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# Blockchain adoption in operations and supply chain management: empirical evidence from an emerging economy

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**ABSTRACT**

The adoption of technologies by the operations and supply chain management (OSCM) field is leading to extraordinary disruptions. And with the rapid emergence of cutting-edge and more disruptive technologies, the OSCM is striving to take advantage of such innovations, but they are bringing in their wake a number of challenges. One of those disruptive technologies is blockchain, which is increasingly accepted in virtually all industries. This study aims to investigate the blockchain technology (BCT) adoption behaviour and possible barriers in the Brazilian OSCM context. We developed a model drawing on the unified theory of acceptance and use of technology (UTAUT) model, the supply chain literature, and the emerging literature on BCT. We empirically validated the proposed model with Brazilian operations and supply chain professionals by using the partial least squares structural equation modelling (PLS-SEM). Our findings revealed that facilitating conditions, trust, social influence, and effort expectancy are the most critical constructs that directly affect BCT adoption. Unexpectedly, performance expectancy appeared not decisive in terms of predicting BCT adoption. This study contributes to advancing and stimulating the theory about BCT adoption behaviour in supply chains, as well as important managerial implications, which may be more critical for emerging economies.

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Blockchain technology; adoption; barriers; UTAUT; emerging economy; trust

## 1. Introduction

With the unparalleled disruptions that the operations and supply chain management (OSCM) field is experimenting (Queiroz, Ivanov, et al. 2020; Ivanov and Dolgui 2020a, 2020b), organisations are challenged to adopt critical technologies to face challenges, improve performance, and gain competitive advantage. Most of these challenges are attributed to the rapid emergence of the information and communication technologies (ICTs), particularly in the Industry 4.0 era (Hahn 2020). As one of the most disruptive technologies that have emerged recently, blockchain (Koh, Orzes, and Jia 2019) – Also called the blockchain Technology (BCT) – is already radically transforming many business models (Y. Chen 2018; Dolgui et al. 2020), thus impacting not only production systems and supply chains (SCs) (Ivanov, Dolgui, and Sokolov 2018; Pournader et al. 2020; Queiroz, Fosso Wamba, et al. 2020), but also the society as a whole (Aste, Tasca, and Di Matteo 2017; Pazaitis, De Filippi, and Kostakis 2017). The BCT consists of a distributed ledger in which the transactions are organised in blocks and linked each other into a chain (Risius and Spohrer 2017). It operates in a peer-to-peer network; that is, the transactions are validated and recorded by consensus (Y. Chen 2018). The capacity of the BCT to transform the SCs and production systems has aroused the interest of a significant number of practitioners and scholars (Schmidt and Wagner 2019; Wang et al. 2019; Chang, Iakovou, and Shi 2020; Dolgui et al. 2020; Fosso Wamba, Queiroz, and Trinchera 2020; Koh, Dolgui, and Sarkis 2020; Pournader et al. 2020; Vatankhah Barenji et al. 2020).

In this regard, considering the recent literature on the technology adoption, there is a great debate about the adoption of cutting-edge technologies (Wang, Wang, and Yang 2010; Shin, Park, and Lee 2018; Yeh and Chen 2018), especially in emerging economies (Ahmadi et al. 2018; Mital et al. 2018; Raut et al. 2018; Karamchandani, Srivastava, and Srivastava 2019), and in supply chain management contexts (Kamble, Gunasekaran, and Arha 2019; Queiroz and Fosso Wamba 2019; Fosso Wamba, Queiroz, and Trinchera 2020; Wong et al. 2020). For instance, Raut et al. (2018) showed that trust, management style, technology innovation, risk analysis, and perceived risk in IT security influence cloud computing

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adoption in the Indian context. In another study, Ahmadi et al. (2018) showed that system affiliation, mimetic pressure competitors, normative pressure, and employees' information system knowledge affect the adoption of information systems by hospitals in Malaysia. Also, Kamble, Gunasekaran, and Arha (2019) found that perceived usefulness, attitude, and perceived behaviour control are essential variables for BCT adoption in India.

The highly disruptive potential of BCT has led to an increased interest in studying this technology in a good number of contexts. Thus, from different angles, blockchain is being investigated in the context of supply chain management (SCM) (Kshetri 2018; Queiroz, Telles, and Bonilla 2019; Rahmanzadeh, Pishvaee, and Rasouli 2019; Li et al. 2020; Wamba and Queiroz 2020). For instance, blockchain-enabled SCM has been investigated in industries such as transport and logistics (Koh, Dolgui, and Sarkis 2020; Pournader et al. 2020), multi-echelon SCs (Manupati et al. 2019), manufacturing (Aghamohammadzadeh and Fatahi Valilai 2020; Vatankhah Barenji et al. 2020), global trade (Chang, Iakovou, and Shi 2020), sustainable SCs (Saberi et al. 2019), humanitarian SCs (Dubey et al. 2020), etc.

Despite these recent advances, BCT is still in its infancy (Fosso Wamba et al. 2020), especially concerning individual adoption behaviour in supply chains. Very few empirical studies of BCT adoption in SCM were conducted recently (Kamble, Gunasekaran, and Arha 2019; Queiroz and Fosso Wamba 2019; Fosso Wamba, Queiroz, and Trinchera 2020; Wong et al. 2020). In addition, the blockchain adoption literature that is specifically focused on the effect of trust in the intention to adopt is scarce (Queiroz and Fosso Wamba 2019; Wong et al. 2020), especially in emerging economies. Furthermore, a deeper understanding of the use of BCT by different industries, especially in the OSCM field, is yet to be provided. Besides, it is fundamental to have an in-depth understanding of the behaviour behind BCT adoption, considering the highly disruptive capacity of this technology (Wamba and Queiroz 2020) and its unprecedented impacts on supply chains (Ivanov 2019; Dolgui et al. 2020).

To bridge this gap, this study aims to identify and gather insights into the driving factors of and possible barriers to BCT adoption behaviour in the Brazilian OSCM context. Thus, our guiding research questions (RQ) are designed as follows: *RQ1. What is the prevailing BCT adoption behaviour in an emerging economy's supply chain environment? RQ2. What are the possible barriers to BCT adoption, and how will they be resolved?* Since BCT is a new technology, IT adoption theories are a suitable approach to understand the behaviour of its potential adopters in the supply chain context. Thus, to answer the questions mentioned above, this study proposes a model that is based on an altered version of the unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al. 2003) to understand blockchain adoption behaviours and possible barriers. Moreover, the proposed model is supported by essential studies from the emerging literature on BCT as well as by the supply chain literature.

We used the partial least squares structural equation modelling (PLS-SEM) (Hair et al. 2017) and have exploited data collected in a Brazilian OSCM context. We were conscious of the fact that unlocking and providing a deeper understanding of blockchain adoption barriers (Saberi et al. 2019) and blockchain adoption behaviour of OSCM professionals from an emerging economy would certainly stimulate and advance the related theory.

