factors selected most and least important in the questionnaire is shown in Table 11. As it can be seen in the latter, Trading Partners' Readiness has been chosen nine times as the most important factor within the Environment category, whereas Government Support leads the way in the opposite ranking, with ten selections as the least important determinant. Remarkably, all the factors have been chosen as "least important" at least once, while three factors (EI, GS, and RS) have never been chosen as "most important".

Table 11:Frequency of environmental factors selected most and least important in the questionnaire

Factor	Selected as most important	Selected as least important
Customers' Influence	5	1
Competitive Pressure	2	3
Cooperation with ICT Providers	1	1
Environmental Impact	0	1
Government Support	0	10
Regulatory Status	0	1
Reputation	3	1
Trading Partners' Readiness	9	2

As it can be noticed from Table 12, the Environment category is a balanced category overall, with the first six factors weights-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 12:Local weights of the environmental factors, computed with the Bayesian BWM

Factor	Weight
Competitive Pressure	0.1403
Customers' Influence	0.1523
Cooperation with ICT Providers	0.1236
Environmental Impact	0.1000
Government Support	0.0827
Regulatory Status	0.1308
Reputation	0.1218
Trading Partners' Readiness	0.1483

The weight-wise ranking of the environmental factors is in line with the reviewed literature, with the exception of Customers' Influence. 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 (German SMEs and US firms respectively). Nonetheless, the present result is backed by Mentzer et al. (2001) and Unilever (2017), who claimed that the increasing consumers' attention for sustainability calls for more efficient and transparent logistics' operations.

4.2.5 GLOBAL WEIGHTS

The global weights of the factors influencing the intention to adopt blockchain technology by SMEs with a logistics operation are shown in Table 13. Each global weight has been computed by multiplying the corresponding category weight of each factor by its local weight.

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 shown in section 4.2.1. 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 a 0.0233 and 0.0261 respectively.

Table 13:Global weights of categories and factors

Factor	Category	Category Weight	Local Weight	Global Weight
Cost	Technology	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
Trialability			0.0852	0.0261
People's Readiness	Organization	0.4263	0.1967	0.0836
Process Readiness			0.2022	0.0859
Technology Readiness			0.1660	0.0708
Top Management Enthusiasm			0.1322	0.0563
Top Management Expertise			0.1133	0.0491
Top Management Support			0.1896	0.0806
Competitive Pressure	Environment	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

4.2.6 CLASSIFICATION COMPARISON

In the present sub-section, the Bayesian BWM is employed to compute the weights of the TOE categories and the local weights of the identified factors by considering separately the (eight) Dutch and (ten) Italian firms among the respondents. For convenience, the two samples will be referred to as the "Dutch" and "Italian" samples/respondents throughout the remainder of this section.

The weights of the categories and factors for the two groups are presented simultaneously with the results of the corresponding Mann Whitney U (MWU) tests, which are performed to understand if the results for the two samples are significantly different. As mentioned in section 3.5.2, the test has been performed with the MATLAB's Ranksum function, which computes the p-value of a two-sided Mann-Whitney U test. The null hypothesis (H_0) states that the two groups come from the same distribution, and it will be rejected if the p-value is smaller than 0.05. The weights that have been used as input of the test are shown in the second section of appendix 8.C.

Table 14:MWU test outcomes categories - Italian versus Dutch

Category	**Weight (Dutch sample)**	**Weight (Italian sample)**	**p-value**
Technology	0.2951	0.3355	0.6334
Organization	0.4513	0.3982	0.4598
Environment	0.2536	0.2662	0.9654

As can be seen from Table 14, Organization is regarded as the most important category by both Dutch and Italian firms, followed by Technology and Environment. However, the BWM's output from the Dutch sample seems to be more pronounced towards Organization, which has a substantially higher weight than its counterpart (0.4513 to 0.3982). On the other hand, Technology and Environment have higher weights in the Italian sample, standing at 0.3355 and 0.2662 respectively. Despite these discrepancies in absolute values, all the p-values are far greater than the threshold of 0.05, which indicates that there are no significant differences between the two groups.

Table 15:MWU test outcomes technological factors - Italian versus Dutch

Factor	**Weight (Dutch sample)**	**Weight (Italian sample)**	**p-value**
Cost	0.1138	0.1108	0.3154
Governance	0.1149	0.1210	0.4082
Perceived Compatibility	0.0795	0.0904	0.0085[19]
Perceived Ease of Use	0.1007	0.0925	0.0343[19]
Perceived Usefulness	0.1201	0.1160	0.2031
Privacy	0.1294	0.1094	0[19]
Results Observability	0.1221	0.1299	0.0343[19]
Security	0.1436	0.1269	0[19]
Trialability	0.0758	0.1030	0.0031[19]

In Table 15, the MWU test outcomes for the factors within the Technology category are presented. As it can be noticed, the test yielded a p-value lower than the 0.05 threshold in six occasions, meaning that the null hypothesis H_0 has been rejected for six factors. The latter are

[19] The p-value is lower than the (predetermined) 0.05 threshold, which indicates that H_0 should be rejected.

Perceived Compatibility, Perceived Ease of Use, Privacy, Results Observability, Security, and Trialability. By looking at their absolute weights, it can be seen that a substantial gap is particularly evident in P, S, and T. Indeed, Security is the only determinant with a weight above 0.14 in the Dutch sample, with its figure being roughly two percentage point above its counterpart from the Italian sample. The latter is true for Privacy as well, which has a weight of 0.1294 and 0.1094 in the Dutch and Italian samples respectively. Conversely, Trialability appears to be more highly regarded by the Italian respondents, with a BWM's output weight of 0.1030 compared to a figure of 0.0758 for the Dutch respondents.

Table 16:MWU test outcomes organizational factors - Italian versus Dutch

Factor	**Weight (Dutch sample)**	**Weight (Italian sample)**	**p-value**
People's Readiness	0.1667	0.2092	0.0009[20]
Process Readiness	0.1998	0.1951	0.6334
Technology Readiness	0.1831	0.1823	0.6965
Top Management Enthusiasm	0.1276	0.1336	0.5726
Top Management Expertise	0.1362	0.1015	0.0343[20]
Top Management Support	0.1865	0.1784	0.4598

In Table 16, the MWU test outcomes for the factors within the Organization category are presented. As it can be noticed, People's Readiness and Top Management Expertise both have a p-value below 0.05. In particular, People's Readiness is, by far, the most important organizational factor in the Italian sample with a weight of 0.2092, which is roughly five percentage points greater than its counterpart in the Dutch sample. Contrarily, Top Management Expertise appears to be more valued by the surveyed Dutch firms.

[20] The p-value is lower than the (predetermined) 0.05 threshold, which indicates that H_0 should be rejected.

Table 17:MWU test outcomes environmental factors - Italian versus Dutch

Factor	Weight (Dutch sample)	Weight (Italian sample)	p-value
Competitive Pressure	0.1346	0.1446	0.0545
Customers' Influence	0.1299	0.1606	0[21]
Cooperation with ICT Providers	0.1111	0.1326	0[21]
Environmental Impact	0.0838	0.1203	0[21]
Government Support	0.0809	0.0810	0.9654
Regulatory Status	0.1588	0.1075	0[21]
Reputation	0.1474	0.1201	0.0031[21]
Trading Partners' Readiness	0.1535	0.1332	0.0676

Table 17 presents the MWU test outcomes for the factors within the Environment category. As it can be seen, the null hypothesis H_0 has been rejected for CUS, CICT, EI, RS, and R. The first three mentioned factors (CUS, CICT, EI) have substantially higher weights in the Italian sample than in the Dutch one, whereas the opposite is true for RS and R. The latter are the two most valued environmental factors in the Dutch sample, with weights of 0.1588 and 0.1474 respectively.

The current section has shown significant differences in the relative importance of the factors that influence blockchain adoption intention in Dutch and Italian SMEs. This, along with the global weights computed in the previous section (4.2) will be used to provide actionable insights to TNO and the Spark! Living Lab in chapter 5.

[21] The p-value is lower than the (predetermined) 0.05 threshold, which indicates that H_0 should be rejected.

4.4 SUMMARY

Chapter 4 presented the global weights obtained with the Bayesian BWM in Table 13, which effectively answer SRQ3 "*What is the relative importance of the factors that are influencing the intention to adopt blockchain by SMEs with a logistics operation?*". Nevertheless, two significant clusters were noticed while analyzing the demographics of the respondents: Italian and Dutch corporations. The latter accounted for 18 of the 20 participants (10 and 8 respectively), which prompted the execution of a comparative analysis of the two samples with a non-parametric statistical test (Mann-Whitney U). This was also motivated by the keen interest of the Spark! Living Lab for Dutch SMEs. The results of the statistical tests revealed several weight differences spanning the Technology, Organization, and Environment category. In particular, the participants employed at Dutch corporations 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 participants working at Italian firms value more highly Trialability, People's Readiness, Customers' Influence, Cooperation with ICT Providers, and Environmental Impact. These findings, along with the global weight-wise ranking of the identified factors, will be used to provide actionable insights to TNO and the Spark! Living in Chapter 5, and ultimately answer the fourth sub-research question "Which factors should the BLL consortium focus on when supporting SMEs in their blockchain journey based on the results of the present study?".

5. RECOMMENDATIONS TO TNO

5.1 INSIGHTS OBTAINED WITH THE BAYESIAN BWM

In the present section, the findings from the Bayesian BWM are exploited to provide TNO and the Spark! Living Lab with insights that can be used to better support SMEs in their blockchain journeys, and, hence, answer the fourth, and final, sub-research question "Which factors should the SLL consortium focus on when supporting SMEs in their blockchain journey based on the results of the present study?". Additionally, the produced insights can aid the consortium in advertising more effectively the project in the future.

The data that supports the below reflections includes the global weights computed with the Bayesian BWM and the results from the Mann-Whitney U tests described in section 4.2.6. The recommendations are mainly focused on those factors that the members of the consortium can directly or indirectly influence with their actions.

First, it can be noticed from Table 18 that the factors' ranking is dominated by organizational factors, which hold the first six positions weight-wise. The latter is justified by the superiority of the Organization category, which has been chosen twelve out of twenty times as the "most important" group of factors influencing blockchain adoption intention.

Table 18:Top half of the Bayesian BWM's global weights ranking

Factor	Global Weight
Process Readiness – O	0.0859
People's Readiness – O	0.0836
Top Management Support – O	0.0806
Technology Readiness – O	0.0708
Top Management Enthusiasm – O	0.0563
Top Management Expertise – O	0.0491
Security – T	0.0416
Competitive Pressure – E	0.0408
Trading Partners' Readiness – E	0.0397
Results Observability – T	0.0386
Customers' Influence – E	0.0376
Governance – T	0.0372
Perceived Usefulness – T	0.0357

Within the six organizational determinants, Process Readiness, People's Readiness, and Top Management Support occupy the three leading spots. This indicates that the respondents are highly concerned with the goodness of fit of distributed ledger technology with the tasks it supports, the employees' Buy-In, and the involvement and understanding of the Top Management.

Table 19:MWU tests outcomes - TME and PEO - Italian versus Dutch

Factor	**Weight (Dutch sample)**	**Weight (Italian sample)**	**p-value**
People's Readiness	0.1667	0.2092	0.0009[22]
Top Management Expertise	0.1362	0.1015	0.0343[22]

Moreover, the outcomes of the MWU tests shown in Table 19 have highlighted a significant difference in the importance placed on the readiness of an organization's employees by respondents employed at Dutch and Italian firms respectively. In particular, the Dutch sample appeared to more highly regard the knowledge of senior managers on blockchain and its deployment models and to be less concerned with the employees' Buy-In. The latter may also be an indicator of a better-than-average technological literacy in the surveyed Dutch companies (especially considering the relatively small number of participants), but it is something to be noted.

Based on these results, the efforts of TNO and the Spark! Living Lab can be directed towards making a visible connection between blockchain and the state-of-the-art processes it enables, perhaps by referring to successful use-cases from the past. For instance, the consortium can showcase the distributed ledgers that TNO is running in its Blockchain Lab, the use-cases and Proof-of-Concepts developed by Blocklab (when that does not interfere with NDAs), and the Supply Chain Visibility ledger developed in the TKI Dinalog project (Dinalog, 2020; TNO, 2020). Furthermore, a physical event could be hosted, when the circumstances allow it, in evofenedex's simulation warehouse, which would go a long way in demonstrating the future outlook of logistics to the stakeholders involved.

Moreover, the learning facilities provided by the consortium, which comprises experts in the matter of digital transformation, could be leveraged to get the interested companies' employees

[22] The p-value is lower than the (predetermined) 0.05 threshold, which indicates that H_0 should be rejected.

up to speed on the processes and tools that they need to master to use a blockchain-enabled platform at its best. Courses and/or masterclasses can be offered by the SLL to the interested companies through the online learning platforms provided by TU Delft and evofenedex. Furthermore, when the circumstances allow it, face-to-face learning sessions can be organized in collaboration with STC as well. The aforementioned courses may be offered by the SLL at a discounted fare so that interested SMEs would be keener to participate.

Lastly, TNO and the Spark! Living Lab should aim for the involvement of the interested companies' senior executives, whose support and guidance appear to be particularly valued by the surveyed Dutch SMEs.

Following the organizational factors, Security can be found on the ranking based on the global weights from Table 18. Furthermore, by looking at the MWU tests' outcomes from Table 20, it can be noticed that Security and Privacy are significantly more relevant in the Dutch sample, qualifying as the two most important factors within the Technology category. Hence, TNO and the Spark! Living Lab can focus, technology-wise, on providing, together with the interested stakeholders, a blockchain-based platform that has confidentiality and reliability as hard requirements. Moreover, since the users' perception of a technology's features is often more important than its actual properties (Chellappa, 2002; Tassabehji & Elliman, 2006), it is vital that TNO and the Spark! Living Lab demonstrate, perhaps with the collaboration of an external auditor (e.g. a privacy officer from an interested company), that blockchain can be GDPR compliant, especially in private and permissioned architectures (Lyons et al., 2018).

Table 20:MWU tests outcomes – PR and S - Italian versus Dutch

Factor	**Weight (Dutch sample)**	**Weight (Italian sample)**	**p-value**
Privacy	0.1294	0.1094	0[23]
Security	0.1436	0.1269	0[23]

As far as the Environment category is concerned, Customers' Influence is the next "most important" factor in the weight-wise ranking from Table 18, but it can hardly be directly or indirectly influenced by TNO and the Spark! Living Lab. Indeed, Customers' Influence refers to the demand for blockchain, or more probably, of one of its applications (e.g. real-time tracking of products) by a firm's customers (Wong et al., 2019).

[23] See footnote 22

Table 21:MWU test outcomes environmental factors - Italian versus Dutch

Factor	Weight (Dutch sample)	Weight (Italian sample)	p-value
Competitive Pressure	0.1346	0.1446	0.0545
Customers' Influence	0.1299	0.1606	0[24]
Cooperation with ICT Providers	0.1111	0.1326	0[24]
Environmental Impact	0.0838	0.1203	0[24]
Government Support	0.0809	0.0810	0.9654
Regulatory Status	0.1588	0.1075	0[24]
Reputation	0.1474	0.1201	0.0031[24]
Trading Partners' Readiness	0.1535	0.1332	0.0676

On the other hand, the MWU tests from Table 21 show several weights from the Dutch sample that are significantly different from the "Italian" ones. In particular, Reputation and Regulatory Status present a wide discrepancy between the two groups and are the two "most important" environmental factors according to the surveyed Dutch firms. Hence, to appeal more effectively to Dutch stakeholders, the commitment of the Spark! Living Lab to be a catalyst for legislators and enforcement authorities could be made more explicit to the public. In this regard, the consortium can seek the collaboration of the Dutch Blockchain Coalition, of which TNO is one of the members. The Dutch Blockchain Coalition comprises governmental partners, knowledge institutions, and associates from the private sector, and is already in the process of identifying bottlenecks in the present regulations (e.g. the settlement of poorly constructed smart contracts), developing standards for interoperability, and implementing use-cases in areas such as SSI and logistics (DBC, 2020).

