FORUM

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INTENTION TO ADOPT BIG DATA IN SUPPLY CHAIN MANAGEMENT: A BRAZILIAN PERSPECTIVE

Intenção de adoção de big data na cadeia de suprimentos: Uma perspectiva brasileira

Intención de adopción de big data en la cadena de suministros: Una perspectiva brasileña

ABSTRACT

Big data applications have been remodeling several business models and provoking strong radical transformations in supply chain management (SCM). Supported by the literature on big data, supply chain management, and the unified theory of acceptance and use of technology (UTAUT), this study aims to evaluate the variables that influence the intention of Brazilian SCM professionals to adopt big data. To this end, we adapted and validated a previously developed UTAUT model. A survey of 152 supply chain respondents revealed that facilitating conditions (e.g., IT infrastructure) have a high influence on their intention to adopt big data. However, social influence and performance expectancy showed no significant effect. This study contributes to the practical field, offering valuable insights for decision-makers considering big data projects. It also contributes to the literature by helping minimize the research gap in big data in the Brazilian context.

KEYWORDS | Big data, supply chain management, adoption, survey, partial least squares structural equation modeling.

RESUMO

As aplicações de big data têm remodelado vários modelos de negócios e provocado grandes transformações na gestão da cadeia de suprimentos (GCS). Apoiado pela literatura emergente de big data, GCS e teoria unificada de aceitação e uso de tecnologia (UTAUT), este estudo tem como objetivo avaliar as variáveis que influenciam os profissionais brasileiros que atuam na GCS a adotar big data. Assim, nós adaptamos e validamos um modelo UTAUT previamente desenvolvido. Um total de 152 profissionais que atuam na gestão de cadeias de suprimentos revelou que condições facilitadoras (como a infraestrutura de TI) têm uma grande influência na adoção de big data. Por outro lado, a influência social e a expectativa de desempenho não apresentaram efeito significativo. Este estudo contribui para a prática, com conhecimentos valiosos para os tomadores de decisão que estão considerando projetos de big data. Além disso, ele ajuda a minimizar a lacuna em relação aos estudos de big data no contexto brasileiro.

PALAVRAS-CHAVE | *Big data, gestão da cadeia de suprimentos, adoção, survey, partial least squares structural equation modeling.*

RESUMEN

Las aplicaciones de big data han estado remodelando varios modelos de negocios y han provocado fuertes transformaciones en la cadena de suministro (CS). Con el apoyo de la literatura de big data, CS y la teoría unificada de aceptación y uso de la tecnología (UTAUT), este estudio tiene objetivo evaluar las variables que afectan a los profesionales brasileños para adoptar big data. Por lo tanto, adaptamos y validamos un modelo UTAUT previamente desarrollado. Un total de 152 encuestados de CS revelaron que las condiciones de facilitación (por ejemplo, la infraestructura de TI) tienen una gran influencia en la adopción de big data. Por otro lado, la influencia social y la expectativa de desempeño no mostraron un efecto significativo. Este estudio contribuye a la práctica, con información valiosa para los responsables de la toma de decisiones que están considerando proyectos de big data. Además, ayudamos a minimizar la brecha con respecto a los estudios de big data en el contexto brasileño.

PALABRAS CLAVE | *Big data, gestión de la cadena de suministro, adopción, survey, partial least squares structural equation modeling.*

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INTRODUCTION

The rapid advancement of information and communication technologies (ICTs) has motivated logistics and supply chain management practitioners and scholars (Zinn & Goldsby, 2017b, 2017a) to understand the role of these new technologies, and to determine how organizations can capture value through ICT adoption. A highly disruptive and significant technology that has emerged recently is big data (Davenport, 2006; Manyika et al., 2011; Rotella, 2012). The amount of data produced everyday has been increasing drastically (Domo, 2017). This growth has imposed several complexities concerning its management. In this context, big data offers a powerful approach to helping organizations analyze (Croll, 2015) large amounts of data to provide insights into the decision-making process (Abawajy, 2015).

The literature considered big data the "next big thing in innovation" (Gobble, 2013, p. 64) and "the fourth paradigm of science" (Strawn, 2012, p. 34). Big data has impacted practically all business models. For instance, 35% of Amazon.com's revenue is generated through the use of big data (Wills, 2014), along with the remodeling of marketing activities that capture rich data on consumer behavior in real-time (Erevelles, Fukawa, & Swayne, 2016). A field that has been making substantial efforts to harness big data is supply chain management (SCM) (Gunasekaran et al., 2017; Kache & Seuring, 2017; Richey, Morgan, Lindsey-Hall, & Adams, 2016; K. J. Wu et al., 2017; R. Zhao, Liu, Zhang, & Huang, 2017).