This study brings valuable contributions to OSCM and production research by proposing and validating a modified UTAUT applied to BCT in supply chains in an emerging economy. In addition, the comparison of our findings with the extant literature revealed significant differences in the variables that predict the intention to adopt blockchain. This, therefore, suggests that the cultural aspects (between countries) should be considered as a potential barrier. A singular contribution of this study here resides in that it demonstrates the importance of including cultural aspects in the new versions of the model.

This paper is organised as follows: In Section 2, we present the theoretical background, including BCT past and new developments, the integration of BCT with SCM, and the UTAUT model. Section 3 is dedicated to introducing the hypotheses and the proposed research model. In sequence, Section 4 draws the methodology adopted, followed by data analysis and findings in Section 5. Section 6 highlights the discussion, showing implications for theory and practice. Finally, Section 7 presents the main conclusions, limitations, and opportunities for future studies.

## 2. Theoretical background

In this section, we provide the theoretical underpinning for the past and new developments of BCT applications, the fundamentals of the supply chain management vision, and the integration of blockchain into supply chains. The section ends with a description of the role of technology acceptance models, highlighting specifically the unified theory of acceptance and use of technology (UTAUT) model.

### 2.1. Blockchain technology: past and new developments

The first appearance of blockchain technologies (BCTs) occurred in the bitcoin market (Nakamoto 2008; Derks, Gordijn, and Siegmann 2018), where it was expected to support transactions; but blockchain applications have since then outperformed this field to span other areas. Regarding the main characteristics of the BCT, each block has a unique hash number and also carries the hash of the previous block. This process connects all blocks into a chain. In addition, the blocks have a mechanism called Merkle root that stores all transaction information. Another essential characteristic is that there is the timestamp whose role is to record the duration of blocks. It saves transaction date and time, thus ensuring integrity, immutability, reliability, and trustworthiness, among others. In general, the validation of transactions is performed by consensus between the network members. The blocks linked into a chain allow the network members to trace any transaction's origin. In other words, the process through the supply chain is characterised by transparency and accountability, all of which tend to be improved (Kshetri 2018).

Many fields have been reporting the potential of BCT applications. For instance, Veuger (2018) studied BCT from a real estate perspective and showed that BCT had the potential to add preventive mediation, fraud prevention, efficiency, and transparency to real estate transactions. Viryasitavat et al. (2018) presented BCT as applied in business process management (BPM), considering its benefits for service composition in the Industry 4.0's landscape. The authors demonstrated that BCT could bring about reliability and trustworthiness to transfer and verify any transactions made by businesses and partners. Other studies have investigated BCT in contexts such as business and entrepreneurship. This is the case of Y. Chen (2018), who reported that BCT with tokens could democratise entrepreneurship and support innovations. If combined with IoT, BCT can strengthen cybersecurity and therefore improve privacy (Kshetri 2017). In terms of BCT benefits and challenges in supply chains (Dolgui et al. 2020; Wamba and Queiroz 2020), a few types of research have been carried out, but plenty of studies and experimentations are still going on.

### 2.2. Supply chain management and the integration with blockchain technologies

Like other areas, supply chain management (SCM) is not yet a universal concept with a commonly accepted definition. A suitable definition was provided by Stock and Boyer (2009), in which they highlight the importance of managing the relationships between the different members in a network, which is possible not only by considering the flow of materials, services, finance, etc. but also through value creation from all the stakeholders, namely the customers and the suppliers. Moreover, SCM has been studied through with different, but complementary angles (Carter, Rogers, and Choi 2015). According to the various identified perspectives, SCM can be viewed as a network; a complex adaptive system; a relative perspective depending on the node; and a system that can be divided into physical (i.e. suppliers, focal firm, final customer) and support entities (financial organisations, transportation, etc). SCM can also be viewed as a setting where the focal members can constrain the visible horizons. It should be noted that a visible horizon of the focal firm varies according to the distance (physical, cultural, closeness centrality) between angles (Carter, Rogers, and Choi 2015).

In this context, SCM networks commonly have several members, which renders relationships very complex. Besides, due to the unprecedented digitalisation of supply chains (Queiroz et al. 2019), BCT has the potential to disrupt all SCM business models and usher in more fluidity and visibility. Nonetheless, it is only recently that BCT has attracted the attention of scholars and practitioners (Aste, Tasca, and Di Matteo 2017; Pazaitis, De Filippi, and Kostakis 2017; Kshetri 2018; Queiroz, Telles, and Bonilla 2019; Rahmanzadeh, Pishvaee, and Rasouli 2019; Saberi et al. 2019; Fosso Wamba et al. 2020; Koh, Dolgui, and Sarkis 2020; Pournader et al. 2020) in the SCM field. SCM operations integrating BCT are recent, even though a large number of organisations are already adopting BCT for their operations (Kshetri 2018). Recently, the blockchain literature has definitely integrated the term 'operation' in the supply chain context (OSCM) (Choi and Luo 2019; Helo and Hao 2019; Wamba and Queiroz 2020) to highlight the several operations that are henceforth performed in the SCM field thanks to blockchain applications (e.g. product traceability, information sharing, transactions, etc.).

In this sense, several benefits of using BCT in OSCM can be achieved. For instance, product traceability (Lu and Xu 2017; R. Y. Chen 2018) is improved significantly, and this has been acknowledged in industries such as the wine sector, where product adulteration and counterfeiting are being overcome owing to BCT (Biswas, Muthukkumarasamy, and Tan 2017). So goes with the food industry, where there is a regular OSCM food traceability with BCT (Tian 2017), coupled with increased security and transparent traceability of the entire journey of a particular product across the chain. Also, BCT can leverage transparency in products traceability and services (Bai and Sarkis 2020).

In several other OSCM contexts, BCT has shown proof of outstanding support. Recently, as Dubey et al. (2020) were exploring the contribution of BCT in the humanitarian supply chain (HSC) context, they demonstrated its fundamental role in supporting disaster relief operations by leveraging the collaboration of the SC members, through swift-trust. Besides, Rodríguez-espíndola, Chowdhury, and Beltagui (2020) proposed an interesting framework combining BCT, artificial intelligence, and 3D printing for HSC. BCT was also studied in global SCM and international trade operations and transactions (Yoon et al. 2020), as well as in platform operations for rental services in SCMs, and it was found to play a vital role in supporting and ensuring trustworthiness between product/service providers and customers (Choi, Feng, and Li 2019).