Ultimately, the "least important" factors overall are introduced.

[24] The p-value is lower than the (predetermined) 0.05 threshold, which indicates that H_0 should be rejected.

Table 22:Bottom half of the Bayesian BWM's global weights ranking

Factor	Global Weight
Privacy	0.0355
Cost	0.0350
Regulatory Status	0.0350
Cooperation with ICT Providers	0.0331
Reputation	0.0326
Perceived Ease of Use	0.0287
Perceived Compatibility	0.0273
Environmental Impact	0.0268
Trialability	0.0261
Government Support	0.0222

The latter are Environmental Impact, Trialability, and Government Support, as it can be noticed in Table 22. The presence of Trialability at the bottom of the weight-wise ranking suggests that providing a free-to-access platform for the interested parties to experiment with should not be the first priority of the Spark! Living Lab. Conversely, the low score for Environmental Impact shows that the surveyed companies are mostly indifferent, or, more probably, not completely aware of the possibility of cutting CO_2 consumption with the sharing modalities enabled by blockchain-powered Supply Chain Visibility (e.g. Synchro Modal Planning). Hence, since responsible innovation and sustainability are the calling cards of the Spark! Living Lab, its members can work towards increasing the interested stakeholders' awareness of the indirect, but beneficial, impact of blockchain adoption on the sustainability of entire supply chains. This could be done by hosting one or more interviews in the future that are specifically focused on showing the potential of data-driven logistics to reduce transport kilometers and optimize modality choices, thus producing efficiency gains while cutting CO_2 consumption.

In conclusion, the present research has generated a set of recommendations that spans the three categories of Technology, Organization, and Environment, and are based on the results of the Bayesian BWM ideated by Mohammadi & Rezaei (2019) and on the Mann-Whitney U tests conducted afterward on the two most significant clusters in the dataset (Italian and Dutch samples). The section that follows is instead focused on sharing, and identifying patterns (if present) that can be useful to the members of the Spark! Living Lab in planning their development efforts.

5.2 WHAT APPLICATION OF BLOCKCHAIN IS MOSTLY DESIRED BY THE RESPONDENTS?

In the present section, the responses of the survey participants to the blockchain-related questions are analyzed to inform TNO and the Spark! Living Lab on the most desired blockchain applications in SCM.

Table 23:Expectations of the respondents from blockchain technology, entire sample, and The Netherlands alone

	Region	
Application	**All**	**Netherlands**
Real time tracking of products	4	3
Disintermediation of financial transactions	5	0
Other	1	1
Paperless transportation documentation	6	2
Smart contracts	4	2

As can be seen from Table 23, there is not one blockchain application that is vastly preferred by the surveyed firms. Indeed, it is shown in the "All" column that the twenty responses are almost evenly distributed among "Real time tracking of products", "Disintermediation of financial transactions", "Smart contracts", and "Paperless transportation documentation", which have all recorded four responses or more. Conversely, it can be noticed from the "Netherlands" column that none of the surveyed Dutch firms has selected "Disintermediation of financial transactions" as the most desirable blockchain application, which appears to be "Real time tracking of products" instead. The latter has been selected three times in the Dutch sample, trailed by "Paperless transportation documentation" and "Smart contracts" with two selections apiece. The disregard of Dutch firms towards "Disintermediation of financial transactions" as a blockchain application may find its explanation in the efficient Dutch banking system. Indeed, the latter is competitive and internationally active to support the export-focused Dutch economy (European Banking Federation, 2018). Hence, the majority of Dutch firms may not feel the urge to change it.

Moreover, further insights can be obtained from the responses of the participants to the open question “Which issues is your company currently facing and which of these issues would you expect blockchain to solve?”. Unfortunately, only five participants have submitted an answer to the aforementioned question, and, of the five answers collected, only one has been submitted by a participant from a Dutch SME. All responses obtained to the above open question are provided in appendix 8.D.

In three of the five responses, it is stated that a blockchain-enabled platform for managing one’s supply chain would lower the number of transactions per product, and, hence, contribute to streamline and optimize internal processes. Furthermore, two of the respondents believe that distributed ledger technology will enable constant traceability of goods and financial transactions in the supply chain. Lastly, one respondent emphasized the possibility of better information sharing between partners.

In summary, the present section has shown mixed preferences of the surveyed respondents when it comes to blockchain applications in SCM. Nevertheless, the responses from the Dutch sample have established (even though this result cannot be easily generalized due to the small size of the dataset) that Dutch SMEs have a keen interest in distributed ledger technology’s applications in real-time tracking of products.

6. CONCLUSION AND DISCUSSION

In the present chapter, the research is first summarized in all of its parts and all research questions are answered. Then, the most important findings of this thesis are outlined, followed by the scientific and practical contribution of the study. Next, the limitations of this research are explored, and suggestions for scientists that may want to repeat or build on this work in the future are provided. Finally, the connection between this thesis and the MoT master (within which this research work has taken place) is highlighted.

6.1 SUMMARY

The present manuscript answered the call of the scientific community for further research on the integration of blockchain and SCM with empirical approaches, which have seldom been employed and reported upon in the field. In particular, this study aims at identifying the key factors that influence the intention to adopt blockchain by SMEs with a logistics operation. The latter has both scientific (as mentioned earlier) and practical relevance, as this research has been conducted in collaboration with TNO and the Spark! Living Lab, with the ultimate goal of providing actionable recommendations for the consortium to better support SMEs in their blockchain journeys. Indeed, SMEs need more help than large corporations as they often have neither the resources nor the expertise to adopt breakthrough technologies, even though the latter can be extremely beneficial for small businesses as well.

To achieve the aforementioned goal, the following Main Research Question was formulated:

MRQ: "How can SMEs with a logistics operation be supported in the adoption of blockchain for Supply Chain Management?"

To assist the researcher in answering the Main Research Question, the following Sub-Research Questions were formulated:

SRQ1: "Which frameworks are available in the literature that investigate the factors that influence the intention to adopt blockchain for Supply Chain Management by SMEs?"

The first sub-research question was answered in the second chapter of this manuscript. In the latter, a systematic literature review was conducted for quantifying the amount of scientific literature available on the topic of blockchain adoption for SCM, finding a suitable technology adoption framework, and ultimately drawing up a conceptual model comprising the factors identified throughout the literature review. The chosen framework was the TOE, which is widely used in IT adoption studies and is highly flexible (Baker, 2011). The TOE acknowledges that three different elements of a firms' context (Technology, Organization, and Environment) influence adoption decisions (Baker, 2011). Thus, according to the selected framework, the factors were classified under the three categories of T, O, and E. Moreover, before the next phase could be started, the list of factors was adapted in line with the expert advice from TNO and the thesis supervision team. The reviewed list of factors can be found in Figure 35 below, whereas the selection process has been described in section 2.6.5. The factors that have been removed present a strikethrough, whereas the factors that have been added are shown in Bold and Italic (combined).

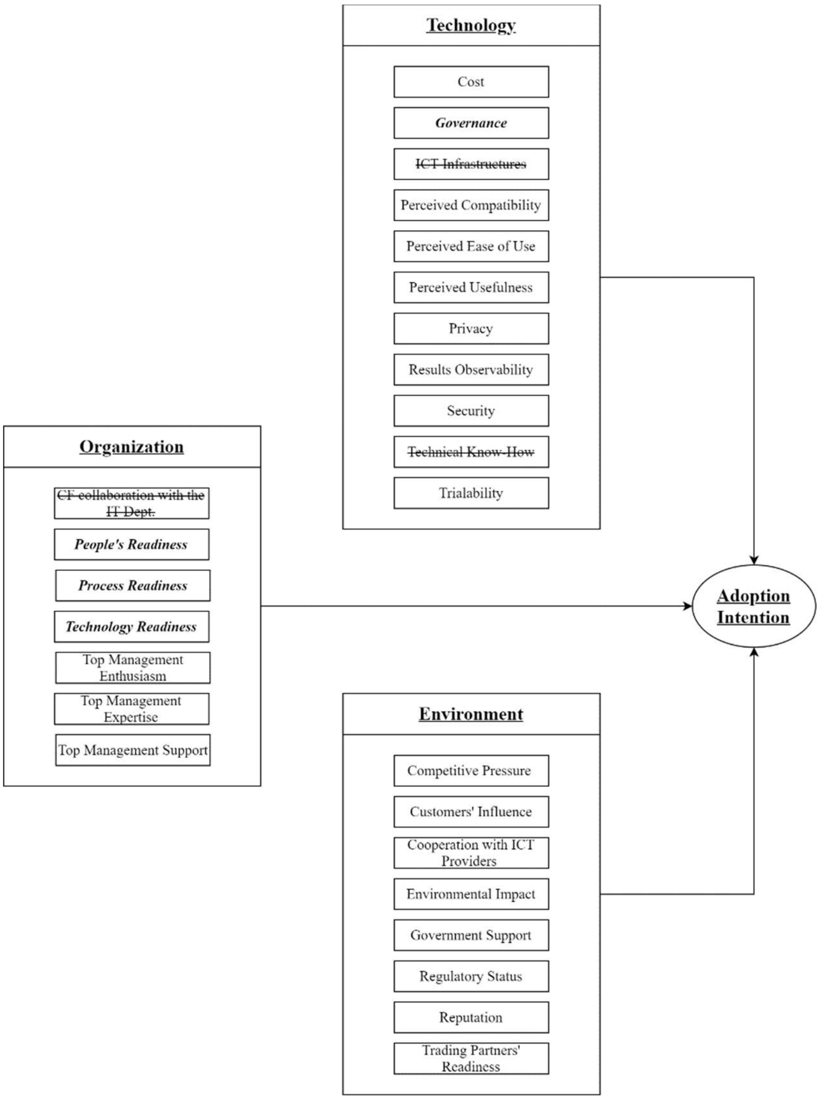


Figure 35:Schematic view of the developed TOE framework, including additions and deletions of factors

SRQ2: "How can the relative importance of each of the factors that are influencing the intention to adopt blockchain by SMEs with a logistics operation be determined?"

The second sub-research question was answered in Chapter 3. In the third chapter, the methods employed to rank the identified factors based on their importance is presented. After careful consideration, the Bayesian BWM was chosen as the most suitable method to tackle the problem at hand. The Bayesian BWM is a Multi-Criteria Decision Making (MCDM) method that can be used to compute the weights of a set of criteria (or factors) based on the preferences of one or more decision-maker(s) (DM) (Mohammadi & Rezaei, 2019). Compared to other popular MCDM methods (such as the AHP), the BWM is not nearly as data-intensive, it is easy to use, and it generates more reliable results (Rezaei, 2015).

To collect the preferences of the target population, an online questionnaire was designed and distributed by leveraging both the network of the Spark! Living Lab and of the thesis supervision team. As mentioned earlier, the target of the survey were DM(s) of SMEs with a logistics operation, or with direct knowledge of digital technologies and their applications for SCM (e.g. a digitalization consultant).

SRQ3: "What is the relative importance of the factors that are influencing the intention to adopt blockchain by SMEs with a logistics operation?"

The third sub-research question has been answered in Chapter 4. The output of the online questionnaire was first cleaned with a Python script (found in appendix 8.B.1). Next, the prepared data was used as input of the Bayesian BWM's MATLAB implementation developed by Mohammadi (2019). As a result, the local and global weights of all the factors were obtained. Remarkably, the Organization category was, by far, the relatively more important category with a weight of 0.4263, followed by Technology and Environment, with weights of 0.3058 and 0.2679 respectively. Due to the superiority of the Organization category, the (global) weight-wise factors' ranking from Table 24 is dominated by organizational determinants, which hold the first six positions. In particular, Process Readiness stands at 0.0839, followed by People's Readiness and Top Management Support at 0.0821 and 0.0810 respectively. Among the technological and environmental factors, Security leads the way with a weight of 0.0416, trailed by Customers' Influence at 0.0408.

Table 24:Top half of the Bayesian BWM's global weights ranking

Factor	**Global Weight**
Process Readiness	0.0859
People's Readiness	0.0836

Factor	Global Weight
Top Management Support	0.0806
Technology Readiness	0.0708
Top Management Enthusiasm	0.0563
Top Management Expertise	0.0491
Security	0.0416
Competitive Pressure	0.0408
Trading Partners' Readiness	0.0397
Results Observability	0.0386
Customers' Influence	0.0376
Governance	0.0372
Perceived Usefulness	0.0357

Furthermore, the fourth chapter continued with a comparative analysis of the Dutch and Italian firms in the sample, which accounted for 18 of the 20 collected responses (8 and 10 respectively). This comparative study was of particular interest to the Spark! Living Lab, which has international reach, but is mainly focused on Dutch SMEs. To compare the two groups in the dataset, Mann-Whitney U tests were used. The non-parametric tests uncovered several statistically significant differences between the two samples, as shown in Table 25. The respondents employed at Dutch corporations 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 participants working at Italian firms value more highly Trialability, People's Readiness, Customers' Influence, Cooperation with ICT Providers, and Environmental Impact.

Table 25:The most significant differences in weights between the Dutch and Italian sample according to the Mann-Whitney U tests

Factor	Weight (Dutch sample)	Weight (Italian sample)	p-value
Privacy	0.1294	0.1094	0
Security	0.1436	0.1269	0
Trialability	0.0758	0.1030	0.0031

Factor	Weight (Dutch sample)	Weight (Italian sample)	p-value
People’s Readiness	0.1667	0.2092	0.0009
Top Management Expertise	0.1362	0.1015	0.0343
Customers’ Influence	0.1299	0.1606	0
Cooperation with ICT Providers	0.1111	0.1326	0
Environmental Impact	0.0838	0.1203	0
Regulatory Status	0.1588	0.1075	0
Reputation	0.1474	0.1201	0.0031

In summary, Chapter 4 presented the local and global weights obtained with the Bayesian BWM, which effectively answer SRQ3 “*What is the relative importance of the factors that are influencing the intention to adopt blockchain by SMEs with a logistics operation?*”. Nevertheless, two significant clusters were evident among the respondents: Italian and Dutch firms. The latter accounted for 18 of the 20 surveyed participants (10 and 8 respectively), which prompted the execution of a comparative analysis of the two samples. This was also motivated by the keen interest of the Spark! Living Lab for Dutch SMEs in particular.

SRQ4: “Which factors should the consortium focus on when supporting SMEs in their blockchain journey based on the results of the present study?”

The fourth sub-research question has been answered in Chapter 5. This last sub-research question has been formulated in the interest of TNO and the Spark! Living Lab, with the intention that the present study would produce actionable insights for the consortium to better support SMEs in their journey to blockchain adoption and implementation.

Based on the results from the previous chapter, TNO and the Spark! Living Lab were suggested to focus on the most important factors weight-wise, and particularly, on those that could be directly or indirectly affected with their actions.

First, since the first six-leading factors weight-wise belonged to the Organization category, as shown in Table 24, the Spark! Living Lab was advised to prioritize those factors. In particular, Process Readiness stood at 0.0859, followed by People's Readiness and Top Management Support at 0.0836 and 0.0806 respectively. Hence, the consortium was suggested to emphasize the visible connection between blockchain and the state-of-the-art processes it enables, to leverage and advertise its training facilities, and to gain the support of the interested companies' senior executives.

Secondly, the consortium was recommended to focus, technology-wise, on providing a blockchain platform that is confidential and reliable. This was justified by the global ranking from Table 24, in which Security was the first non-organizational factor to appear, with a weight of 0.0416. Moreover, the results of the Mann-Whitney U tests from Table 25 show that Security and Privacy were significantly different and inherently more important to Dutch SMEs, which are the target of the Spark! Living Lab.

Lastly, the Mann-Whitney U tests' results have also revealed a substantial difference in the relative importance placed on Regulatory Status, which is more highly valued by Dutch SMEs. Hence, the Spark! Living Lab was advised to put more emphasis on its role as a catalyst for legislators and enforcement authorities.

In conclusion, the four above sub-research questions have aided the author of this manuscript in answering the *MRQ: "How can SMEs with a logistics operation be supported in the adoption of blockchain for Supply Chain Management?"*, which has resulted in the identification of a pioneering set of factors (shown in Figure 35, and Table 24) that influence blockchain adoption intention by SMEs with a logistics operation in Europe. Moreover, the findings derived from this study have been translated into actionable recommendations that aim to assist TNO and The Spark! Living Lab in better supporting SMEs in their blockchain journeys.