Moreover, reinforcing the possible gains of this integration, previous research deployed considerable efforts to identify some of the main benefits of BCT in SCM-related fields (Manupati et al. 2019; Tozanlı, Kongar, and Gupta 2020; Yoon et al. 2020). Authors highlighted the following BCT advantages: increased transparency in operations and transactions (Kim and Laskowski 2017), accountability and trust (Zou et al. 2018; Vatankhah Barenji et al. 2020), the security of information (Tian 2017), fraud prevention (R. Y. Chen 2018), transparency (Biswas, Muthukkumarasamy, and Tan 2017; Lu and Xu 2017), operational efficiency (Aste, Tasca, and Di Matteo 2017), costs reduction (Kshetri 2018), among others. Despite such benefits, the current literature has just begun to tackle BCT adoption issues in the SCM field (Kamble, Gunasekaran, and Arha 2019; Queiroz and Fosso Wamba 2019; Fosso Wamba, Queiroz, and Trinchera 2020; Wong et al. 2020).

### *2.3. Unified theory of acceptance and use of technology model*

The literature concerning technology adoption models is rich (Davis 1989; Venkatesh and Davis 2000; Venkatesh et al. 2003; Venkatesh and Bala 2008; Venkatesh, Thong, and Xu 2012). A very widespread model dubbed unified theory of acceptance and use of technology model (UTAUT) is increasingly being used in research; it was first introduced by Venkatesh et al. (2003). Thereafter, many adoption contexts have relied on the UTAUT (Rana et al. 2016; Dwivedi, Rana, Jeyaraj, et al. 2017; Chua et al. 2018). The UTAUT model aimed to unify previous acceptance models described in the extant literature. Venkatesh et al. (2003) derived this model from the following models: theory of reasoned action (Fishbein and Ajzen 1975), technology acceptance model (Davis 1989), the model of PC utilisation proposed by (Thompson, Higgins, and Howell 1991), innovation diffusion theory (Rogers 1962; Moore and Benbasat 1991), the theory of planned behaviour (Ajzen 1991), motivational model (Davis, Bagozzi, and Warshaw 1992), social cognitive theory (Compeau and Higgins 1995), and the combination of the technology acceptance model with the theory of planned behaviour (Taylor and Todd 1995).

The UTAUT model is made of four main constructs (performance expectancy, effort expectancy, social influence, and facilitating conditions) that predict behavioural intention. In this vein, use behaviour is predicted by behavioural intention. The model is built on four moderators, namely: gender, age, voluntariness, and experience. Following the recent literature, we did not incorporate these moderators (Dwivedi, Rana, Janssen, et al. 2017; Dwivedi, Rana, Jeyaraj, et al. 2017) in our proposed model, as they cannot be applied to any context exerting good influence.

In a recent study of BCT adoption in SCM, Wong et al. (2020) applied a modified version of the UTAUT and found that performance expectancy, effort expectancy and trust had no significant positive effect on the behavioural intention to adopt blockchain in Malaysia. In another study using UTAUT as model's base, Queiroz and Fosso Wamba (2019) investigated the intention to adopt BCT for SCM in India and in the USA. The results obtained looked somewhat different from those reported by Wong et al. (2020), thus suggesting the existence of adoption disparities across countries. Concerning the barriers related to BCT adoption in SCM, various authors identified a number of headwinds. For example, Saberi et al. (2019), highlighted potential unfavourable factors with different natures: intra-organisational (e.g. lack of tools, knowledge), inter-organisational (e.g. collaboration, culture), external (e.g. lack of governmental policies and stakeholders involvement), and systems related (e.g. security, technology immaturity).

## 3. Hypotheses and research model development

We developed a research model (Figure 1) based on the UTAUT (Venkatesh et al. 2003; Venkatesh, Thong, and Xu 2012) variables to which we added the trust construct (Gefen, Karahanna, and Straub 2003; Alalwan, Dwivedi, and Rana 2017). The model, therefore, consists of five variables, assuming that they may more significantly affect the behavioural intention to adopt BCT. Moreover, in order to predict the intention to use blockchain in supply chains, UTAUT constructs have been successfully used (Queiroz and Fosso Wamba 2019; Nuryyev et al. 2020; Wong et al. 2020).

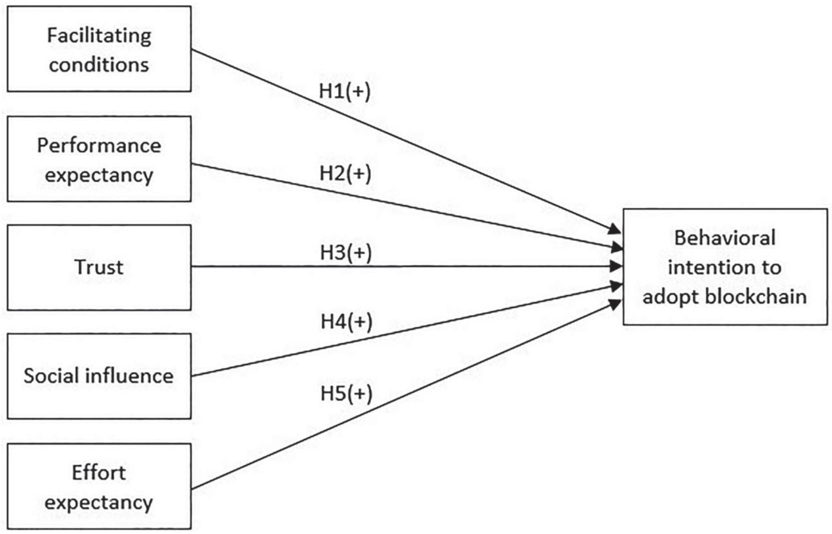


**Figure 1.** Research model.

### 3.1. Facilitating conditions, and performance expectancy

In the UTAUT model, facilitating conditionsand performance expectancy, have the following definitions. Facilitating conditions refer to 'the degree to which an individual believes that an organisational and technical infrastructure exists to support the use of the system' (Venkatesh et al. 2003, 453). Then, performance expectancy is defined as 'the degree to which an individual believes that using the system will help him or her to attain gains in job performance' (Venkatesh et al. 2003, 447).

The extant literature showed that 'facilitating condi tions' construct is a good predictor of the behavioural intention to adopt the technology (Venkatesh et al. 2003; Venkatesh, Thong, and Xu 2012; Hew et al. 2015; Rana et al. 2017). With regard to BCT, the facilitating conditions can be influenced by organisational support (Francisco and Swanson 2018), IT resources, cloud services, internet speed, amongst other factors. Similarly, the 'performance expectancy' construct is being recognised in the literature as a good predictor of technology adoption intention (Batara et al. 2017; Dwivedi, Rana, Jeyaraj, et al. 2017; Chua et al. 2018). In SCM with BCT, it is expected that both effort expectancy and performance expectancy impact the behavioural intention to adopt BCT (Francisco and Swanson 2018). Thus, productivity, efficiency (Kshetri 2018), and performance of professionals can be significantly improved as well. Therefore, we propose the following hypotheses:

H1: Facilitating conditions positively affect the behavioral intention to adopt blockchain.

H2: Performance expectancy positively affects behavioral intention to adopt blockchain.

### 3.2. The role of Trust and Social Influence and Effort Expectancy

The trust construct refers to

> the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party. (Mayer, Davis, and Schoorman 1995, 712)

Social influence refers to 'the degree to which an individual perceives that important others believe he or she should use the new system' (Venkatesh et al. 2003, 451). For instance, peers (Wang 2017), colleagues, and family members can significantly influence technology adoption. This is also true for social influence, which can affect effort expectancy and behavioural intention (Sung et al. 2015). Lastly, effort expectancy refers to 'the degree of ease associated with the use of the system' (Venkatesh et al. 2003, 450). Also, previous studies have seen in effort expectancy a good predictor of behavioural intention (Venkatesh et al. 2003; Alalwan, Dwivedi, and Rana 2017; Dwivedi, Rana, Jeyaraj, et al. 2017). Moreover, with BCT and smart contracts (Marsal-Llacuna 2017; Dolgui et al. 2020; Jabbar and Dani 2020), effort expectancy should be improved in supply chain operations.

Regarding the trust construct, the recent literature has highlighted its power in predicting the behaviour intention to adopt a technology (Alalwan, Dwivedi, and Rana 2017; Raut et al. 2018). If SCM mainstreams BCT, trust can generate more transparency and accountability between supply chain members (Kshetri 2018). Despite the complex nature of trust in SCM, a guaranteed level of security in transactions can enable BCT to bring in and enhance trust across the SCM network (Aste, Tasca, and Di Matteo 2017). As BCT generally makes transactions immutable, any reconciliation will be eliminated, thus supporting a unique form of truth (Aste, Tasca, and Di Matteo 2017). Hence, we propose the following hypotheses:

H3: Trust positively affects the behavioral intention to adopt blockchain.

H4: Social influence positively affects the behavioral intention to adopt blockchain.

H5: Effort expectancy positively affects the behavioral intention to adopt blockchain.

**Table 1.** Demographic profile.

| Items | *N* | % |
|---|---|---|
| *Age* | | |
| 18–25 | 21 | 11.41 |
| 26–33 | 35 | 19.02 |
| 34–41 | 42 | 22.83 |
| 42–49 | 58 | 31.52 |
| 50+ | 28 | 15.22 |
| *Gender* | | |
| Male | 135 | 73.37 |
| Female | 46 | 25.00 |
| Others | 3 | 1.63 |
| *Highest educational level* | | |
| Secondary | 5 | 2.72 |
| Bachelor degree | 60 | 32.61 |
| Postgraduate degree (Specialisation) | 80 | 43.48 |
| Postgraduate degree (Master/Ph.D.) | 39 | 21.19 |
| *Number of years working in the organisation* | | |
| Less than one year | 41 | 22.28 |
| 2–5 years | 62 | 33.70 |
| 6–10 years | 34 | 18.48 |
| 11–15 years | 12 | 6.52 |
| 16–20 years | 15 | 8.15 |
| Over 20 years | 20 | 10.87 |

## 4. Methodology

### 4.1. Sampling and questionnaire design

We used a questionnaire to survey the Brazilian OSCM professionals. Since our interest is related to the beha viour intention towards blockchain for OSCM, all types of blockchain were considered (e.g. public, private, consortium, hybrid) as well as their different uses (e.g. tokens, smart contracts, traceability systems, etc.). Therefore, we developed a survey in order to capture the views and opinions of OSCM practitioners about the rationale behind intending to adopt blockchain technologies. The questionnaire was adapted following previous scales validated by the extant literature. Variables such as performance expectancy, effort expectancy, social influence, facilitating conditions, and behavioural intention to use, were adapted from Alalwan, Dwivedi, and Rana (2017), Venkatesh et al. (2003), Venkatesh, Thong, and Xu (2012), while trust was adapted from Alalwan, Dwivedi, and Rana (2017), Gefen, Karahanna, and Straub (2003).

Data were collected via social networking sites (Gupta and George 2016; Queiroz and Telles 2018), including specifically LinkedIn. It is important to note that the respondents had not implemented any blockchain technology yet, and that their know-know concerning the topic was mainly based on different non technical sources (e.g. news, courses, adoption/implementation studies by practitioners discovering the technology). We filtered profiles on BCT know-how from the LinkedIn platform, which therefore enabled us to deal only with all respondents a certain level of know-know in BCT. Before sending the questionnaire to the respondents, it was tested using ten experienced supply chain professionals. We then measured the constructs by means of a 7-point Likert scale (i.e. '1 = strongly disagree' to '7 = strongly agree') (Leroux and Pupion 2018; Raut et al. 2018). Out of the 650 firms that were randomly selected for the survey, the ones that replied adequately helped us to obtain 184 useful responses, representing a response rate of 28.31%.

The respondents' demographic profile is presented in Table 1. Regarding the age distribution, the majority of participants fell in the age brackets 42–49 (31.52%) and 34–41 (22.83%). As for gender distribution, the male represented 73.37% of the responses. In terms of education, the highest level was a postgraduate degree (Specialisation), which accounted for almost half of the respondents (43.48%), followed by the bachelor's degree (32.61%). When classifying respondents by years of professional experience, we have those with 2–5 years of experience achieved (33.70%), followed by those with less than one year (22.28%). The recent Brazilian recession can justify this employees' turnover.

## 5. Data analysis and findings

The two main approaches of SEM are covariance-based (CB-SEM) and variance-based (VB-SEM) (Hair et al. 2014; Hair et al. 2017). The use of such approaches is justified when the study aims to confirm theories (Hair et al. 2014) by employing a covariance matrix for the sample. A popular VB-SEM approach is Partial Least Squares Structural Equation Modeling (PLS-SEM). As PLS-SEM uses much multiple regression analysis, it has good fit for exploratory studies (Hair et al. 2014) (like in our case), among other reasons for preferring PLS-SEM over CB-SEM: (i) small sample sizes; (ii) formative constructs; and (iii) non-normal data. In this study, we used

**Table 2.** Measurement items, Loading factors, Cronbach's alpha ($\alpha$), Composite reliability (CR), and Average variance extracted (AVE).