6.2 KEY FINDINGS

The weights yielded by the Bayesian BWM revealed the dominant position of organizational factors (i.e. Process Readiness, People's Readiness, and Top Management Support), which 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), which came, to a large extent, as a surprise. Indeed, previous studies conducted by Awa & Ojiabo (2016), Dinca et al. (2019), Kühn et al. (2019) and Queiroz & Fosso Wamba (2019) have supported that technology adoption is more heavily influenced by technological factors rather than by organizational and environmental ones. This discrepancy with previous research may find its explanation in the different time frame and environment in which the study has taken place, and technology under investigation, as explained in section 4.2. Furthermore, two significant clusters were noticed among the respondents: Dutch and Italian firms, which accounted for 18 of the 20 collected responses. This, along with the keen interest of the Spark! Living Lab for Dutch SMEs, prompted a comparative analysis of the two groups. Thus, the factors' weights were computed separately for the two clusters and then compared with Mann-Whitney U tests. The statistical tests produced several interesting findings: the respondents employed at Dutch corporations 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 participants working at Italian firms value more highly Trialability, People's Readiness, Customers' Influence, Cooperation with ICT Providers, and Environmental Impact. These differences may be explained by the above-average digital fitness of Dutch corporations (IMD, 2019) (which would justify the relatively lower importance placed on People's Readiness, Cooperation with ICT Providers, and Trialability) and the cultural differences between the two countries.

On the other hand, by examining the participants' responses to the multiple-choice questions on blockchain, it can be noted that the respondents' preferences are balanced and that there is not one blockchain application that is vastly preferred by the surveyed firms, as shown in section 6.1.2. However, if only the respondents employed at Dutch firms are considered, it can be noticed that none of them has selected "Disintermediation of financial transactions" as his/her favored application, perhaps due to the efficiency of the Dutch banking firms, which none of the surveyed Dutch firms feels the urge to abandon. Conversely, "Real-time tracking of products" has been selected the highest number of times by the Dutch sample (3), trailed by "Paperless Transportation Documentation" and "Smart Contracts", which were both selected two times each.

The above findings have then been employed to provide recommendations to the Spark! Living Lab and TNO so that SMEs can be supported more effectively in the adoption of blockchain for Supply Chain Management.

6.3 CONTRIBUTION

In the present subsection, evidence on the scientific and practical relevance of this study will be provided.

6.3.1 SCIENTIFIC RELEVANCE

The literature review conducted in Chapter 2 revealed the increasing attention paid by the scientific community to SMEs' research in recent years, with the output of the Scopus query *SMEs OR "Small and medium sized enterprises" OR "Small and medium sized businesses" OR "Small enterprises" OR "Small businesses" OR "Small firms" AND ("Definition" OR "What are" OR "What is")* increasing from 851 to 1069 papers between 2016 and 2020. Furthermore, the increase was even more evident within the Supply Chain Management niche, with the publications returned by the Scopus query *"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")* almost doubling from 191 to 370 in the same timeframe. Nonetheless, the outlook changed dramatically when blockchain was added to the mix: only five scientific articles in total were returned by the Scopus query *"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 "Block chain" OR "Distributed ledger") AND ("Benefits" OR "Advantages" OR "Opportunities" OR ''Positive'' OR ''Impact'')*. On the other hand, if the "SMEs" constraint was removed, the Scopus' output showed, once again, a sharp rise in publications, which skyrocketed from a total of 4 in 2016 to 179 in 2019.

Hence, based on the above, it can be asserted that the present study locates itself in a relatively unexplored niche. Indeed, despite the increasing attention paid by the scientific community to SMEs' research, and the integration of Blockchain and Supply Chain Management, the two areas have seldom been explored jointly.

Moreover, by searching for literature on blockchain adoption for Supply Chain Management by SMEs on Scopus (*"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 "Block chain" OR "Distributed ledger") AND ("Adoption" OR "Appropriation"))* only one article, by Wong et al. (2019), was found, leading to the inclusion of non-blockchain related terms (OR "ICT" OR "Information Technology") in the query.

Wong et al. (2019) have administered a survey to more than 200 SMEs in Malaysia to identify the factors driving the intention to adopt blockchain for Supply Chain Management, and have apparently contributed to the only available study of this sort. This knowledge gap has also been highlighted by Fosso Wamba & Queiroz (2020), who conducted a literature review of their own and emphasized the need to further investigate the adoption challenges with distributed ledger technology, especially with empirical approaches.

In summary, the present research has resulted in a weight-based ranking of 23 factors (shown in Figure 35), which were found to be relevant for the blockchain adoption intention by SMEs with a logistics operation. Hence, this study contributes towards bridging the existing knowledge gap on blockchain and supply chain integration from the standpoint of SMEs, and to identify a pioneering set of factors that is relevant for blockchain adoption by SMEs in Europe with empirical methods (an online questionnaire). Indeed, compared to the research conducted by Wong et al. (2019), the present thesis work was conducted in a different setting (Europe), considered a wider range of determinants (23 against 7), and employed a different method of analysis (Bayesian BWM), thus resulting in different, and original findings. Even though it is hardly feasible to make a one-to-one comparison of the two studies, it is striking that Top Management Support, the third factor weight-wise in the present research, was not a significant predictor of adoption intention in Wong et al. (2019). Furthermore, Perceived Ease-of-Use appeared in the bottom half of the global-weight wise ranking from Table 22, while being the second most important factor in the model developed by Wong et al. (2019). These discrepancies have perhaps been partially caused by the evident differences in approach, but may also find an explanation in the higher digital competitiveness of European countries on average (IMD, 2019), and the cultural diversity of the respondents.

Moreover, a further scientific contribution of this thesis lies in the TOE-based conceptual framework from Figure 35. Indeed, the TOE has hardly ever been applied in the context of blockchain adoption, with the exception of the studies conducted by Kühn et al. (2019) and Wong et al. (2019). Lastly, this research contributes to lending empirical validity to the novel Bayesian Best-Worst-Method, which, as of July 2020, has only been employed five times (Garousi Mokhtarzadeh et al., 2020; Guo et al., 2020; Li et al., 2020; Yang, Chuang, et al., 2020; Yang, Lo, et al., 2020).

6.3.2 SOCIETAL RELEVANCE

As a result of the present study, the Spark! Living Lab was provided with guidance on the factors they should put more emphasis on when supporting SMEs in their blockchain journeys. 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 over the determinants they should consider when making a technology adoption decision, and which ones are weighted more heavily by their peers. On a higher level, this research has increased the public exposure of the Spark! Living Lab, as the questionnaire was shared through various wide-reaching channels, as explained in section 3.4.3.

6.4 LIMITATIONS

In the present section, the limitations of this research work are presented. The impediments faced concern, namely the online questionnaire's sample size and the completeness and generalizability of the conceptual model. Acknowledging these limitations goes a long way towards helping other researchers that will repeat this study in the future.

6.4.1 SAMPLE SIZE

A sample is a subgroup of the population that a researcher studies to be able to draw conclusions that are generalizable to the entire population of interest (Sekaran & Bougie, 2016). 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. Indeed, despite having relied on trusted and well-respected partners (such as evofenedex and Blocklab) for the survey distribution, only a handful of responses was collected through these channels. This lack of responsiveness may have been due to several reasons. First, the detrimental economic climate brought about by the Covid-19 pandemic may have led many of the target companies to be less inclined to participate in a student's research about a breakthrough technology. Secondly, the complexity of the questionnaire may have been the cause of the substantial percentage of respondents (~40%) that abandoned the survey halfway. Lastly, the absence of a concrete "gain" for the participants, other than receiving this study's final report, may have led to even more rejections.

Nonetheless, it can be noticed from Tables 5, 7, 9, and 11 that, despite the small sample size, there appear to be a tendency for the majority of the respondents to lean towards the same most/least important factors (e.g. the Organization category, which has been chosen 12 out of 20 times as the most important category), which suggests that the group's overall preferences might remain unchanged even if the sample size is increased. It has to be stressed, however, that the selection of the best and worst category/factor is only the initial part of the BWM's pairwise comparisons process, and that the scores provided by the respondents at a later stage in the process may contradict their initial selection, as it has repeatedly occurred in the present study (e.g. Technology Readiness was picked as the most important organizational factor the highest number of times, but was only the fourth factor weight-wise based on the pairwise comparisons scores). Moreover, the obtained weight-wise factors' ranking is tentative, with the confidence in the superiority of each factor's weight over the others shown in the credal rankings in appendix 8.C.2. Even though most credal orderings appear to be well consolidated (i.e. confidence≥70%), it can be seen that in some instances the "superiority" margin only slightly exceeds the 50% threshold (e.g. Perceived Usefulness is relatively more important than Privacy with 51% certainty), which indicates that these factors' ranking positions might be reverted if/when more responses are collected.

Considering the aforementioned issues, the following recommendations are provided for researchers that want to repeat this study in the future.

First, the introduction of a pecuniary prize or gift-card that will be awarded to one or more of the respondents via a lottery could lead to an increased response rate. Moreover, sending a reminder(s) to the potential participants may also trigger more responses. This was not possible in the present research due to the ongoing pandemic, as the companies contacted may have perceived a survey's reminder as spam among the countless Covid-related updates they were receiving. Lastly, even though it was attempted to make the questionnaire's wording as unambiguous as possible, several improvements can be introduced. For instance, the comparison between the most/least important factor and each of the remaining factors may be more easily understood by the respondents if each couple of factors compared was on the same line (e.g. Best Factor is …. than Other Factor). However, this feature was not available on Qualtrics, the software used for designing the survey.

6.4.2 CONCEPTUAL MODEL: COMPLETENESS AND GENERALIZABILITY

The TOE framework has been chosen for this research due to its comprehensiveness, adaptability, and empirical validity (Awa & Ojiabo, 2016; Baker, 2011; Kühn et al., 2019). The TOE has indeed been used numerous times in ICT adoption inquiries, with different authors employing the model with different factors (Baker, 2011). Using case-specific explanatory factors in a technology adoption model is recommended by Baker (2011), as it has been shown through history that different types of innovations have different factors that influence their adoption. Unfortunately, it was not entirely possible to use blockchain-specific determinants in the conceptual model built in this study. Indeed, as shown in Chapter 2, only one scientific paper turned up when searching for ((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 “Block chain” OR “Distributed ledger”) AND (“Adoption” OR “Appropriation”)), which forced the inclusion of terms such as “IT”, “ICT”, and “Information Technology” in alternative to “Blockchain”. Hence, journal articles on the adoption of ERP Software, Cloud Computing, and e-commerce by SMEs were comprised in the results. 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. Lastly, the results obtained with the conceptual model from Figure 35 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 (e.g. if the survey was distributed during a more prosperous time, and not during a global pandemic).

To tackle the aforementioned issues with the completeness and generalizability of the model, the following arrangements are suggested.

First, if the 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. Indeed, as stated in section 6.2.1, this is still a nearly unexplored field, but more publications can be expected in due time. Moreover, interviewing with experts from the field, or perhaps several representatives of the target population, would lower the chance of overlooking one or more factors. A factors’ selection and integration were also performed in section 2.6.5 in collaboration with the supervision team and experts from TNO, resulting in a more comprehensive, and application-focused, set of factors. Finally, to make the literature review more exhaustive, and, hence, diminish the risk of missing out on any relevant factor, different versions of a word could be added to the search string (e.g. “adopt*” instead of adoption, which would identify all the scientific literature that contains any word derived from “adopt*” in its title or abstract). The latter was only partially done in this study as this issue had arisen when much of the research work had already been done.

6.5 SUGGESTIONS FOR FUTURE RESEARCH

In the present section, further research directions are suggested for scholars that may want to take on similar research in the future.

First, addressing the limitations that have been highlighted in section 6.2 would substantially improve the validity and generalizability of the obtained results. Indeed, whilst the BWM yields a consistent and reliable output even with a small sample size (Rezaei, 2015), repeating the same study with more respondents would legitimate this research's outcome. Moreover, it could be of interest to explore the underlying differences of the Italian and Dutch samples in the dataset, which have yielded thirteen (out of twenty-four) weight discrepancies according to the Mann-Whitney U tests performed in section 4.2.6. The non-parametric tests should be repeated with a bigger sample size, which will make the test more powerful (Yue & Wang, 2002). Then, interviews could be conducted with several respondents from the two groups to understand the reasons behind the weight differences. Furthermore, initiating a face to face dialogue with the participants would also enable future researchers to understand what exactly are their concerns regarding, for instance, the readiness of their processes and the security of a blockchain platform. The latter would be an important step towards implementing the Bayesian BWM's recommendations. Equally interesting would be the exploration of the interrelationships (e.g. correlation, or the existence of intervening variables) among the identified factors, which were out of the scope of this study. The newly available information could then be used in combination with the weight-wise ranking resulting from the Bayesian BWM to better support SMEs in their blockchain journeys. Lastly, the conceptual model developed throughout this research could be applied to analyze the factors that influence blockchain adoption intention in other sectors or industries. Indeed, most of the examined factors encompass technologies and sectors, and, by referring to literature from the relevant field, they could be made fit for this purpose.

6.6 CONNECTION WITH THE MOT PROGRAM

The present research identifies the most relevant factors that influence blockchain adoption for Supply Chain Management at the corporate level, and by SMEs in particular. The factors' ranking obtained was then used to provide actionable recommendations to TNO and the Spark! Living Lab, so that small-to-medium-sized businesses can be better supported in their blockchain journeys.

The knowledge from several MoT courses was applied in the process.

First, the module "Research Methods" provided invaluable knowledge on how to conduct, and design, a scientific research project. Hence, the notions acquired in the course served as guidance throughout all the steps taken in this thesis work. Moreover, the course that I have most recently taken ("Preparation for the Master Thesis") gave me the opportunity to familiarize myself with the process of reviewing literature, which happened to be a significant part of my study.

Secondly, the courses “Emerging & Breakthrough Technologies”, “Leadership and Technology Management”, and “Technology, Strategy, and Entrepreneurship” thought me that technological innovation is dominated by uncertainty, and that technical superiority alone is not enough for the success of an innovative product. Indeed, innovation can be seen as a combination of a core product or technology, an appropriate marketing-mix, and the organizational and environmental contexts in which it is deployed.

Lastly, the “Inter and intra-organizational decision making” module emphasized that decision making is a complex and intricate process, where decisions are seldom made in isolation. During the course, Multi-Criteria Decision Making (MCDM) methods were introduced, including the Best-Worst-Method, which was selected as the most suitable technique to establish a weight-wise ranking of the relevant factors (or criteria) in my thesis work.

7. BIBLIOGRAPHY

Addison, C., Boto, I., Heinen, T., Communication, A., & Lohento, K. (2019). *Opportunities of Blockchain for agriculture*. Accessed on February 7, 2020. https://brusselsbriefings.files.wordpress.com/2019/05/bb55-reader_blockchain-opportunities-for-agriculture_en.rev_.pdf

Akyuz, G. A., & Gursoy, G. (2020). Transformation of Supply Chain Activities in Blockchain Environment. In *Contributions to Management Science* (pp. 153–175). Springer. https://doi.org/10.1007/978-3-030-29739-8_8

AL-Shboul, M. A. (2019). Towards better understanding of determinants logistical factors in SMEs for cloud ERP adoption in developing economies. *Business Process Management Journal*, *25*(5), 887–907. https://doi.org/10.1108/BPMJ-01-2018-0004

Alemi-ardakani, M., Milani, A. S., Yannacopoulos, S., & Shokouhi, G. (2016). On the effect of subjective , objective and combinative weighting in multiple criteria decision making : A case study on impact optimization of composites. *Expert Systems With Applications*, *46*, 426–438. https://doi.org/10.1016/j.eswa.2015.11.003

Anjum, A. (2019). Information and communication technology adoption and its influencing factors: A study of indian SMEs. *Humanities and Social Sciences Reviews*, *7*(5), 1238–1253. https://doi.org/10.18510/hssr.2019.75163

Aste, T., Tasca, P., & Di Matteo, T. (2017). Blockchain Technologies: The Foreseeable Impact on Society and Industry. *Computer*, *50*(9), 18–28. https://doi.org/10.1109/MC.2017.3571064

Awa, H. O., & Ojiabo, O. U. (2016). A model of adoption determinants of ERP within T-O-E framework. *Information Technology and People*, *29*(4), 901–930. https://doi.org/10.1108/ITP-03-2015-0068

Badev, A. I., & Chen, M. (2015). Bitcoin: Technical Background and Data Analysis. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2544331

Baker, J. (2011). The Technology-Organization-Environment Framework. In *Information Systems Theory* (pp. 231–245). University of Hamburg. https://doi.org/10.1007/978-1-4419-6108-2_12

Barron, F. H., & Barrett, B. E. (1996a). Decision quality using ranked attribute weights.