| Construct | Measurement items | Item | Loading | $\alpha$ | CR | AVE |
|---|---|---|---|---|---|---|
| BINT | I intend to use blockchain in the future. | BINT1 | 0.958 | 0.959 | 0.973 | 0.924 |
| | I predict I would use blockchain in the future | BINT2 | 0.957 | | | |
| | I plan to use blockchain in the future. | BINT3 | 0.969 | | | |
| EEXP | Learning how to use blockchain is easy for me. | EEXP1 | 0.854 | 0.902 | 0.931 | 0.773 |
| | My interaction with blockchain is clear and understandable. | EEXP2 | 0.956 | | | |
| | I find blockchain easy to use. | EEXP3 | 0.911 | | | |
| | It is easy for me to become skilful in using blockchain. | EEXP4 | 0.789 | | | |
| FCON | I have the necessary resources to use blockchain. | FCON1 | 0.857 | 0.863 | 0.908 | 0.713 |
| | I have the knowledge necessary to use blockchain. | FCON2 | 0.766 | | | |
| | Blockchain is compatible with other technologies I use. | FCON3 | 0.809 | | | |
| | I can get help from others when I have difficulties in using blockchain. | FCON4 | 0.936 | | | |
| PEXP | I find blockchain useful in my daily life. | PEXP1 | 0.923 | 0.903 | 0.931 | 0.772 |
| | Using blockchain increases my chances of achieving tasks that are important to me. | PEXP2 | 0.734 | | | |
| | Using blockchain helps me to accomplish tasks more quickly. | PEXP3 | 0.929 | | | |
| | Using blockchain increases my productivity. | PEXP4 | 0.913 | | | |
| SINF | People who are important to me think that I should use blockchain. | SINF1 | 0.841 | 0.837 | 0.902 | 0.755 |
| | People who influence my behaviour think that I should use blockchain. | SINF2 | 0.914 | | | |
| | People whose opinions I value prefer that I use blockchain. | SINF3 | 0.850 | | | |
| TRUS | I believe that blockchain is trustworthy. | TRUS1 | 0.913 | 0.946 | 0.958 | 0.822 |
| | I trust blockchain. | TRUS2 | 0.943 | | | |
| | I have no doubt on blockchain's reliability. | TRUS3 | 0.876 | | | |
| | I feel assured that legal and technological structures adequately protect me from blockchain-related problems. | TRUS4 | 0.879 | | | |
| | Blockchain has the ability to fulfil its task. | TRUS5 | 0.920 | | | |

Note: *BINT = Behavioural intention to adopt; *EEXP = Effort expectancy; *FCON = Facilitating conditions; *PEXP = Performance expectancy; *SINF = Social influence; **TRUS = Trust. Adapted from *(Venkatesh et al. 2003; Venkatesh, Thong, and Xu 2012; Alalwan, Dwivedi, and Rana 2017); **(Gefen, Karahanna, and Straub 2003; Alalwan, Dwivedi, and Rana 2017).

PLS-SEM (Hajli et al. 2015; Chen and Hung 2016; Mital et al. 2018; Popa, Soto-Acosta, and Perez-Gonzalez 2018), and precisely SmartPLS 3 (Ringle, Wende, and Becker 2015; Hair et al. 2017; Peng, Prybutok, and Xie 2020), to analyse the data collected. PLS-SEM has proved to be an adequate tool for data analysis in emerging subjects (Mital et al. 2018; Shin, Park, and Lee 2018), as it was the case here with data from supply chain professionals to study BCT adoption behaviour and adoption barriers in Brazil. Therefore, our study being of exploratory nature for investigating BCT in Brazilian supply chains, PLS-SEM definitely appears as a suitable approach.

### 5.1. Measurement model

We measured the reliability of the scales by means of the Cronbach's alpha, composite reliability, and average variance extracted. Table 2 highlights the results of Cronbach's alpha and composite reliability were higher than the 0.70 threshold recommended in the literature (Nunnally 1978; Hair et al. 2017), and the average variance extracted outperformed the 0.50 threshold (Hair et al. 2014; Hair et al. 2017). In addition, Table 3 reports the factors loadings, the results of which ensure convergent validity (Fornell and Larcker 1981), since all items loadings outperformed the 0.70 threshold (Fornell and Larcker 1981; Hair et al. 2017). Finally, in order to assess the discriminant validity of constructs, all constructs were analysed based on the Fornell-Larcker criterion. Thus, the AVE square root of all constructs should be higher than the correlations between this particular construct and all other constructs. The results (Table 3) reported a discriminant of constructs (Fornell and Larcker 1981) because the diagonal values outperformed the correlations between the particular construct and all other constructs.

**Table 3.** Discriminant validity.

| Construct | BINT | EEXP | FCON | PEXP | SINF | TRUS |
|---|---|---|---|---|---|---|
| BINT | **0.961** | | | | | |
| EEXP | 0.524 | **0.879** | | | | |
| FCON | 0.570 | 0.626 | **0.844** | | | |
| PEXP | 0.364 | 0.413 | 0.599 | **0.879** | | |
| SINF | 0.727 | 0.524 | 0.618 | 0.592 | **0.869** | |
| TRUS | 0.600 | 0.571 | 0.642 | 0.646 | 0.721 | **0.906** |

Note: BINT = Behavioural intention to adopt; EEXP = Effort expectancy; FCON = Facilitating conditions; PEXP = Performance expectancy; SINF = Social influence; TRUS = Trust.

#### 5.1.1. Common method and nonresponse bias

When a single respondent is used, a common method bias (CMB), also known as common method variance (CMV), can appear (Chua et al. 2018; Dubey et al.

2019). That is, the relationship between the exogenous and endogenous variables can be inflated (Podsakoff and Organ 1986). Method biases are generally avoided by means of several strategies, including the selection of respondents with some experience in the subject (MacKenzie and Podsakoff 2012). In order to examine if our model could be inflated, we performed the Harman's single factor test (Podsakoff and Organ 1986; Wong et al. 2020) by using IBM SPSS. Our result for CMB was 49.40%, which is lower than the 50% threshold (Bhatia and Kumar Srivastava 2019; Kamble, Gunasekaran, and Arha 2019; Wong et al. 2020), thus demonstrated that CMB was not a concern in our model (Appendix 1). In addition, we tested the nonresponse bias (Armstrong and Overton 1977; Lin 2014; Dubey et al. 2019) of the early (89%) and late (11%) respondents by applying an independent t-test (Ramkumar et al. 2019; Singh et al. 2019), coupled with the ANOVA analysis (Salem et al. 2019). We found no significant differences at a 5% level of significance (Bhatia and Kumar Srivastava 2019) (Appendix 2). Therefore, our model was not affected by any nonresponse bias.

### 5.2. Structural model assessment

We employed SmartPLS 3 (Ringle, Wende, and Becker 2015; Fadaki, Rahman, and Chan 2019; Peng, Prybutok, and Xie 2020) to test the hypotheses of the model. Firstly, in order to evaluate the predictive power of the model, we employed the Stone-Geisser's $Q^2$ test (Stone 1974; Hair et al. 2017; Khor and Hazen 2017; Sreedevi and Saranga 2017; Bhatia and Kumar Srivastava 2019; Ramkumar et al. 2019). We then used a blindfolding method (Shmueli et al. 2016; Khor and Hazen 2017; Sreedevi and Saranga 2017), which is based on a cross-validated redundancy, by estimating the model and its parameters. According to Sharma et al. (2018, 5),

> This metric builds on the blindfolding procedure, which omits single points in the data matrix, imputes the omitted elements, and estimates the model parameters. Using these estimates as input, the blindfolding procedure predicts the omitted data points. This process is repeated until every data point has been omitted and the model reestimated.

$Q^2$ values above 0 represent the power prediction of the model. Moreover, according to Hair et al. (2019), the rule of thumb for $Q^2$ values suggests that $Q^2$ values higher than 0.25 and 0.50 depict a medium and a large predictive relevance of the PLS-path model, respectively. We obtained a $Q^2 = 0.538$, which clearly illustrates a predictive relevance of the model. We further ran the PLSpredict test (Shmueli et al. 2016; Ramkumar et al. 2019), using a technique based on holdout and sample training to assess the predictions from the PLS model (Ramkumar et al. 2019). The $Q^2$ (0.577) of the holdout test confirmed the robustness of the prediction model (Please see the PLS Predict details in Appendix 3) (Table 4).

**Table 4.** Cross-validation and holdout test.

| | | | |
|---|---|---|---|
| Blindfolding | | | |
| LV | SSO | SSE | $Q^2$ (= 1-SSE/SSO) |
| BINT | 552 | 255.109 | 0.538 |
| PLSpredict | | | |
| LV | RMSE | MAE | $Q^2$_predict |
| BINT | 0.658 | 0.521 | 0.577 |

Note: LV = Latent variable; SSO; MAE = Mean absolute error; RMSE = Root mean squared error; SSE = Sum of squares of prediction errors; SSO = Sum of squares of observations.

#### 5.2.1. Hypotheses model assessment

By applying our PLS model (Table 5), we sook to assess the likelihoodness of the various hypotheses. H1 theorised that facilitating conditions positively affect the behavioural intention to adopt blockchain; it was eventually supported as well ($\beta = 0.183$, $p = 0.013$), thus demonstrating that facilitating conditions have a significant influence on behavioural intention to adopt BCT.

In H2, we argued that performance expectancy positively affects the behavioural intention to adopt blockchain. Surprisingly, the results showed a significant negative effect ($\beta = -0.222$, $p = 0.000$). This is an unexpected result but supported by the recent blockchain adoption article (Wong et al. 2020). Consequently, the H2 was not supported.

In H3, we hypothesised that trust positively affects the behavioural intention to adopt blockchain. This hypothesis was supported ($\beta = 0.140$, $p = 0.042$), but it should be noted that this result was contrary to the one reported by Wong et al. (2020) for BCT adoption in the Malaysian context. Therefore, the Brazilian context is quite conducive for a significant influence of trust on the intention to adopt BCT.

With regard to the effect of social influence on BCT, H4 postulated a positive impact on the behavioural intention to adopt blockchain. The results ($\beta = 0.582$, $p = 0.000$) strongly supported this hypothesis. This outcome is in line with most conclusions regarding the rationale behind the intention to adopt blockchain.

Finally, H5 assumed that effort expectancy positively affects the behavioural intention to adopt blockchain. The results ($\beta = 0.119$, $p = 0.040$) showed a significant positive effect, leading to the acceptance of this hypothesis. However, the finding from the verification of this hypothesis contrasts with the outcome reported by Wong et al. (2020) for the Malaysian context.

**Table 5.** Path coefficients, standard deviation, t-statistics, and *p*-values.

| Hypothesis | Path | Coefficient | Standard deviation | *t*-statistics | *p*-values | Decision |
|---|---|---|---|---|---|---|
| H1 | FCON → BINT | 0.183 | 0.073 | 2.482 | 0.013 | Supported |
| H2 | PEXP → BINT | −0.222 | 0.058 | 4.070 | 0.000 | Not supported |
| H3 | TRUS → BINT | 0.140 | 0.071 | 2.038 | 0.042 | Supported |
| H4 | SINF → BINT | 0.582 | 0.072 | 8.174 | 0.000 | Supported |
| H5 | EEXP → BINT | 0.119 | 0.057 | 2.058 | 0.040 | Supported |

Note: BINT = Behavioural intention to adopt blockchain; EEXP = Effort expectancy; FCON = Facilitating conditions; PEXP = Performance expectancy; SINF = Social influence; TRUS = Trust.

### *5.2.2. Structural model's results*

We measured the structural model using regression analysis (Hair et al. 2017; Das 2018). Our proposed model achieved a good explanation (58.1%) of variation in the intention to adopt blockchain for Brazilian supply chains. In this regard, our $R^2$ 0.581 was in line with the original UTAUT (Venkatesh et al. 2003), and with recent studies of blockchain adoption in different countries. For instance, Kamble, Gunasekaran, and Arha (2019) studied supply chains in India by applying variables such as the technology acceptance model, the technology readiness index and the theory of planned behaviour); for Malaysian supply chains, (Wong et al. 2020) used a modified UTAUT.

## 6. Discussion

This study established a modified UTAUT model to enable a better understanding of the rationale behind and possible barriers to blockchain adoption among OSCM professionals operating in Brazil. Empirical results unveiled the model's value. Additionally, we identified the primary variable that can be a barrier to the adoption process. Discussions of the determinants affecting blockchain adoption were made, with consideration for the research implications in terms of theory and practice.

### *6.1. Implications for theory*

Our study hauls important implications and contributions to the OSCM theory. As an emerging and hot topic, blockchain has been the subject of very few empirical studies in operations, production, and supply chain fields (Fosso Wamba et al. 2020; Fosso Wamba, Queiroz, and Trinchera 2020; Wong et al. 2020), especially as regards BCT adoption (Kamble, Gunasekaran, and Arha 2019; Queiroz and Fosso Wamba 2019; Fosso Wamba, Queiroz, and Trinchera 2020; Wong et al. 2020). To investigate an essential aspect of BCT adoption in OSCM with convincing results, our study proposed and validated an extended and altered version of the UTAUT model (Venkatesh et al. 2003), with the inclusion of the trust construct (Gefen, Karahanna, and Straub 2003), in the Brazilian OSCM context. In line with the original UTAUT, the proposed model provided a great explanation (R square adjusted = 0.58) of the intention of supply chain professionals in Brazil to adopt blockchain. Regarding the results obtained, most of which are consistent with and even similar to those of recent studies that investigated BCT adoption in the SCM context (Kamble, Gunasekaran, and Arha 2019; Wong et al. 2020) on blockchain adoption in other representative emerging economies, namely Malaysia and India). Moreover, following studies that used facilitating conditions (H1) in technology adoption (Venkatesh et al. 2003; Venkatesh, Thong, and Xu 2012; Hew et al. 2015; Rana et al. 2017), our model showed that facilitating conditions positively affect the behavioural intention to adopt a technology (in this case, BCT). In this vein, it means that both the organisational infrastructure and IT influence the OSCM professionals' expectancy.