Management Science, *42*(11), 1515–1523. https://doi.org/10.1287/mnsc.42.11.1515

Barron, F. H., & Barrett, B. E. (1996b). The efficacy of SMARTER - Simple Multi-Attribute Rating Technique Extended to Ranking. *Acta Psychologica*, *93*(1–3), 23–36. https://doi.org/10.1016/0001-6918(96)00010-8

Baxter, M., Di Marzo, A., Ganesh, S., & Olsen, T. (2018). *Wolf in Sheep's Clothing: Disruption Ahead for Transaction Banking*. Accessed on May 20, 2020. http://www.bain.com/Images/BAIN_BRIEF_Wolf_in_Sheeps_Clothing_Disruption_in_Transaction_Banking.pdf

Berte, D.-R. (2018). Defining the IoT. *Proceedings of the International Conference on Business Excellence*, *12*(1), 118–128. https://doi.org/10.2478/picbe-2018-0013

Beyer, S., Rainer Hofmann, G., Lundborg, M., Markel, C., & Mundo, A. (2019). *Whitepaper: Blockchain in SMEs - eco*. Accessed on February 25, 2020. https://international.eco.de/topics/blockchain/whitepaper-die-blockchain-im-mittelstand/

Blockchain Council. (2018). *Blockchain Use Case #2 | Supply Chain Management*. Accessed on April 13, 2020. https://www.youtube.com/watch?v=bR5Cd4o2Sfw

Blockstart. (2020, April 7). *Identified SME challenges in three sectors | Interreg NWE*. Accessed on May 20, 2020. https://www.nweurope.eu/projects/project-search/blockstart/news/identified-sme-challenges-in-three-sectors/

Bottomley, P. A., & Doyle, J. R. (2001). A comparison of three weight elicitation methods: Good, better, and best. *Omega*, *29*(6), 553–560. https://doi.org/10.1016/S0305-0483(01)00044-5

Burnham, J. F. (2006). Scopus database: A review. *Biomedical Digital Libraries*, *3*, 1–8. https://doi.org/10.1186/1742-5581-3-1

Caballero, R., & Go, T. (2010). ASurveyonStochasticMulticriteriaAcceptabilityAnalysisMethods. *Journal of MultiCriteria Decision Analysis*, *110*(October 2009), 79–110. https://doi.org/10.1002/mcda

Carson, B., Romanelli, G., Walsh, P., & Zhumaev, A. (2018). *The strategic business value of the blockchain market | McKinsey*. Accessed on February 23, 2020. https://www.mckinsey.com/business-functions/mckinsey-digital/ourinsights/blockchain-beyond-the-hype-what-is-the-strategic-business-value

Ceballos, B., Lamata, M. T., & Pelta, D. A. (2016). A comparative analysis of multi-criteria decision-making methods. *Progress in Artificial Intelligence*, *5*(4), 315–322. https://doi.org/10.1007/s13748-016-0093-1

Chellappa, R. K. (2002). Consumers ’ Trust in Electronic Commerce Transactions : The Role of Perceived Privacy and Perceived Security. *Thesis*, 1–38.

Chen, I. J., & Popovich, K. (2003). Understanding customer relationship management (CRM): People, process and technology. *Business Process Management Journal*, *9*(5), 672–688. https://doi.org/10.1108/14637150310496758

Chong, S., Hoekstra, R., Lemmers, O., Beveren, I. Van, Berg, M. Van Den, Wal, R. Van Der, & Verbiest, P. (2019). The role of small - and medium - sized enterprises in the Dutch economy : an analysis using an extended supply and use table. *Journal of Economic Structures*, 1–24. https://doi.org/10.1186/s40008-019-0139-1

Christopher, M. (2011). *Logistics & Supply Chain Management* (Fourth). Pearson.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User Acceptance of Computer Technology: A Comparison of Two Theoretical Models. *Management Science*, *35*(8), 982–1003. https://doi.org/10.1287/mnsc.35.8.982

DBC. (2020). *About the Dutch Blockchain Coalition - Blockchain*. Accessed on July 16, 2020. https://dutchblockchaincoalition.org/en/about-dbc

Depaoli, S., Clifton, J. P., & Cobb, P. R. (2016). Just Another Gibbs Sampler (JAGS): Flexible Software for MCMC Implementation. *Journal of Educational and Behavioral Statistics*, *41*(6), 628–649.

DePietro, R., Wiarda, E., & Fleisher, M. (1990). The context for change: Organization, Technology and Environment. In L. G. Tornatzky & M. Fleischer (Eds.), *The Process of Technological Innovation* (pp. 151–175). Lexington Books.

DHL. (2018). Blockchain in logistics. In *DHL Customer Solutions & Innovation*. Accessed on May 29, 2020. https://www.logistics.dhl/content/dam/dhl/global/core/documents/pdf/glo-core-blockchain-trend-report.pdf

Diffie, W., Diffie, W., & Hellman, M. E. (1976). New Directions in Cryptography. *IEEE Transactions on Information Theory*, *22*(6), 644–654. https://doi.org/10.1109/TIT.1976.1055638

Dinalog. (2020). *Home - Dinalog*. Accessed on July 16, 2020. https://www.dinalog.nl/

Dinca, V. M., Dima, A. M., & Rozsa, Z. (2019). Determinants of cloud computing adoption by SMEs. *Journal of Business Economics and Management*, *20*(4), 798–820. https://doi.org/10.1504/IJBIS.2016.076878

Edison Awards. (2020). *Edison Awards - Winners*. Accessed on March 27, 2020. https://edisonawards.com/winners2020.php

European Banking Federation. (2018). Banking in Europe: EBF Facts & Figures 2018. *EBF Economic Outlook*, *43*, 1–114.

European Union. (2005, February 23). *Intermodal transport: intermodality of goods transport*. Accessed on May 15, 2020. https://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=LEGISSUM:l24179&from=EN

Farahani, N. Z., Noble, J. S., Klein, C. M., & Enayati, M. (2018). A decision support tool for energy efficient synchromodal supply chains. *Journal of Cleaner Production*, *186*, 682–702. https://doi.org/10.1016/j.jclepro.2018.03.070

Fisher, R. A. (1992). Statistical Methods for Research Workers. In *Breakthroughs in Statistics* (pp. 66–70). Springer, New York, NY. https://doi.org/10.1007/978-1-4612-4380-9_6

Fosso Wamba, S., & Queiroz, M. M. (2020). Blockchain in the operations and supply chain management: Benefits, challenges and future research opportunities. *International Journal of Information Management*, *52*. https://doi.org/10.1016/j.ijinfomgt.2019.102064

Gao, B., Zhou, Q., Li, S., & Liu, X. (2019). A Real Time Stare in Market Strategy for Supply Chain Financing Pledge Risk Management. *IEEE International Conference on Industrial Engineering and Engineering Management*, 1116–1119. https://doi.org/10.1109/IEEM.2018.8607805

Garousi Mokhtarzadeh, N., Amoozad Mahdiraji, H., Jafari-Sadeghi, V., Soltani, A., & Abbasi Kamardi, A. A. (2020). A product-technology portfolio alignment approach for food industry: a multi-criteria decision making with z-numbers. *British Food Journal*. https://doi.org/10.1108/BFJ-02-2020-0115

Goodhue, D. L., & Thompson, R. L. (1995). Task-technology fit and individual performance. *MIS Quarterly: Management Information Systems*, *19*(2), 213–233. https://doi.org/10.2307/249689

Guo, S., Zhang, W., & Gao, X. (2020). Business risk evaluation of electricity retail company in China using a hybrid MCDM method. *Sustainability (Switzerland)*, *12*(5). https://doi.org/10.3390/su12052040

Gupta, H., & Barua, M. K. (2016). Identifying enablers of technological innovation for Indian MSMEs using best-worst multi criteria decision making method. *Technological Forecasting and Social Change*, *107*, 69–79. https://doi.org/10.1016/j.techfore.2016.03.028

Hammer, M., & Champy, J. (1993). *Reengineering the Corporation: A Manifesto for Business Revolution*. Harper Collins.

Hazari, S. S., & Mahmoud, Q. H. (2019). A parallel proof of work to improve transaction speed and scalability in blockchain systems. *2019 IEEE 9th Annual Computing and Communication Workshop and Conference, CCWC 2019*, 916–921. https://doi.org/10.1109/CCWC.2019.8666535

Hepp, T., Wortner, P., Schönhals, A., & Gipp, B. (2018). Securing Physical Assets on the Blockchain: Linking a novel Object Identification Concept with Distributed Ledgers. *Proceedings of the 1st Workshop on Cryptocurrencies and Blockchains for Distributed Systems*, 60–65. https://doi.org/10.1145/3211933.3211944

Herman, M. W., & Koczkodaj, W. W. (1996). A Monte Carlo study of pairwise comparison. *Information Processing Letters*, *57*(1), 25–29. https://doi.org/10.1016/0020-0190(95)00185-9

Hofstee, E. (2006). Extract from Constructing a Good Dissertation A Practical Guide to Finishing a Master ' s , MBA or PhD on Schedule. In *Constructing a Good Dissertation A Practical Guide to Finishing a Master ' s , MBA or PhD on Schedule* (pp. 91–106). Exactica.

Hughes, L., Dwivedi, Y. K., Misra, S. K., Rana, N. P., Raghavan, V., & Akella, V. (2019).

Blockchain research, practice and policy: Applications, benefits, limitations, emerging research themes and research agenda. *International Journal of Information Management*, *49*, 114–129. https://doi.org/10.1016/j.ijinfomgt.2019.02.005

Iansiti, M., & Lakhani, K. R. (2017). The Truth About Blockchain. *Harvard Business Review*, 118–127.

IBM. (2017). *IBM News room - 2017-03-05 Maersk and IBM Unveil First Industry-Wide Cross-Border Supply Chain Solution on Blockchain - United States*. Accessed on February 24, 2020. https://www-03.ibm.com/press/us/en/pressrelease/51712.wss

IBM. (2020). *IBM.com*. Accessed on April 12, 2020. https://www.ibm.com/ibm/us/en/?lnk=fab

Icograms. (2020). *Supply Chain Diagram*. Accessed on July 22, 2020. https://icograms.com/usage-supply-chain-diagram.php

Ilori, M. O., & Irefin, I. A. (1997). Technology decision making in organisations. *Technovation*, *17*(3), 153–160. https://doi.org/10.1016/S0166-4972(96)00086-7

IMD. (2019). IMD World Digital Competitiveness Ranking 2019. *IMD World Competitiveness Center*, 180. https://doi.org/10.1080/01442870420000208233

Ivanov, D., Dolgui, A., & Sokolov, B. (2019). The impact of digital technology and Industry 4.0 on the ripple effect and supply chain risk analytics. *International Journal of Production Research*, *57*(3), 829–846. https://doi.org/10.1080/00207543.2018.1488086

Janssen, M., Weerakkody, V., Ismagilova, E., Sivarajah, U., & Irani, Z. (2020). A framework for analysing blockchain technology adoption: Integrating institutional, market and technical factors. *International Journal of Information Management*, *50*(September 2019), 302–309. https://doi.org/10.1016/j.ijinfomgt.2019.08.012

Jia, J., Fischer, G. W., & Dyer, J. S. (1998). Attribute weighting methods and decision quality in the presence of response error: A simulation study. *Journal of Behavioral Decision Making*, *11*(2), 85–105. https://doi.org/10.1002/(SICI)1099-0771(199806)11:2<85::AID-BDM282>3.0.CO;2-K

JP Morgan. (2020, January 20). *Largest Number of Banks to Join J.P. Morgan Interbank Information Network | J.P. Morgan*. Accessed on May 19, 2020. https://www.jpmorgan.com/global/treasury-services/IIN

Kass, R. E., Carlin, B. P., Gelman, A., & Neal, R. M. (1998). Markov Chain Monte Carlo in Practice: A Roundtable Discussion. *The American Statistician*, *52*(2), 93. https://doi.org/10.2307/2685466

Kheybari, S., Mahdi Rezaie, F., & Rezaei, J. (2019). Measuring the Importance of Decision-Making Criteria in Biofuel Production Technology Selection. *IEEE Transactions on Engineering Management*, 1–15. https://doi.org/10.1109/TEM.2019.2908037

Kim, K., Beck, S., Claire Tayag, M., Concepcion Latoja, M., & Development Bank, A. (2019). *2019 Trade Finance Gaps, Growth, and Jobs Survey*. *5*(113). https://doi.org/10.22617/BRF190389-2

Kitchenham, B., & Charters, S. (2007). Guidelines for performing systematic literature reviews in software engineering. In *Technical report, Ver. 2.3 EBSE Technical Report*.

Kraft, T., Valdés, L., & Zheng, Y. (2018). Supply chain visibility and social responsibility: Investigating consumers' behaviors and motives. *Manufacturing and Service Operations Management*, *20*(4), 617–636. https://doi.org/10.1287/msom.2017.0685

Kraft, T., Valdés, L., & Zheng, Y. (2019). Consumer Trust in Social Responsibility Communications: The Role of Supply Chain Visibility. *SSRN Electronic Journal*, 1–32. https://doi.org/10.2139/ssrn.3407617

Kshetri, N. (2018). 1 Blockchain's roles in meeting key supply chain management objectives. *International Journal of Information Management*, *39*(June 2017), 80–89. https://doi.org/10.1016/j.ijinfomgt.2017.12.005

Kühn, O., Jacob, A., & Schuller, M. (2019). Blockchain Adoption at German Logistics Service Providers. *Hamburg International Conference of Logistics(HICL)*, *September*, 387–411.

Kwon, Y., Kim, H., Shin, J., & Kim, Y. (2019). Bitcoin vs. Bitcoin cash: Coexistence or downfall of bitcoin cash? *Proceedings - IEEE Symposium on Security and Privacy*, *2019-May*, 935–951. https://doi.org/10.1109/SP.2019.00075

Landerreche, E., & Stevens, M. (2018). *On Immutability of Blockchains*. Accessed on February 23, 2020. https://doi.org/10.18420/blockchain2018_04

Leavitt, H. J. (1965). Applied Organisational Change in Industry: Structural, Technological, and Humanistic Approaches. *Handbook of Organization*, *March*, 1144–1170.

Li, N., Zhang, H., Zhang, X., Ma, X., & Guo, S. (2020). How to select the optimal electrochemical energy storage planning program? a hybridmcdmmethod. *Energies*, *13*(4), 1–20. https://doi.org/10.3390/en13040931

Lyons, T., Courcelas, L., & Timsit, K. (2018). *Blockchain and the GDPR*. 4–31. https://www.eublockchainforum.eu/sites/default/files/reports/20181016_report_gdpr.pdf

Manning, C. D., Prabhakar, R., & Schutze, H. (2009). *An Introduction to Information Retrieval*. Cambridge University Press.

Mardani, A., Jusoh, A., Nor, K. M. D., Khalifah, Z., Zakwan, N., & Valipour, A. (2015). Multiple criteria decision-making techniques and their applications - A review of the literature from 2000 to 2014. *Economic Research-Ekonomska Istrazivanja* , *28*(1), 516–571. https://doi.org/10.1080/1331677X.2015.1075139

Mathu, K., & Tlare, M. T. (2017). The impact of IT adoption in SMEs supply chain South Africa.pdf. *South Africa Journal of Business Management*, *48*(3), 63–71.

Mentzer, J. T., Dewitt, W., Keebler, J. S., Min, S., Nix, N. W., Smith, C. D., & Zacharia, Z. G. (2001). DEFINING SUPPLY CHAIN MANAGEMENT. In *Journal of business logistics : JBL* (Vol. 22, Issue 2).

Mes, M. R. K., & Iacob, M. E. (2015). Synchromodal transport planning at a logistics service provider. In *Logistics and Supply Chain Innovation: Bridging the Gap between Theory and Practice* (pp. 23–36). Springer International Publishing. https://doi.org/10.1007/978-3-319-22288-2_2

Mingxiao, D., Xiaofeng, M., Zhe, Z., Xiangwei, W., & Qijun, C. (2017). A review on consensus algorithm of blockchain. *2017 IEEE International Conference on Systems, Man, and Cybernetics, SMC 2017*, *2017-Janua*, 2567–2572. https://doi.org/10.1109/SMC.2017.8123011

Mittal, V. (2019). *SME supply chain financing solution on blockchain distributed ledger technology (DLT)*. https://doi.org/10.13140/RG.2.2.31751.04005

Mohammadi, M. (2019). *GitHub - Majeed7/BayesianBWM*. Accessed on June 18, 2020. https://github.com/Majeed7/BayesianBWM

Mohammadi, M., & Rezaei, J. (2019). Bayesian best-worst method: A probabilistic group decision making model. *Omega (United Kingdom)*, *xxxx*, 102075.

https://doi.org/10.1016/j.omega.2019.06.001

Morgan, R. M., & Hunt, S. D. (1994). The Commitment-Trust Theory of Relationship Marketing. *Journal of Marketing*, *58*(3), 20. https://doi.org/10.2307/1252308

Nachar, N. (2008). The Mann-Whitney U: A Test for Assessing Whether Two Independent Samples Come from the Same Distribution. *Tutorials in Quantitative Methods for Psychology*, *4*(1), 13–20. https://doi.org/10.20982/tqmp.04.1.p013

Nakamoto, S. (2008). *Bitcoin: A Peer-to-Peer Electronic Cash System*. Accessed on February 19, 2020. www.bitcoin.org

Németh, B., Molnár, A., Bozóki, S., Wijaya, K., Inotai, A., Campbell, J. D., & Kaló, Z. (2019). Comparison of weighting methods used in multicriteria decision analysis frameworks in healthcare with focus on low-and middle-income countries. *Journal of Comparative Effectiveness Research*, *8*(4), 195–204. https://doi.org/10.2217/cer-2018-0102

Nike. (2005). *Sourcing Standards | Nike Purpose*. Accessed on February 22, 2020. https://purpose.nike.com/sourcing-manufacturing-standards

Okazaki, Y. (2018). Unveiling the Potential of Blockchain for Customs. *World Customs Organization*, *45*, 1–24.

Ølnes, S., Ubacht, J., & Janssen, M. (2017). Blockchain in government: Benefits and implications of distributed ledger technology for information sharing. *Government Information Quarterly*, *34*(3), 355–364. https://doi.org/10.1016/j.giq.2017.09.007

Olsen, T., Mattios, G., & Di marzo, A. (2018). *Trade Tech-A New Age for Trade and Supply Chain Finance In collaboration with Bain & Company*. Accessed on March 2, 2020. http://www3.weforum.org/docs/White_Paper_Trade_Tech_report_2018.pdf

Ooi, K. B., Hew, J. J., & Lin, B. (2018). Unfolding the privacy paradox among mobile social commerce users: a multi-mediation approach. *Behaviour and Information Technology*, *37*(6), 575–595. https://doi.org/10.1080/0144929X.2018.1465997

Pamučar, D., Stević, Ž., & Sremac, S. (2018). A new model for determiningweight coefficients of criteria in MCDM models: Full Consistency Method (FUCOM). *Symmetry*, *10*(9), 1–22. https://doi.org/10.3390/sym10090393

Qualtrics. (2020a). *Embedded Data - Overview*. Accessed on May 13, 2020. https://www.qualtrics.com/support/survey-platform/survey-module/survey-flow/standard-elements/embedded-data/

Qualtrics. (2020b). *Piped Text - Overview*. Accessed on May 14, 2020. https://www.qualtrics.com/support/survey-platform/survey-module/editing-questions/piped-text/piped-text-overview/

Qualtrics. (2020c). *Qualtrics - Carry Forward Choices Overview*. Accessed on May 14, 2020. https://www.qualtrics.com/support/survey-platform/survey-module/question-options/carry-forward-choices/

Queiroz, M. M., & Fosso Wamba, S. (2019). Blockchain adoption challenges in supply chain: An empirical investigation of the main drivers in India and the USA. *International Journal of Information Management*, *46*(November 2018), 70–82. https://doi.org/10.1016/j.ijinfomgt.2018.11.021

Queiroz, M. M., Telles, R., & Bonilla, S. H. (2019). Blockchain and supply chain management integration: a systematic review of the literature. *Supply Chain Management*, *25*(2), 241–254. https://doi.org/10.1108/SCM-03-2018-0143

Randolph, P. H. (1969). Applied Statistical Decision Theory. *Technometrics*, *11*(1), 205. https://doi.org/10.1080/00401706.1969.10490676

Rao, J. J., & Kumar, V. (2019). Technology Adoption in the SME Sector for Promoting Agile Manufacturing Practices. In *Smart Intelligent Computing and Applications* (pp. 659–665). Springer Singapore. https://doi.org/10.1007/978-981-13-1927-3

Ren, J., Liang, H., & Chan, F. T. S. (2017). Urban sewage sludge, sustainability, and transition for Eco-City: Multi-criteria sustainability assessment of technologies based on best-worst method. *Technological Forecasting and Social Change*, *116*, 29–39. https://doi.org/10.1016/j.techfore.2016.10.070

Revilla, M., & Ochoa, C. (2017). Ideal and Maximum Length for a Web Survey. *International Journal of Market Research*, *59*(5), 557–565. https://doi.org/10.2501/IJMR-2017-039

Rezaei, J. (2015). Best-worst multi-criteria decision-making method. *Omega (United Kingdom)*, *53*, 49–57. https://doi.org/10.1016/j.omega.2014.11.009

Rezaei, J. (2016). Best-worst multi-criteria decision-making method: Some properties and a linear model. *Omega (United Kingdom)*, *64*, 126–130. https://doi.org/10.1016/j.omega.2015.12.001

Rezaei, J. (2020a). A Concentration Ratio for Nonlinear Best Worst Method. *International Journal of Information Technology & Decision Making*, *19*(03), 891–907. https://doi.org/10.1142/s0219622020500170

Rezaei, J. (2020b). *Best Worst Method: A multi-criteria decision making method*. Accessed on April 2, 2020. http://bestworstmethod.com/

Rikken, O., Janssen, M., & Kwee, Z. (2019). Governance challenges of blockchain and decentralized autonomous organizations. *Information Polity*, *24*(4), 397–417. https://doi.org/10.3233/ip-190154

Rogers, E. M. (1962). *Diffusion of Innovations* (Third). Free Press.

Roszkowska, E. (2013). Rank Ordering Criteria Weighting Methods – a Comparative Overview. *Optimum. Studia Ekonomiczne*, *5*(5(65)), 14–33. https://doi.org/10.15290/ose.2013.05.65.02

Saaty, T. L. (2008). Decision making with the analytic hierarchy process. *International Journal of Services Sciences*, *1*(1), 283–290. https://doi.org/10.1016/0305-0483(87)90016-8

Segers, L., Ubacht, J., Rukanova, B., & Tan, Y. H. (2019). The use of a blockchain-based smart import declaration to reduce the need for manual cross-validation by customs authorities. *ACM International Conference Proceeding Series*, 196–203. https://doi.org/10.1145/3325112.3325264

Sekaran, U. (1992). *Research Methods for Business: A Skill-Building Approach*. Wiley.

Sekaran, U., & Bougie, R. (2016). *Research Methods for Business: A Skill-Building Approach* (Seventh). Wiley.

Sikarwar, T. (2017). *A Handbook of Case Studies in Finance* (First). Cambridge Scholars Publishing.

Sodhi, A., Tang, M. S., Sodhi, M. S., & Tang, C. S. (2018). Research Opportunities in Supply Chain Transparency. *Production and Operations Management*, *28*(12), 2946–2959.

https://doi.org/https://doi.org/10.1111/poms.13115

Srivastava, J., Connolly, T., & Beach, L. R. (1995). Do ranks suffice? A comparison of alternative weighting approaches in value elicitation. In *Organizational Behavior and Human Decision Processes* (Vol. 63, Issue 1, pp. 112–116). https://doi.org/10.1006/obhd.1995.1066

Sureeyatanapas, P. (2016). Comparison of rank-based weighting methods for multi-criteria decision making. *Kku Engineering Journal*, *43*(S3), 376–379. https://doi.org/10.14456/kkuenj.2016.134

Surjandy, Meyliana, Hidayanto, A. N., & Prabowo, H. (2019). The latest adoption blockchain technology in supply chain management: A systematic literature review. *ICIC Express Letters*, *13*(10), 913–920. https://doi.org/10.24507/icicel.13.10.913

Swan, M. (2015). *Blockchain : Blueprint for a New Economy* (First). O'Reilly.

Takahashi, K. (2016). Blockchain technology and electronic bills of lading. *The Journal Of International Maritime Law*, *22*(March), 202–211.

Tang, C. S., Zimmerman, J. D., & Nelson, J. I. (2009). Managing New Product Development and Supply Chain Risks: The Boeing 787 Case. *Supply Chain Forum: An International Journal*, *10*(2), 74–86. https://doi.org/10.1080/16258312.2009.11517219

Tassabehji, R., & Elliman, T. (2006). Generating citizen trust in e-government using a trust verification agent: A research note. *Proceedings of the European and Mediterranean Conference on Information Systems, EMCIS 2006*, *Swartz 2004*, 1–11.

Thoo, A. C., Sulaiman, Z., Choi, S. L., & Kohar, U. H. A. (2017). Understanding Supply Chain Management Practices for Small and Medium-Sized Enterprises. *IOP Conference Series: Materials Science and Engineering*, *215*(1). https://doi.org/10.1088/1757-899X/215/1/012014

TNO. (2020). *TNO and Blockchains | TNO*. Accessed on July 16, 2020. https://blockchain.tno.nl/tno-and-blockchains/

Triantaphyllou, E., Shu, B., Sanchez, S. N., & Ray, T. (1998). Multi-Criteria Decision Making : An Operations Research Approach. *Electronics*, *15*, 175–186.

Tsang, Y. P., Choy, K. L., Wu, C. H., Ho, G. T. S., & Lam, H. Y. (2019). Blockchain-Driven

IoT for Food Traceability with an Integrated Consensus Mechanism. *IEEE Access*, *7*(September), 129000–129017. https://doi.org/10.1109/ACCESS.2019.2940227

Tzeng, G. H., Chen, T. Y., & Wang, J. C. (1998). A weight-assessing method with habitual domains. *European Journal of Operational Research*, *110*(2), 342–367. https://doi.org/10.1016/S0377-2217(97)00246-4

UNECE. (2020). *About UNECE*. Accessed on May 20, 2020. https://www.unece.org/mission.html

van de Kaa, G., Kamp, L., & Rezaei, J. (2017). Selection of biomass thermochemical conversion technology in the Netherlands: A best worst method approach. *Journal of Cleaner Production*, *166*, 32–39. https://doi.org/10.1016/j.jclepro.2017.07.052

van Engelenburg, S., Janssen, M., & Klievink, B. (2018). A Blockchain Architecture for Reducing the Bullwhip Effect. *Springer Nature*, *319*, 69–82. https://doi.org/10.1007/978-3-319-94214-8

van Hoek, R. (2019). Unblocking the chain – findings from an executive workshop on blockchain in the supply chain. *Supply Chain Management*, *2*(March 2019), 255–261. https://doi.org/10.1108/SCM-11-2018-0383

Velthuijsen, J. W., Yildirim, B., Kramer, G., & Schmidl, R. (2018). *Innovation and Digital Transformation: How do European SMEs perform?* Accessed on February 25, 2020. https://www.pwc.nl/en/topics/economic-office/europe-monitor/the-digital-transformation-of-smes.html

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer Acceptance and Use of Information Technology: Extedning the Unified Theory of Acceptance and Use of Technology. *MIS Quarterly*, *36*(1), 157–178. https://doi.org/10.1042/bst0120672

Vyas, N., Beije, A., & Krishnamachari, B. (2019). *Blockchain and the supply chain - concepts, strategies and practical applications*. KoganPage.

Walker, J. H., Saffu, K., & Mazurek, M. (2016). An Empirical Study of Factors Influencing E-Commerce Adoption/Non-Adoption in Slovakian SMEs. *Journal of Internet Commerce*, *15*(3), 189–213. https://doi.org/10.1080/15332861.2016.1191049

Wang, X., & Disney, S. M. (2016). The bullwhip effect: Progress, trends and directions. In *European Journal of Operational Research* (Vol. 250, Issue 3, pp. 691–701). Elsevier

B.V. https://doi.org/10.1016/j.ejor.2015.07.022

Wang, Y., Han, J. H., & Beynon-Davies, P. (2019). Understanding blockchain technology for future supply chains: a systematic literature review and research agenda. In *Supply Chain Management* (Vol. 24, Issue 1, pp. 62–84). Emerald Group Publishing Ltd. https://doi.org/10.1108/SCM-03-2018-0148

Webster, J., & Watson, R. T. (2002). Analyzing the Past to Prepare for the Future: Writing a Literature Review. *MIS Quarterly*, *26*(2), xiii–xxiii. https://doi.org/10.1.1.104.6570

Weisstein, E. (2020). *Eigenvalue*. MathWorld - A Wolfram Web Resource. Accessed on April 22, 2020. https://mathworld.wolfram.com/Eigenvalue.html

Winter, K., Buckl, S., Matthes, F., & Schweda, C. (2010). Investigating the State-of-the-Art in Enterprise Architecture Management Method in Literature and Practice. *Proceedings of the Mediterranean Conference on Information Systems*, *September*, 1–12.

Wong, L. W., Leong, L. Y., Hew, J. J., Tan, G. W. H., & Ooi, K. B. (2019). Time to seize the digital evolution: Adoption of blockchain in operations and supply chain management among Malaysian SMEs. *International Journal of Information Management*, *June*, 101997. https://doi.org/10.1016/j.ijinfomgt.2019.08.005

Yang, J. J., Chuang, Y. C., Lo, H. W., & Lee, T. I. (2020). A two-stage MCDM model for exploring the influential relationships of sustainable sports tourism criteria in Taichung City. *International Journal of Environmental Research and Public Health*, *17*(7). https://doi.org/10.3390/ijerph17072319

Yang, J. J., Lo, H. W., Chao, C. S., Shen, C. C., & Yang, C. C. (2020). Establishing a sustainable sports tourism evaluation framework with a hybrid multi-criteria decision-making model to explore potential sports tourism attractions in Taiwan. *Sustainability (Switzerland)*, *12*(4), 1–20. https://doi.org/10.3390/su12041673

Yue, S., & Wang, C. Y. (2002). Power of the Mann – Whitney test for detecting a shift in median or mean of hydro-meteorological data. *Stochastic Environmental Research and Risk Assessment*, *16*, 307–323. https://doi.org/10.1007/s00477-002-0101-9

Zavadskas, E. K., Govindan, K., Antucheviciene, J., & Turskis, Z. (2016). Hybrid multiple criteria decision-making methods: A review of applications for sustainability issues. *Economic Research-Ekonomska Istrazivanja* , *29*(1), 857–887.

https://doi.org/10.1080/1331677X.2016.1237302

8. APPENDICES

A. QUESTIONNAIRE SAMPLE

Presented below is a sample of the English version of the questionnaire. To comprehend it in all of its parts, a brief explanation of the included Qualtrics functions is provided.