Similarly, trust (H3) (Gefen, Karahanna, and Straub 2003; Raut et al. 2018) appeared to considerably affect the prediction of the behavioural intention to adopt blockchain in the OSCM context. However, our finding on trust did not match the result obtained by Wong et al. (2020) for blockchain adoption in the Malaysian SCM field. Better still, our outcome reinforces the positive influence of trust on collaborations, on resilience in humanitarian operations (Dubey et al. 2020), SCM platform operations (Choi, Feng, and Li 2019), as well as on the relationship between SCM members (Pournader et al. 2020), among others.

Concerning the social influence (H4) construct, it was proved to be a good predictor of the behavioural intention to adopt BCT (Sung et al. 2015). This finding suggests that coworkers (colleagues) influence the behaviour toward blockchain adoption in OSCM in the Brazilian context. On the other hand, this finding is in line with a previous result concerning SCM in India, another emerging representative economy (Queiroz and Fosso Wamba 2019), but also in Taiwan (Nuryyev et al. 2020).

Contrary to previous literature on the power of performance expectancy (H2) in predicting directly the behavioural intention to adopt a technology (Venkatesh et al. 2003; Maruping et al. 2017; Makanyeza and Mutambayashata 2018), surprisingly, we identified a significant negative effect of this construct (performance expectancy) on blockchain adoption in Brazilian OSCM. This unexpected result is in line with a recent study on blockchain adoption in SCM in Malaysia (Wong et al. 2020) and in other contexts, like intention adoption for e-government services (Mensah 2019) and eHealth services (Koivumäki et al. 2017).

This work is among the first studies on OSCM blockchain adoption that reported this intriguing behaviour. This result suggests that in Brazil, supply chain actors cannot adopt BCT just because of its potential to improve productivity. In addition, results revealed that effort expectancy (H5) has a direct effect on BCT adoption. In other words, the ease of use of BCT act in favour of the adoption of this technology.

Given the unexpected result concerning the performance expectancy, this variable appears as a possible barrier to BCT adoption by Brazilian OSCM professionals. In addition, following recent papers on SCM-related blockchain adoption in emerging economies (Queiroz and Fosso Wamba 2019; Wong et al. 2020), it is clear that national particularities (e.g. culture) can lead to different results based on the various variables considered. In this vein, our finding on performance expectancy, which describes it as a possible strong barrier, suggests the existence of other productivity-related variables that could impede BCT adoption in Brazil OSCM context. These potential barriers, like other variables, had already been identified by a recent study (Saberi et al. 2019) as headwinds to BCT adoption. Ultimately, national circumstances or peculiarities may increase or downgrade the importance of some variables considered for BCT adoption. This finding carries along an interesting theoretical implication to be investigated in the future. In addition, we believe that the adoption intention behaviour can differ from one industry to the other with the same country.

### *6.2. Implications for practice*

The findings of this study bring valuable insights and implications for OSCM, production managers, practitioners, decision-makers, and all those involved in the adoption of any cutting-edge technology, including BCT. Our results showed that, while most emerging economies consider infrastructure as a challenge, the facilitating conditions positively influence blockchain adoption in Brazil's supply chains. This result suggests to managers that they should heavily invest in organisational capabilities and infrastructure (e.g. internet speed, cloud services, integration with SCM, training, among others).

Similarly, the significant effect of trust should be a focus of attention for managers and OSCM practitioners. This means that they should be interested in why and to which extent supply chain professionals having confidence in BCT can impact on these actors' towards BCT adoption. Considering our finding on a positive impact of trust on the intention to adopt BCT, managers should continuously monitor OSCM in order to identify behaviours that can affect trusting BCT quickly. For example, Babich and Hilary (2020) highlighted that trust for blockchain in SCs is essential not only for business models, but also for operations. According to the authors, '[ . . . ] cannabis, fish, and coffee blockchain applications rely on the validation strength of the technology'.

In addition, trusting blockchain entails the availability of and confidence in the information that is shared between the members of the supply chain. Moreover, managers need to deploy efforts to ensure consensus for blockchain adoption and use, while effectively guaranteeing trust in transactions (Schmidt and Wagner 2019). The validation of transactions actually leverages and builds on trust between SC members. This leads to a need for trusting process integrity without necessarily understanding the whole technical features, and for relying on information sharing through supply chains, etc. (Babich and Hilary 2020).

In the same light, there is a positive effect of social influence by supply chain members on BCT adoption and of effort expectancy for BCT on supply chain operations; therefore, OSCM and production managers have to fully grasp such relationships. Lastly, the performance expectancy appeared as a possible barrier to directly predicting BCT adoption. In these conditions, managers and practitioners need to invest (in strategies or other training) for a full awareness of blockchain's performance in SCM operations, and the ease of use of the technology.

## 7. Conclusion and limitations

This study sook to examine the blockchain adoption and barriers in operations and supply chains in an emerging representative country, namely Brazil. To achieve this objective, we developed and validated a modified version of the UTAUT model (Venkatesh et al. 2003) in which we included the trust construct (Gefen, Karahanna, and Straub 2003; Raut et al. 2018; Wong et al. 2020). The proposed model showed good power to predict blockchain adoption in the Brazilian OSCM context.

We identified facilitating conditions, trust, social influence, and effort expectancy as critical constructs in predicting BCT adoption intention in the Brazilian OSCM field. In parallel, it appeared that the performance expectancy construct is a possible barrier to the adoption of BCT in Brazilian OSCM field, a result that contrasted with the one reported by Kamble, Gunasekaran, and Arha

(2019) for Indian supply chains, as perceived usefulness was proved by their research to be a critical factor for BCT adoption. Thus, our findings suggest that performance expectancy may also constitute an impediment to BCT adoption for OSCM in the Brazilian context.

This study hauls a number of contributions, including the following: (i) the possibility to use a new theory deriving from an extension and modification of the UTAUT, with high power of explanation (58.1%); (ii) the identification of variables that affect positively BCT adoption intention, and the variable that may rather represent a barrier to blockchain adoption for OSCM in Brazil; and (iii) our results demonstrate the paramount importance of cultural variables as part of national differences to consider for any work on technology adoption.

Regarding the main limitations of this work, one of them may be the scarcity of empirical studies involving BCT adoption in SCM contexts (Kamble, Gunasekaran, and Arha 2019; Queiroz and Fosso Wamba 2019; Wong et al. 2020), which limits comparison of results. Another limitation resides in the difficulty of generalising research methods, findings, and results, as this study was conducted in a single country. That notwithstanding, it gives room for more studies by scholars, researchers, and practitioners, who could apply and extend our validated model in other countries. For instance, they may compare emerging economies or compare an emerging country with and a developed country in terms of results and findings.