${QID/ChoiceGroup/SelectedChoices}:

This function is included within the "Piped Text" tool from Qualtrics. Piped Text is "a line of code you add to your survey that pulls information from different sources(e.g. a previous question) and displays that information to the respondent" (Qualtrics, 2020b). ${QID/ChoiceGroup/SelectedChoices} pulls the selected choice(s) from a previous question and conveniently enables the editor to "pipe" it later in the survey.

${e://Field/Unselected1}:

This function also belongs to the Piped Text tool. The latter has been used to "pipe" the "Embedded Data" Unselected1, which has been created by the editor. Embedded Data consists of a field (which is the name of the variable, e.g. Unselected1) and a value, which is assigned to the field (Qualtrics, 2020a). In this case, the editor has added a custom Javascript (JS) (shown below) to set the value of Unselected1 to the string representing (one of) the unselected choices of the respondent. The custom JS has been added to Q1 to assign one of the unselected choices from "Of the below categories of factors(TOE), which one is, in your opinion, the **MOST IMPORTANT** category you would consider when deciding whether to adopt blockchain or not?" to Unselected1, and pipe it in Q3 to offer an example to the respondent on how to properly answer the question (if you select 9 for ${e://Field/Unselected1}, it means that **${Q1/ChoiceGroup/SelectedChoices}** is much more important than ${e://Field/Unselected1}). The same custom JS, with an adjustment to the exit condition of the for loop depending on the number of choices available, has also been added to Q5, Q9, and Q13 with the same purpose.

Code 1:Custom JS to assign one of the unselected choices to Embedded 1

```
var selected_name;

Qualtrics.SurveyEngine.addOnPageSubmit(function()

{

        var temp= this.getChoiceAnswerValue();
```

```
        selected_name=this.getChoiceVariableName(temp);

        var all_codes=this.getChoices();

        var all_names=[];

        for(let i=0; i<3; i++) {

                all_names.push(this.getChoiceVariableName(all_codes[i]));

        }

        var unselected_names=all_names.filter(name => name!=selected_name);

        Qualtrics.SurveyEngine.setEmbeddedData('Unselected1', unselected_names[0]);

});
```

${Q1/ChoiceDescription/1}:

This Piped Text is the output of Qualtrics' Carry Forward Logic. The latter is a built-in function that enables the editor to "carry forward" the choices from one question and bring them into a future question in your survey (Qualtrics, 2020c). In this case, the editor has employed the function to carry forward the available choices from Q1 to Q3 (which elicits the preferences of Best-to-Others vector from the respondent). Then, by applying Display Logic, which is another built-in tool from Qualtrics, the editor was able to hide Q1's selected choice (the MOST IMPORTANT category) from Q3's available choices.

As it can be noticed below, the aforementioned logic has also been applied to Q4, Q7 & Q8, Q11 & Q12, and Q15 & Q16.

A.1 OPENING STATEMENT

Dear Sir/Madam,

You are invited to participate in a research study titled *Blockchain in Supply Chain Management: An empirical study into the key factors influencing the intention to adopt blockchain by SMEs*. This study is conducted by Filippo Lanzini, a Master student at TU Delft and intern at TNO Data Science.

We would like to know from you, as a decision-maker in a Small-to-Medium-sized Business, which factors would you consider if you were to adopt blockchain.

The data will be presented, in aggregate form only, in Filippo's Master Thesis report and any potential publications that might arise from it. The results will then be used to understand what is important to you, and thus, which elements the Spark! Living Lab should focus on when guiding SMEs in their blockchain journey, of which you will hopefully be part one day.

This questionnaire requires approximately 15 minutes to complete. Your participation in this study is entirely voluntary and you may withdraw at any time by closing the browser.

At the end of the questionnaire, you can provide your email address to receive the outcome of the study. We hereby assure you that your email address will **only be used to contact you in the context of this study** and that it will be stored completely confidentially and securely in the project's folder until the research expected completion date (16th of July 2020), after which it will be deleted. If you change your mind, and you wish to delete your contact information before the 16th of July, you can contact filippo.lanzini@tno.nl at any time.

We want to thank you dearly for taking the time to complete this survey as your participation represents a valuable contribution to this research. If you have any questions regarding the questionnaire or the research, please do not hesitate to contact us.

Sincerely,

Filippo Lanzini - TNO/TU Delft (filippo.lanzini@tno.nl)

A.2 VIDEO INTRODUCTION TO BT FOR SCM

Thank you again for participating in this study, your contribution is really appreciated. At the end of the survey, you will have to possibility to provide your email if you would like to receive the outcome of this research.

In this page, a brief video-introduction(courtesy of Blockchain Council^{TM}) will be provided on Blockchain Technology and its implications for Supply Chain Management and Logistics. If you are already familiar with the technology and its applications, you may decide to skip this page.

A.3 CATEGORIES' PAIRWISE COMPARISONS

In the questionnaire, we will ask you to assess which factors you consider the most and least important within a predetermined list. Then, we will ask you to compare the factors to each other. Finally, the survey will end with a few general questions about your company.

In the present question, you will be asked to assess your category(Technology, Organization or Environment) preferences.

Technology	Organization	Environment
Cost	People's Readiness	Competitive pressure
Governance	Process Readiness	Customers' Influence
Perceived Compatibility	Technology Readiness	Cooperation with ICT Providers
Perceived Ease of Use	Top Management Enthusiasm	Environmental Impact
Perceived Usefulness	Top Management Expertise	Government Support
Privacy	Top Management Support	Regulatory Status
Results Observability		Reputation
Security		Trading Partners' Readiness
Trialability		

Q1

Suppose, as a decision-maker in a Small-to-Medium-sized Enterprise, that an opportunity has come up to adopt blockchain.

Of the below categories of factors(TOE), which one is, in your opinion, the **MOST IMPORTANT** category you would consider when deciding whether to adopt blockchain or not?

- O Technology
- O Organization
- O Environment

Q2
Of the below categories of factors(TOE), which one is, in your opinion, the **LEAST IMPORTANT** category you would consider when deciding whether to adopt blockchain or not?

- O Technology
- O Organization
- O Environment

Q3
You have selected **${Q1/ChoiceGroup/SelectedChoices}** as the **MOST IMPORTANT** category.

Please indicate how much you prefer ${Q1/ChoiceGroup/SelectedChoices} over each of the remaining factors(e.g. if you select 9 for ${e://Field/Unselected1}, it means that **${Q1/ChoiceGroup/SelectedChoices}** is much more important than ${e://Field/Unselected1})

The measurement scale you will have to use ranges from 1 to 9, where:
1: Equally important *9: Much more important*

	1	2	3	4	5	6	7	8	9
${Q1/ChoiceDescription/1}									
${Q1/ChoiceDescription/2}									
${Q1/ChoiceDescription/3}									

Q4
You have selected **${Q2/ChoiceGroup/SelectedChoices}** as the **LEAST IMPORTANT** category.

Please indicate how much you prefer each of the remaining factors over **${Q2/ChoiceGroup/SelectedChoices}**(e.g. if you select 1 for ${e://Field/Unselected2}, it means that ${e://Field/Unselected2} is equally important as **${Q2/ChoiceGroup/SelectedChoices}**)

The measurement scale you will have to use ranges from 1 to 9, where:

1: Equally important *9: Much more important*

	1	2	3	4	5	6	7	8	9
${Q1/ChoiceDescription/1}									
${Q1/ChoiceDescription/2}									
${Q1/ChoiceDescription/3}									

A.4 TECHNOLOGY's PAIRWISE COMPARISONS

In the following section, you will be asked to assess your factor preferences within the Technology category. If you wish to consult the factors' definitions before answering the upcoming questions, click on read more.

Read more

Q5

Suppose, as a decision-maker in a Small-to-Medium-sized Enterprise, that an opportunity has come up to adopt blockchain.

Of the below Technology factors, which is, in your opinion, the **MOST IMPORTANT** factor you would consider when deciding whether to adopt blockchain or not?

- O Cost
- O Governance
- O Perceived Compatibility
- O Perceived Ease of Use
- O Perceived Usefulness
- O Privacy
- O Results Observability
- O Security
- O Trialability

Q6

Of the below Technology factors, which is, in your opinion, the **LEAST IMPORTANT** factor you would consider when deciding whether to adopt blockchain or not?

- O Cost
- O Governance
- O Perceived Compatibility
- O Perceived Ease of Use
- O Perceived Usefulness
- O Privacy
- O Results Observability
- O Security
- O Trialability

Q7

You have selected **${Q5/ChoiceGroup/SelectedChoices}** as the **MOST IMPORTANT** factor.

Please indicate how much you prefer ${Q5/ChoiceGroup/SelectedChoices} over each of the remaining factors(e.g. if you select 9 for ${e://Field/Unselected5}, it means that ${Q5/ChoiceGroup/SelectedChoices} is much more important than ${e://Field/Unselected5})

The measurement scale you will have to use ranges from 1 to 9, where:

1: Equally important *9: Much more important*

	1	2	3	4	5	6	7	8	9
${Q5/ChoiceDescription/1}									
${Q5/ChoiceDescription/2}									
${Q5/ChoiceDescription/3}									
${Q5/ChoiceDescription/4}									
${Q5/ChoiceDescription/5}									
${Q5/ChoiceDescription/6}									
${Q5/ChoiceDescription/7}									

${Q5/ChoiceDescription/8}
${Q5/ChoiceDescription/9}

Q8

You have selected **${Q6/ChoiceGroup/SelectedChoices}** as the **LEAST IMPORTANT** factor.

Please indicate how much you prefer each of the remaining factors over ${Q6/ChoiceGroup/SelectedChoices}(e.g. if you select 1 for ${e://Field/Unselected6}, it means that ${e://Field/Unselected6} is equally important as ${Q6/ChoiceGroup/SelectedChoices})

The measurement scale you will have to use ranges from 1 to 9, where:

1: Equally important *9: Much more important*

	1	2	3	4	5	6	7	8	9
${Q5/ChoiceDescription/1}									
${Q5/ChoiceDescription/2}									
${Q5/ChoiceDescription/3}									
${Q5/ChoiceDescription/4}									
${Q5/ChoiceDescription/5}									
${Q5/ChoiceDescription/6}									
${Q5/ChoiceDescription/7}									
${Q5/ChoiceDescription/8}									
${Q5/ChoiceDescription/9}									

A.5 ORGANIZATION's PAIRWISE COMPARISONS

In the following section, you will be asked to assess your factor preferences within the Organization category. If you wish to consult the factors' definition before answering the upcoming questions, click on read more.

Read more

Q9
Suppose, as a decision-maker in a Small-to-Medium-sized Enterprise, that an opportunity has come up to adopt blockchain.

Of the below Organization factors, which is, in your opinion, the **MOST IMPORTANT** factor you would consider when deciding whether to adopt blockchain or not?

- O People's Readiness
- O Process Readiness
- O Technology Readiness
- O Top Management Enthusiasm
- O Top Management Expertise
- O Top Management Support

Q10
Of the below Organization factors, which is, in your opinion, the **LEAST IMPORTANT** factor you would consider when deciding whether to adopt blockchain or not?

- O People's Readiness
- O Process Readiness
- O Technology Readiness
- O Top Management Enthusiasm
- O Top Management Expertise
- O Top Management Support

Q11
You have selected **${Q9/ChoiceGroup/SelectedChoices}** as the **MOST IMPORTANT** factor.

Please indicate how much you prefer **${Q9/ChoiceGroup/SelectedChoices}** over each of the remaining factors(e.g. if you select 9 for ${e://Field/Unselected9}, it means that **${Q9/ChoiceGroup/SelectedChoices}** is much more important than ${e://Field/Unselected9})

The measurement scale you will have to use ranges from 1 to 9, where:

1: Equally important *9: Much more important*

	1	2	3	4	5	6	7	8	9
${Q9/ChoiceDescription/1}									
${Q9/ChoiceDescription/2}									
${Q9/ChoiceDescription/3}									
${Q9/ChoiceDescription/4}									
${Q9/ChoiceDescription/5}									
${Q9/ChoiceDescription/6}									

Q12

You have selected **${Q10/ChoiceGroup/SelectedChoices}** as the **LEAST IMPORTANT** factor.

Please indicate how much you prefer each of the remaining factors over ${Q10/ChoiceGroup/SelectedChoices}(e.g. if you select 1 for ${e://Field/Unselected10}, it means that ${e://Field/Unselected10} is equally important as ${Q10/ChoiceGroup/SelectedChoices})

The measurement scale you will have to use ranges from 1 to 9, where:

1: Equally important *9: Much more important*

	1	2	3	4	5	6	7	8	9
${Q10/ChoiceDescription/1}									
${Q10/ChoiceDescription/2}									
${Q10/ChoiceDescription/3}									
${Q10/ChoiceDescription/4}									
${Q10/ChoiceDescription/5}									
${Q10/ChoiceDescription/6}									

A.6 ENVIRONMENT's PAIRWISE COMPARISONS

In the following section, you will be asked to assess your factor preferences within the Environment category. If you wish to consult the factors' definition before answering the upcoming questions, click on read more.

Read more

Q13

Suppose, as a decision-maker in a Small-to-Medium-sized Enterprise, that an opportunity has come up to adopt blockchain.

Of the below Environment factors, which is, in your opinion, the **MOST IMPORTANT** factor you would consider when deciding whether to adopt blockchain or not?

- O Competitive Pressure
- O Customers' Influence
- O Cooperation with ICT Providers
- O Environmental Impact
- O Government Support
- O Regulatory Status
- O Reputation
- O Trading Partners' Readiness

Q14

Of the below Environment factors, which is, in your opinion, the **LEAST IMPORTANT** factor you would consider when deciding whether to adopt blockchain or not?

- O Competitive Pressure
- O Customers' Influence
- O Cooperation with ICT Providers
- O Environmental Impact
- O Government Support
- O Regulatory Status
- O Reputation

O Trading Partners' Readiness

Q15
You have selected **${Q13/ChoiceGroup/SelectedChoices}** as the **MOST IMPORTANT** factor.

Please indicate how much you prefer ${Q13/ChoiceGroup/SelectedChoices} over each of the remaining factors(e.g. if you select 9 for ${e://Field/Unselected13}, it means that ${Q13/ChoiceGroup/SelectedChoices} is much more important than ${e://Field/Unselected13})

The measurement scale you will have to use ranges from 1 to 9, where:
1: Equally important *9: Much more important*

	1	2	3	4	5	6	7	8	9
${Q13/ChoiceDescription/1}									
${Q13/ChoiceDescription/2}									
${Q13/ChoiceDescription/3}									
${Q13/ChoiceDescription/4}									
${Q13/ChoiceDescription/5}									
${Q13/ChoiceDescription/6}									
${Q13/ChoiceDescription/7}									
${Q13/ChoiceDescription/8}									

Q16
You have selected **${Q14/ChoiceGroup/SelectedChoices}** as the **LEAST IMPORTANT** factor.

Please indicate how much you prefer each of the remaining factors over ${Q14/ChoiceGroup/SelectedChoices}(e.g. if you select 1 for ${e://Field/Unselected14}, it means that ${e://Field/Unselected14}is equally important as ${Q14/ChoiceGroup/SelectedChoices})

The measurement scale you will have to use ranges from 1 to 9, where:
1: Equally important *9: Much more important*

	1	2	3	4	5	6	7	8	9
${Q13/ChoiceDescription/1}									

${Q13/ChoiceDescription/2}

${Q13/ChoiceDescription/3}

${Q13/ChoiceDescription/4}

${Q13/ChoiceDescription/5}

${Q13/ChoiceDescription/6}

${Q13/ChoiceDescription/7}

${Q13/ChoiceDescription/8}

A.7 GENERAL INQUIRIES

In the following section, a few general questions will be asked about yourself and your company. The information provided will only be used for statistical analysis and no individual responses will be shared.

At the end of this section, you will have the chance to provide your email address if you would like to receive a digital copy of this study's report.

Q17

What is your gender?

O Male

O Female

O Other / Prefer not to say

Q18

What is your age?

O <25

O 25-34

O 35-44

O 45-54

O 55 and above

Q19

What is your main job position?

O Junior Manager

O Middle Manager or Head of Department

O Senior Manager or Director

O Other ____

Q20
What is your primary job scope?

O R&D

O Production

O Marketing

O Administration

O Technology

O Procurement

O Other ____

Q21
How many years have you been with the present organization?

O Less than one

O 1-5

O 6-9

O 10 or more

Q22
How old is your current organization?

O Less than one
O 1-5
O 6-9
O 10 or more

Q23
What is the size of your organization?

O Less than 50

O 50-100

O 100-250

O 250 or more

Q24
Where is your company located?

If other, please specify.

O The Netherlands

O Belgium

O Germany

O Other ____

Q25
What is the sector of your organization?

O Manufacturing

O Transport and/or Logistics

O Consultancy and Management

O Construction

O Real Estate

O Retail (Trade)

Q26
Which category of products does your organization produce/transport?

O Electronics

O Chemicals

O Textile

O Food

O Rubber and Plastic

O Machinery and Hardware

O Other

Q27
Which of the following best describes your present level of understanding on Blockchain Technology?

O Interested in the technology

- O Learning the technology
- O Testing the technology
- O Implementing the technology
- O None

Q28
Based on your experience or knowledge, which application or functionality of blockchain do you consider more desirable?

- O Real Time Tracking of Products
- O Disintermediation of Financial Transactions
- O Smart Contracts
- O Paperless Transportation Documentation

Q29
Which issues(especially supply chain related) is your company currently facing and which of these issues would you expect blockchain to solve(e.g. excessive paper documentation)?

This question is not mandatory. This means that you may skip it if you wish. Nonetheless, we will really appreciate it if you decide to share your thoughts with us.

____

Q30
Would you like to receive a digital report of this study after it is concluded?
If Yes, please insert your email below.

- O Yes ____
- O No

B. BAYESIAN BWM IMPLEMENTATION

B.1 DATA PREPARATION WITH PYTHON

```
import pandas as pd
```

```
Survey_output=pd.read_excel(r'C:\Users\filip\Desktop\BWM
Survey_Qualtrics_Output.xlsx')

Survey_output=Survey_output.drop([0],axis=0)

Survey_output=Survey_output.reset_index(drop=True)

#I only want one column with the country. So, where there is "Other", I want to switch it with
the next

new_values_country=[]

for i in range(len(Survey_output)):

    if Survey_output.loc[i,'Q31']=='Other':

        new_values_country.append(Survey_output.loc[i,'Q31_4_TEXT'])

    else:

        new_values_country.append(Survey_output.loc[i,'Q31'])

Survey_output.rename(columns={'Q31':'Country'},inplace=True)

for i in range(len(Survey_output)):

    if Survey_output.loc[i,'Country']=='Other':

        Survey_output.loc[i,'Country']=new_values_country[i]

#I now filter the results of the survey based on their completeness and on the size of the
firms, which have to be SMEs

Survey_output=Survey_output[Survey_output['Finished']=='True']

Survey_output=Survey_output[Survey_output['Q30']!='250 or more']

#I only keep the columns that contain numerical values that are needed as input for the
Bayesian BWM

Survey_output=Survey_output.iloc[:,18:78]

Survey_output=Survey_output.reset_index(drop=True)

#I create one dataframe for the rating of the categories and the factors within each category

cat_v=Survey_output.iloc[:,:8]

tech_v=Survey_output.iloc[:,8:28]

org_v=Survey_output.iloc[:,28:42]

env_v=Survey_output.iloc[:,42:60]

#Create a dictionary with the factors and their positions in the list of answers

cat=['Technology','Organization','Environment']

tech_f=['Cost','Governance','Perceived Compatibility'

        ,'Perceived Ease of Use','Perceived Usefulness'
```

```
       ,'Privacy','Results Observability','Security'
        ,'Trialability']
org_f=["People's Readiness",'Process Readiness'
,'Technology Readiness','Top Management Enthusiasm'
,'Top Management Expertise','Top Management Support']
env_f=['Competitive Pressure',"Customers' Influence"
,'Cooperation with ICT Providers','Environmental Impact'
,'Government Support','Regulatory Status'
,'Reputation',"Trading Partners' Readiness"]
def create_dic(lst):
   return dict(zip(lst,range(len(lst))))
cat=create_dic(cat)
tech_f=create_dic(tech_f)
org_f=create_dic(org_f)
env_f=create_dic(env_f)
#I create a function that fills the empty values (e.g. in the second set of comparisons the Best to Worst value has been omitted from the survey questions, as it has already been provided in the first set of comparisons)
def get_clean_answersheet(dframe,dic):
   clean_df=dframe.copy()
   for i in range(len(dframe)):
      #temp1 is the most_important factor, whereas temp2 is the least important factor
      temp1=dframe.iloc[i,0]
      temp2=dframe.iloc[i,1]
      #the position of the most important factor in the first set of comparisons (Best to Others) is 2 (which are the two positions occupied by the most and least important factors)+the position of the factor in the dictionary I have constructed (e.g. Technology would be the first one     in the dictionary and hence add 0)
      p1=2+dic[temp1]
      #The same is true for the least important factor
      p2=2+dic[temp2]
      #the position of the most important factor in the second set of comparisons (Others to Worst) is 2 (which are the two positions occupied by the most and least important factors)+ the space occupied by the first set of comparison plus the position of the factor in the
```

dictionary I have constructed (e.g. Technology would be the first one in the dictionary and hence add 0)

```
        p3=2+len(dic)+dic[temp1]
        #The same is true for the least important factor
        p4=2+len(dic)+dic[temp2]
        #I assign a value of 1 to Best to Best
        clean_df.iloc[i,p1]=1
        #I assign the same value of the B to W comparison from the first set to the B to W comparison in the second set
        clean_df.iloc[i,p3]=dframe.iloc[i,p2]
        #I assign a value of 1 to Worst to Worst
        clean_df.iloc[i,p4]=1
    return clean_df
#I define a function that separates the Best to Others Matrix and the Others to Worst Matrix
def get_AB_and_AW(dframe,dic):
    AB=dframe.iloc[:,:len(dic)]
    AW=dframe.iloc[:,len(dic):2*len(dic)]
    return(AB,AW)
#I generate the two matrices AB and AW for all the categories
cat_v=get_clean_answersheet(cat_v,cat)
cat_v=cat_v.drop(cat_v.columns[0],axis=1)
cat_v=cat_v.drop(cat_v.columns[0],axis=1)

tech_v=get_clean_answersheet(tech_v,tech_f)
tech_v=tech_v.drop(tech_v.columns[0],axis=1)
tech_v=tech_v.drop(tech_v.columns[0],axis=1)

org_v=get_clean_answersheet(org_v,org_f)
org_v=org_v.drop(org_v.columns[0],axis=1)
org_v=org_v.drop(org_v.columns[0],axis=1)

env_v=get_clean_answersheet(env_v,env_f)
env_v=env_v.drop(env_v.columns[0],axis=1)
```

```
env_v=env_v.drop(env_v.columns[0],axis=1)

cat_AB,cat_AW=get_AB_and_AW(cat_v,cat)
tech_AB,tech_AW=get_AB_and_AW(tech_v,tech_f)
org_AB,org_AW=get_AB_and_AW(org_v,org_f)
env_AB,env_AW=get_AB_and_AW(env_v,env_f)

#I create an Excel csv file for each matrix in a format that can directly be used by MATLAB
cat_AB.to_csv(r'C:\Users\filip\OneDrive\Documents\MATLAB\cat_AB.csv', header=False, index=False)
cat_AW.to_csv(r'C:\Users\filip\OneDrive\Documents\MATLAB\cat_AW.csv', header=False, index=False)
tech_AB.to_csv(r'C:\Users\filip\OneDrive\Documents\MATLAB\tech_AB.csv', header=False, index=False)
tech_AW.to_csv(r'C:\Users\filip\OneDrive\Documents\MATLAB\tech_AW.csv', header=False, index=False)
org_AB.to_csv(r'C:\Users\filip\OneDrive\Documents\MATLAB\org_AB.csv', header=False, index=False)
org_AW.to_csv(r'C:\Users\filip\OneDrive\Documents\MATLAB\org_AW.csv', header=False, index=False)
env_AB.to_csv(r'C:\Users\filip\OneDrive\Documents\MATLAB\env_AB.csv', header=False, index=False)
env_AW.to_csv(r'C:\Users\filip\OneDrive\Documents\MATLAB\env_AW.csv', header=False, index=False)
```

B.2 INPUTS TO THE BAYESIAN BWM

B.2.1 TOE

Table 26:"Best-to-Others" (AB) and "Best-to-Worst" (AW) matrices of the TOE categories

	AB				***AW***		
	Category				**Category**		
ID	**T**	**O**	**E**		**T**	**O**	**E**
1	7	9	1		9	1	9
2	6	1	4		1	6	2
3	1	9	4		4	7	1
4	8	1	9		3	9	1
5	5	5	1		5	1	5
6	3	6	1		1	5	3

	AB				*AW*		
	Category				**Category**		
ID	**T**	**O**	**E**		**T**	**O**	**E**
7	1	1	5		5	5	1
8	4	1	7		4	7	1
9	7	1	8		7	8	1
10	6	1	5		5	5	1
11	1	6	2		2	6	1
12	7	1	4		1	7	4
13	3	1	9		7	9	1
14	7	1	6		3	6	1
15	5	1	6		5	6	1
16	6	1	6		6	6	1
17	2	1	2		1	2	1
18	9	5	1		1	7	9
19	1	9	4		4	7	1
20	8	9	1		8	1	9

B.2.2 TECHNOLOGY FACTORS

Table 27:"Best-to-Others" (AB) and "Best-to-Worst" (AW) matrices of the Technology factors

	AB										**AW**								
	Category										Category								
ID	C	G	PC	PEOU	PU	PR	RO	S	T		C	G	PC	PEOU	PU	PR	RO	S	T
1	7	8	8	2	2	2	1	2	8		8	8	9	9	8	8	8	7	1
2	4	5	5	4	1	3	5	2	4		5	6	4	5	4	6	5	8	1
3	9	8	7	6	7	8	5	1	2		5	8	6	6	7	9	5	2	1
4	4	2	4	5	1	4	4	4	7		6	6	5	5	7	3	6	7	1
5	5	5	5	5	5	1	5	5	5		5	1	5	5	5	5	5	5	5
6	4	1	5	8	8	8	5	7	5		5	8	7	1	7	5	5	5	5
7	1	2	5	5	5	2	2	1	1		5	5	5	1	5	5	5	5	5
8	5	5	5	5	5	5	1	5	5		5	5	5	5	5	1	5	5	5
9	2	2	7	4	1	4	4	3	3		9	7	1	7	7	7	7	8	8
10	7	7	6	6	1	2	5	7	7		8	8	6	7	2	1	7	8	8
11	7	6	7	7	6	2	7	7	1		4	3	4	4	3	1	4	4	2
12	3	2	9	4	1	3	2	1	3		8	8	1	8	9	8	8	8	8
13	1	1	1	1	1	1	1	1	1		1	1	1	1	1	1	1	1	1
14	6	1	7	9	7	5	7	7	5		6	9	5	1	5	5	6	8	6
15	4	1	5	8	8	6	5	2	5		7	8	6	1	6	5	6	8	6
16	4	5	5	4	1	4	4	1	1		1	3	1	3	4	1	2	2	2
17	2	2	2	2	2	1	1	1	2		1	1	1	1	1	2	2	2	1
18	1	3	1	1	1	2	1	1	9		9	9	9	9	9	9	9	9	1
19	1	2	5	5	5	2	2	1	9		9	8	4	4	4	8	8	9	1
20	7	8	7	5	5	3	1	2	9		4	4	5	5	4	7	9	8	1

B.2.3 ORGANIZATION FACTORS

Table 28:"Best-to-Others" (AB) and "Best-to-Worst" (AW) matrices of the Organization factors

	AB							**AW**					
	Organization factor							Organization factor					
ID	PEO	PR	TR	TMEN	TME	TMS		PEO	PR	TR	TMEN	TME	TMS
1	1	1	2	7	7	1		9	7	8	3	1	7
2	2	2	3	2	5	1		4	5	4	6	1	5
3	5	6	1	7	7	7		1	6	5	7	7	7
4	2	1	7	7	6	8		8	8	5	7	6	1
5	5	5	5	5	1	5		5	5	5	1	5	5
6	7	7	8	8	5	1		7	5	7	6	1	5
7	5	5	1	5	5	5		5	5	5	5	1	5
8	1	7	7	7	7	7		7	4	4	1	4	4
9	3	3	2	2	6	1		9	9	9	9	1	6
10	8	8	8	4	8	1		8	8	8	1	8	4
11	2	1	1	2	3	1		7	8	3	4	1	4
12	1	2	5	8	9	2		8	7	5	3	1	9
13	5	1	6	9	9	1		7	9	8	1	3	9
14	1	2	1	4	5	1		1	1	2	4	3	9
15	1	2	4	5	9	3		9	8	6	8	1	9
16	2	2	1	1	1	1		9	9	1	6	1	6
17	2	2	2	1	1	1		1	1	1	1	1	2
18	2	1	9	2	2	1		9	9	1	9	9	9
19	5	3	1	8	5	6		5	6	8	1	5	4
20	7	4	1	9	2	9		4	6	9	1	7	2

B.2.4 ENVIRONMENT FACTORS

Table 29:Best-to-Others" (AB) and "Best-to-Worst" (AW) matrices of the Environment factors

	AB									AW							
	Environment factor									Environment factor							
ID	CP	CUS	CICT	EI	GS	RS	R	PR		CP	CUS	CICT	EI	GS	RS	R	PR
1	7	1	6	3	4	4	1	4		7	4	8	7	1	5	9	7
2	2	4	3	4	5	1	2	1		4	1	4	3	4	6	6	4
3	2	5	8	5	5	6	1	7		1	6	7	5	6	6	2	7
4	7	5	3	9	9	2	4	1		8	6	3	1	1	9	9	9
5	5	5	5	5	5	5	1	5		5	5	5	5	5	5	5	1
6	1	7	7	7	5	4	7	6		5	7	7	7	1	7	7	7
7	5	5	1	5	5	5	5	5		5	5	5	5	1	5	5	5
8	1	7	7	7	7	7	7	7		7	5	5	5	5	1	5	5
9	2	1	3	4	8	6	5	4		8	8	8	5	1	5	7	7
10	8	1	8	5	5	6	8	7		8	5	8	1	5	6	8	8
11	3	2	3	4	5	4	5	1		1	5	3	3	1	1	3	3
12	2	2	6	8	9	3	6	1		8	8	4	2	1	5	6	9
13	7	4	5	9	9	2	6	1		3	6	7	1	1	8	4	9
14	2	4	8	7	7	3	1	7		7	4	1	4	4	3	8	2
15	2	2	5	4	9	3	7	1		8	8	7	5	1	4	6	9
16	3	3	3	4	5	5	4	1		1	4	3	3	1	1	3	3
17	1	1	2	2	2	2	1	1		2	2	2	2	1	2	1	2
18	9	1	3	9	2	1	9	1		9	9	9	9	9	9	1	9
19	3	3	5	8	9	4	7	1		7	7	5	2	1	6	3	9
20	4	1	6	3	5	5	7	8		6	8	5	6	5	5	4	1