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## Disclosure statement

No potential conflict of interest was reported by the author(s).

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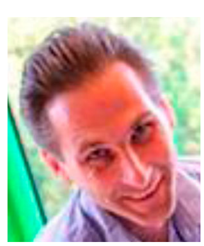

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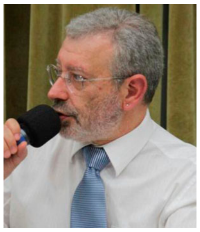

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## Appendices

### *Appendix 1. Harman’s single factor test.*

| | Factor loadings | | KMO measure of sampling adequacy |
|---|---|---|---|
| | Factor | | |
| Item | 1 | Uniqueness | MSA |
| FCON1 | 0.636 | 0.595 | 0.743 |
| FCON2 | 0.704 | 0.504 | 0.770 |
| FCON3 | 0.605 | 0.634 | 0.736 |
| FCON4 | 0.691 | 0.523 | 0.771 |
| PEXP1 | 0.723 | 0.478 | 0.872 |
| PEXP2 | 0.537 | 0.712 | 0.876 |
| PEXP3 | 0.621 | 0.614 | 0.835 |
| PEXP4 | 0.634 | 0.599 | 0.847 |
| TRUS1 | 0.850 | 0.278 | 0.829 |
| TRUS2 | 0.865 | 0.251 | 0.845 |
| TRUS3 | 0.804 | 0.354 | 0.806 |
| TRUS4 | 0.759 | 0.423 | 0.767 |
| TRUS5 | 0.875 | 0.235 | 0.909 |
| SINF1 | 0.697 | 0.515 | 0.849 |
| SINF2 | 0.737 | 0.457 | 0.859 |
| SINF3 | 0.713 | 0.492 | 0.761 |
| EEXP1 | 0.482 | 0.767 | 0.791 |
| EEXP2 | 0.736 | 0.459 | 0.836 |
| EEXP3 | 0.648 | 0.581 | 0.699 |
| EEXP4 | 0.602 | 0.638 | 0.716 |
| BINT1 | 0.723 | 0.477 | 0.931 |
| BINT2 | 0.668 | 0.554 | 0.819 |
| BINT3 | 0.705 | 0.503 | 0.796 |
| | | *Summary* | |
| Factor | S.S. Loadings | **% of Variance** | **Cumulative %** |
| 1 | 11.4 | **49.4** | **49.4** |
| | Bartlett’s Test of Sphericity | | KMO Overall |
| $\chi^2$ | df | *p* | |
| 5320 | 253 | < .001 | 0.812 |

Note: ‘Maximum likelihood’ extraction method was used in combination with a ‘none’ rotation.

## *Appendix 2. Nonresponse bias t-test and ANOVA analysis.*

| | *t*-test | | | ANOVA | | | |
|---|---|---|---|---|---|---|---|
| Item | statistic | df | *p* | *F* | df1 | df2 | *p* |
| FCON1 | 0.322 | 98 | 0.748 | 0.104 | 1 | 97.3 | 0.748 |
| FCON2 | 0.517 | 98 | 0.606 | 0.267 | 1 | 97.3 | 0.606 |
| FCON3 | −0.999 | 98 | 0.320 | 0.999 | 1 | 96.4 | 0.320 |
| FCON4 | −0.261 | 98 | 0.795 | 0.068 | 1 | 97.1 | 0.795 |
| PEXP1 | 0.424 | 98 | 0.673 | 0.179 | 1 | 98.0 | 0.673 |
| PEXP2 | −0.868 | 98 | 0.388 | 0.753 | 1 | 97.9 | 0.388 |
| PEXP3 | −0.596 | 98 | 0.553 | 0.355 | 1 | 97.6 | 0.553 |
| PEXP4 | −0.377 | 98 | 0.707 | 0.142 | 1 | 96.8 | 0.707 |
| TRUS1 | −0.150 | 98 | 0.881 | 0.023 | 1 | 95.9 | 0.881 |
| TRUS2 | −0.640 | 98 | 0.524 | 0.409 | 1 | 95.9 | 0.524 |
| TRUS3 | −0.396 | 98 | 0.693 | 0.157 | 1 | 97.8 | 0.693 |
| TRUS4 | −0.445 | 98 | 0.658 | 0.198 | 1 | 98.0 | 0.658 |
| TRUS5 | −0.472 | 98 | 0.638 | 0.223 | 1 | 97.9 | 0.638 |
| SINF1 | −0.773 | 98 | 0.441 | 0.597 | 1 | 96.4 | 0.441 |
| SINF2 | −0.533 | 98 | 0.596 | 0.284 | 1 | 91.6 | 0.596 |
| SINF3 | −0.787 | 98 | 0.433 | 0.619 | 1 | 97.3 | 0.433 |
| EEXP1 | −0.074 | 98 | 0.941 | 0.005 | 1 | 94.8 | 0.941 |
| EEXP2 | 0.166 | 98 | 0.869 | 0.027 | 1 | 91.0 | 0.869 |
| EEXP3 | −0.073 | 98 | 0.942 | 0.005 | 1 | 89.9 | 0.942 |
| EEXP4 | −0.327 | 98 | 0.744 | 0.107 | 1 | 85.9 | 0.744 |
| BINT1 | −0.439 | 98 | 0.661 | 0.193 | 1 | 97.3 | 0.661 |
| BINT2 | −0.104 | 98 | 0.917 | 0.011 | 1 | 97.5 | 0.917 |
| BINT3 | −0.363 | 98 | 0.717 | 0.132 | 1 | 95.5 | 0.717 |

## *Appendix 3. PLS predict settings in SmartPLS.*

**Number of Folds**

Default: 10

In k-fold cross-validation the algorithm splits the full dataset into k equally sized subsets of data. The algorithm then predicts each fold (hold-out sample) with the remaining *k*–1 subsets, which, in combination, become the training sample. For example, when k equals 10 (i.e. 10-folds), a dataset of 200 observations will be split into 10 subsets with 20 observations per subset. The algorithm then predicts ten times each fold with the nine remaining subsets.

**Number of Repetitions**

Default: 10

The number of repetitions indicates how often PLS predict algorithm runs the k-fold cross validation on random splits of the full dataset into k folds.

Traditionally, cross-validation only uses one random split into k-folds. However, a single random split can make the predictions strongly dependent on this random assignment of data (observations) into the k-folds. Due to the random partition of data, executions of the algorithm at different points of time may vary in their predictive performance results (e.g. RMSE, MAPE, etc.).

Repeating the k-fold cross-validation with different random data partitions and computing the average across the repetitions ensures a more stable estimate of the predictive performance of the PLS path model'

Source: https://www.smartpls.com/documentation/algorithms-and-techniques/predict