B.3 CREDAL RANKINGS

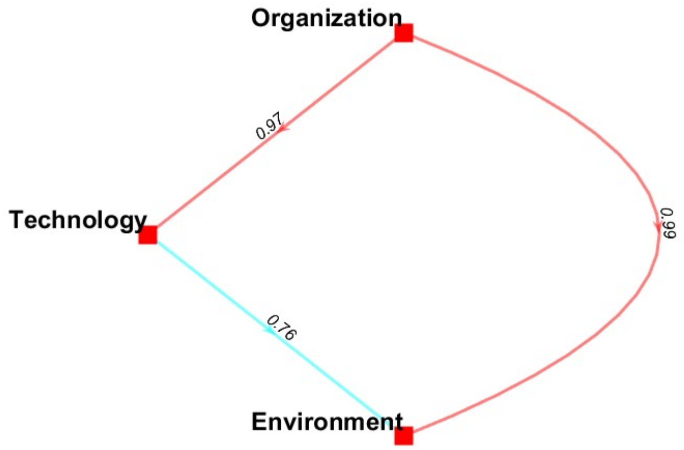


Figure 36: Categories' Credal Ranking

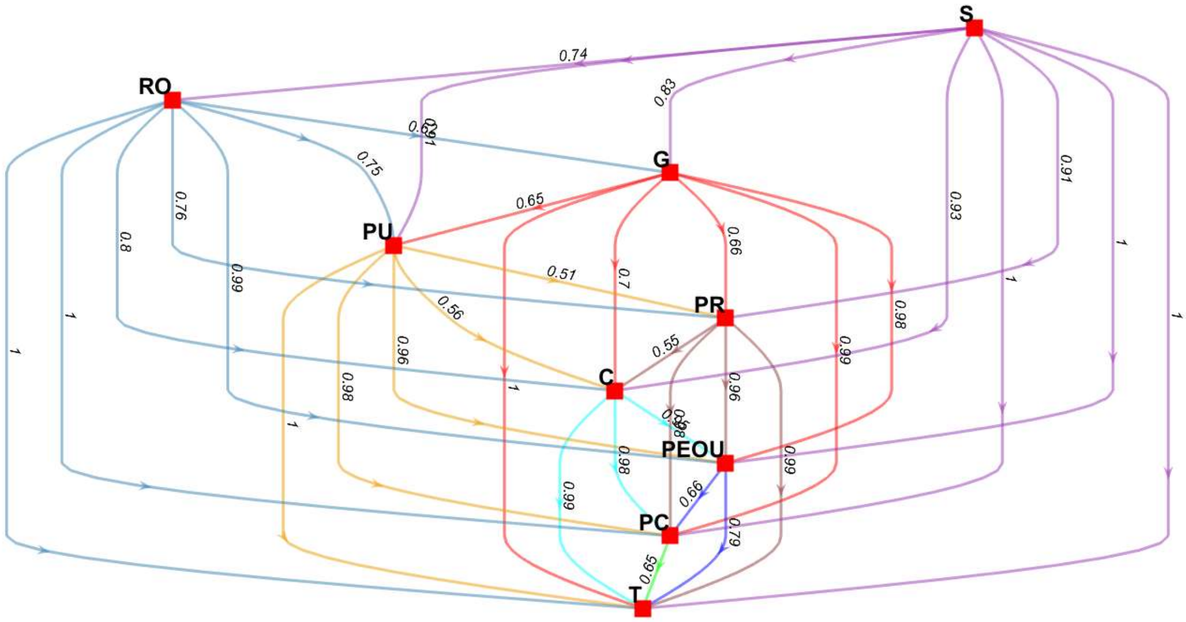


Figure 37: Credal Ranking of the technological factors

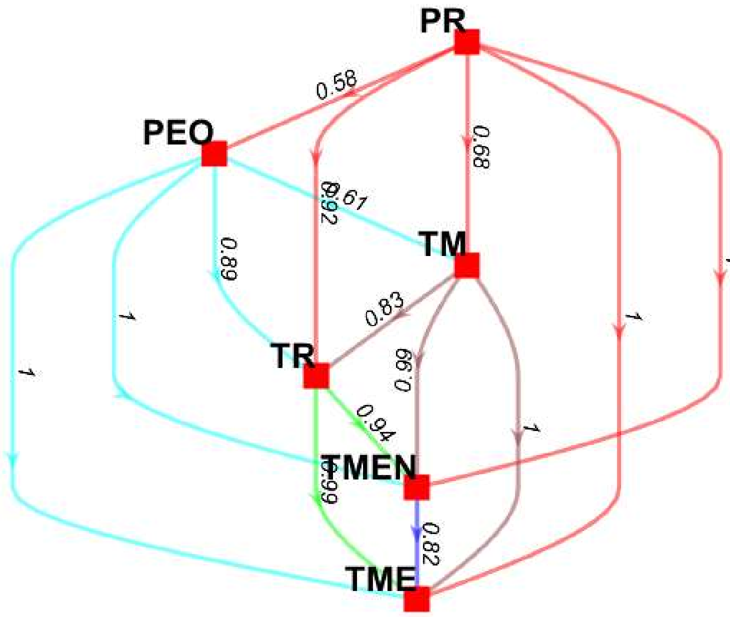


Figure 38:Credal Ranking of the organizational factors

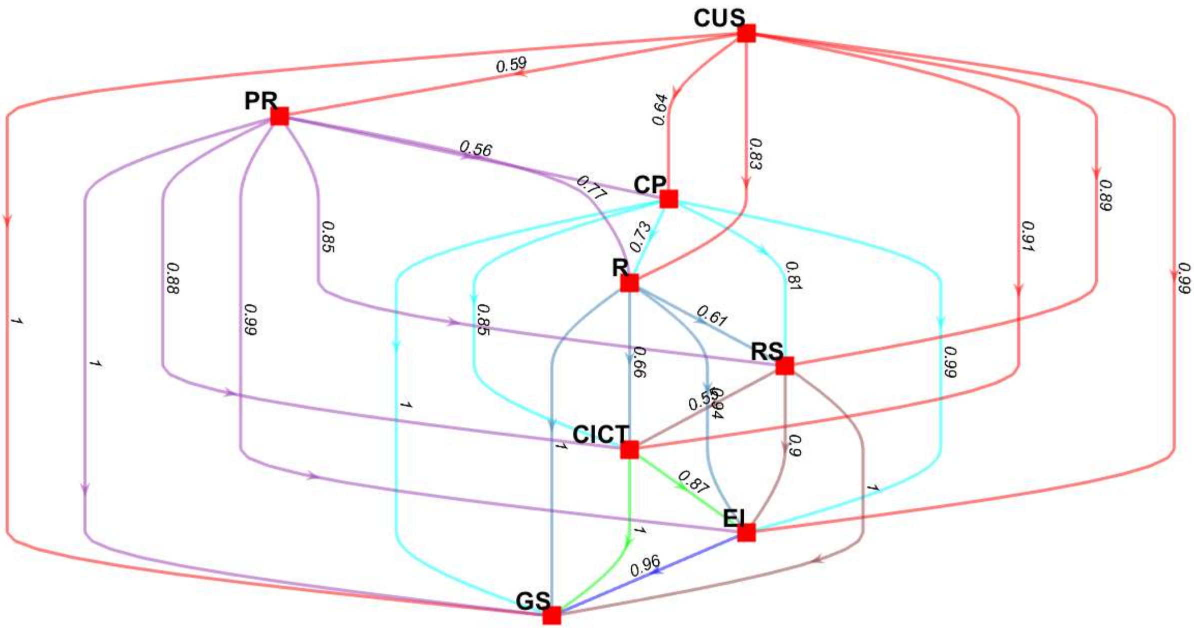


Figure 39:Credal Ranking of the environmental factors

C. MANN-WHITNEY U TEST

C.1 MATLAB IMPLEMENTATION

function f = MWW_Trial(filename1,filename2)

#I assign two variables to the matrices containing the weights of the Dutch and Italian sample, which I had previously stored in csv files

a=csvread(filename1);

b=csvread(filename2);

#I compute the size of one of the matrix, to know how many column (and hence, factors) I have to go through

```
[m,n]=size(a);
x=[];
```

#I cycle through the columns of the two matrices and I calculate the p-value corresponding to each column (factor)'s set of weights, and I store them in a vector x, which is the function's output

```
for i = 1:1:n
    temp=ranksum(a(:,i),b(:,i));
    x(i)=temp;
end
f=x;
end
```

C.2 INPUTS TO THE MANN-WHITNEY U TESTS

C.2.1 TOE

Table 30:Bayesian BWM's computed category weights for the Dutch sample

NL	Category		
ID	Technology	Organization	Environment
1	0.18430996	0.57639907	0.23929097
2	0.418628543	0.332554434	0.248817025
3	0.213016084	0.626559953	0.160423963
4	0.313773794	0.262810678	0.423415527
5	0.166151987	0.554430689	0.279417323
6	0.354122661	0.526274236	0.119603106
7	0.275288226	0.470679055	0.254032717
8	0.425364248	0.327681556	0.246954196

Table 31:Bayesian BWM's computed category weights for the Italian sample

IT	Category		
ID	Technology	Organization	Environment
1	0.344768702	0.183115339	0.472115957
2	0.281369203	0.334505485	0.384125311
3	0.413687166	0.441004828	0.145308003
4	0.308444603	0.53257159	0.158983806
5	0.310202324	0.520219692	0.169577983

IT	Category		
ID	**Technology**	**Organization**	**Environment**
6	0.301791126	0.488655572	0.209553301
7	0.367551409	0.357773146	0.274675444
8	0.242355261	0.553459602	0.204185137
9	0.316636142	0.493269355	0.190094503
10	0.315599079	0.193250004	0.491150918

C.2.2 TECHNOLOGY FACTORS

Table 32:Bayesian BWM's computed Technology factors weights for the Dutch sample

NL	Technology Factor								
ID	C	G	PC	PEOU	PU	PR	RO	S	T
1	0.1116	0.1123	0.0808	0.1024	0.1235	0.1306	0.1141	0.1528	0.0720
2	0.1013	0.1147	0.0884	0.1053	0.1184	0.1280	0.1196	0.1381	0.0862
3	0.1150	0.1230	0.0874	0.0988	0.1342	0.1159	0.1212	0.1406	0.0640
4	0.1125	0.0999	0.0887	0.1032	0.1174	0.1385	0.1188	0.1346	0.0863
5	0.1146	0.1187	0.0536	0.1024	0.1293	0.1258	0.1240	0.1427	0.0888
6	0.1136	0.1144	0.0824	0.1016	0.1193	0.1278	0.1209	0.1410	0.0791
7	0.1103	0.1110	0.0807	0.0988	0.1157	0.1333	0.1266	0.1459	0.0776
8	0.1307	0.1245	0.0767	0.0910	0.1041	0.1353	0.1297	0.1530	0.0549

Table 33:Bayesian BWM's computed Technology factors weights for the Italian sample

IT	Technology Factor								
ID	C	G	PC	PEOU	PU	PR	RO	S	T
1	0.1048	0.1086	0.0914	0.1106	0.1236	0.1190	0.1368	0.1282	0.0772
2	0.1145	0.1415	0.1037	0.0792	0.1121	0.1013	0.1251	0.1166	0.1061
3	0.1181	0.1226	0.0885	0.0773	0.1081	0.1134	0.1293	0.1307	0.1120
4	0.1106	0.1183	0.0960	0.0976	0.1144	0.0968	0.1384	0.1228	0.1050
5	0.1219	0.1229	0.0687	0.0963	0.1224	0.1081	0.1228	0.1270	0.1098
6	0.1114	0.1186	0.0949	0.0991	0.1150	0.1044	0.1277	0.1227	0.1061
7	0.1085	0.1161	0.0939	0.0956	0.1123	0.1142	0.1228	0.1205	0.1160
8	0.1111	0.1438	0.0920	0.0771	0.1089	0.1105	0.1216	0.1258	0.1092
9	0.1036	0.1156	0.0842	0.0962	0.1306	0.1025	0.1231	0.1321	0.1120
10	0.1008	0.1048	0.0903	0.0974	0.1109	0.1221	0.1507	0.1418	0.0812

C.2.3 ORGANIZATION FACTORS

Table 34:Bayesian BWM's computed Organization factors weights for the Dutch sample

NL	Organization Factor					
ID	**PEO**	**PR**	**TR**	**TMEN**	**TME**	**TMS**
1	0.1684	0.1995	0.1696	0.1622	0.1001	0.2002

NL	Organization Factor					
ID	**PEO**	**PR**	**TR**	**TMEN**	**TME**	**TMS**
2	0.1382	0.1834	0.2058	0.1461	0.1504	0.1762
3	0.2059	0.2334	0.1537	0.1399	0.1444	0.1227
4	0.1658	0.1850	0.1754	0.1152	0.1817	0.1770
5	0.1690	0.2353	0.1778	0.0886	0.1022	0.2271
6	0.1554	0.1682	0.1764	0.1301	0.1181	0.2518
7	0.1583	0.1854	0.1715	0.1396	0.1462	0.1990
8	0.1625	0.2067	0.2319	0.0959	0.1455	0.1575

Table 35:Bayesian BWM's computed Organization factors weights for the Italian sample

IT	Organization Factor					
ID	PEO	PR	TR	TMEN	TME	TMS
1	0.2302	0.2056	0.1971	0.0992	0.0732	0.1948
2	0.1959	0.1734	0.1728	0.1399	0.1129	0.2052
3	0.1922	0.1831	0.2057	0.1446	0.1021	0.1723
4	0.2525	0.1740	0.1664	0.1210	0.1218	0.1642
5	0.2017	0.1931	0.1925	0.1630	0.0737	0.1760
6	0.1896	0.1815	0.1740	0.1313	0.1320	0.1916
7	0.2136	0.2208	0.1694	0.1355	0.0857	0.1750
8	0.2247	0.2014	0.1662	0.1449	0.0710	0.1918
9	0.2196	0.2098	0.1449	0.1512	0.0929	0.1816
10	0.1716	0.1990	0.2361	0.1015	0.1629	0.1289

C.2.4 ENVIRONMENT FACTORS

Table 36:Bayesian BWM's computed Environment factors weights for the Dutch sample

NL	Environment factors							
ID	CP	CUS	CICT	EI	GS	RS	R	PR
1	0.1348	0.1048	0.1127	0.0845	0.0825	0.1703	0.1558	0.1546
2	0.1250	0.1318	0.1108	0.0995	0.1019	0.1457	0.1431	0.1422
3	0.1287	0.1262	0.1098	0.0646	0.0634	0.1744	0.1568	0.1760
4	0.1306	0.1275	0.1154	0.0988	0.0972	0.1468	0.1601	0.1236
5	0.1114	0.1372	0.1252	0.0686	0.0672	0.1773	0.1287	0.1844
6	0.1595	0.1301	0.0864	0.0875	0.0858	0.1495	0.1802	0.1210
7	0.1374	0.1334	0.1114	0.0897	0.0815	0.1512	0.1417	0.1537
8	0.1482	0.1453	0.1136	0.0734	0.0652	0.1544	0.1174	0.1825

Table 37:Bayesian BWM's computed Environment factors weights for the Italian sample

IT	Environment factors							
ID	CP	CUS	CICT	EI	GS	RS	R	PR
1	0.1329	0.1546	0.1296	0.1261	0.0777	0.1077	0.1382	0.1331
2	0.1495	0.1496	0.1287	0.1195	0.0820	0.1187	0.1196	0.1323
3	0.1402	0.1526	0.1430	0.1209	0.0805	0.1109	0.1207	0.1310
4	0.1623	0.1501	0.1287	0.1195	0.0917	0.0992	0.1194	0.1291
5	0.1513	0.1672	0.1391	0.1177	0.0684	0.1023	0.1205	0.1334
6	0.1388	0.1625	0.1298	0.1098	0.0935	0.1116	0.1208	0.1332
7	0.1373	0.1687	0.1339	0.1201	0.0791	0.1031	0.1166	0.1412
8	0.1518	0.1645	0.1303	0.1180	0.0661	0.1084	0.1119	0.1491
9	0.1382	0.1625	0.1347	0.1210	0.0800	0.1008	0.1207	0.1420
10	0.1457	0.1741	0.1270	0.1295	0.0916	0.1108	0.1116	0.1097

D. SURVEY's OPEN QUESTION

In the present section, the five responses that have been submitted by this study's participants to the open question "Which issues is your company currently facing and which of these issues would you expect blockchain to solve?" are presented.

1. "Constant traceability of the goods and money between supplier and buyer"

2. "Better information sharing. delivery time reduction. internal process optimization"

3. "Streamlining and tracking processes"

4. "Excessive transactions"

5. "Blockchain MAY have a role in an eco-system with a very specific (and limited) objective. This can still be crucial. in particular as an enabler (long term) to completely change business structures and processes. Why is it that nobody seems to understand the very basics of blockchain and that it is just an embedded methodology (with a very limited application scope) requiring a genius eco-system (socio-tecnical)around to really make a difference."