Despite the potential benefits of employing big data in supply chain management (Hazen, Boone, Ezell, & Jones-Farmer, 2014; Kache & Seuring, 2017; Schoenherr & Speier-Pero, 2015), awareness of and initiatives on big data in the Brazilian SCM context are rare, and the literature lacks strong empirical results (Queiroz & Telles, 2018). The current initial stage of big data adoption presents an opportunity for scholars and practitioners to fill this gap. For example, to the best of our knowledge, no previous study analyzed the intention of Brazilian SCM professionals to adopt big data. To bridge this gap, this study provides an in-depth understanding of Brazilian supply chain professionals' intention to use big data. We adapt a previously developed and validated unified theory of acceptance and use of technology (UTAUT) model (Venkatesh, Morris, Davis, & Davis, 2003; Queiroz & Wamba, 2019), by including a trust construct. More specifically, this study answers the following research question: How do the variables from the UTAUT model explain Brazilian SCM professionals' intention to adopt big data?

To answer this question, this work draws on the literature on big data (Davenport, 2006; Manyika et al., 2011; Queiroz & Telles, 2018), supply chain management (Carter, Rogers, & Choi, 2015; Mentzer et al., 2001), and UTAUT (Venkatesh et al., 2003; Venkatesh, Thong, & Xu, 2012; Queiroz & Wamba, 2019) to develop the hypotheses and model. The conceptual model was adapted and validated with partial least squares structural equation modeling (PLS-SEM). The main findings offer strong theoretical and managerial implications. From the managerial perspective, we verified that facilitating conditions (e.g., infrastructure) exert high influence on the behavioral intention of big data adoption. From the theoretical lens, our findings revealed that neither social influence nor performance expectancy are good predictors of the behavioral intention of big data adoption in Brazilian SCM professionals.

This paper is organized as follows: next, we present the emerging theoretical foundations for big data research, SCM, and UTAUT. Then, the hypotheses and the research model are described, followed by the survey methodology and analysis using PLS-SEM. That is succeeded by a discussion on managerial and theoretical implications as well as limitations of the current work and directions for future research. Finally, our conclusions are elucidated.

THEORETICAL BACKGROUND

Big Data: Fundamentals, concepts, and challenges

Big Data has emerged as a highly disruptive information and communication technology (ICT). A well-articulated and suitable definition of Big Data is "[...] datasets whose size is beyond the ability of typical database software tools to capture, store, manage, and analyze" (Manyika et al., 2011, p. 1). Thus, Big Data can be regarded as providing a robust approach to exploring data in the context of descriptive, prescriptive, and predictive decisions (Phillips-Wren & Hoskisson, 2015). This approach is commonly called Big Data analytics (BDA), and is represented by a 5V approach (volume, velocity, variety, veracity, and value) (Queiroz & Telles, 2018; Wamba et al., 2017). In other words, BDA uses sophisticated statistics, mathematical and computational techniques to explore a large set of data to provide insights to decision-makers. In this study, we use the definition of Big Data proposed by Phillips-Wren and Hoskisson (2015).The authors described Big Data as data that overtake the organization's capabilities, regarding storage, and analysis to support and bring insights to the decision-making process.

The volume of data has increased drastically in recent years, mainly because of the variety of data produced today (Bibri &

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Krogstie, 2017) (e.g., ERP systems, Twitter, Facebook, Google, Linkedin, GPS, among others) and the velocity of its spread (Munshi & Mohamed, 2017; Srinivasan & Swink, 2018). This complex scenario impels organizations to develop distinctive capabilities for storing, processing, and analyzing data to support the decision-making process. However, creating value is not a trivial task, mainly because of organizations' limited capacity to process and analyze a variety of data. Moreover, data veracity, which indicates data quality and trustworthiness (Munshi & Mohamed, 2017; Nobre & Tavares, 2017), seems to be a huge challenge for organizations.

In the SCM-related fields, Big Data is being newly explored in different contexts: in SCM agility enhancement with Big Data and multi-agent-based systems (Giannakis & Louis, 2016), in an optimization of green SCM considering hazardous materials and carbon emission (R. Zhao et al., 2017), in the manufacturing sector (Zhong, Newman, Huang, & Lan, 2016), and in the information exploitation of SCM (Kache & Seuring, 2017). It is clear that Big Data can improve organizations' performance significantly (Akter, Wamba, Gunasekaran, Dubey, & Childe, 2016; Gunasekaran et al., 2017; Wamba, Akter, Edwards, Chopin, & Gnanzou, 2015; G. Wang, Gunasekaran, Ngai, & Papadopoulos, 2016).

Supply chain management and the impacts of cutting-edge technologies

Recently, the logistics and SCM fields have been significantly impacted by the exponential growth in ICT usage. Accordingly, scholars and practitioners have strived to understand its potential effects and application opportunities in their business models (Zinn & Goldsby, 2017a, 2017b). In this context, SCM is defined as:

> The management of a network of relationships within a firm and between interdependent organizations and business units consisting of material suppliers, purchasing, production facilities, logistics, marketing, and related systems that facilitate the forward and reverse flow of materials, services, finances and information from the original producer to final customer with the benefits of adding value, maximizing profitability through efficiencies, and achieving customer satisfaction (Stock & Boyer, 2009, p. 706).

Moreover, SCM can be viewed as a network (Carter et al., 2015) as well as a complex adaptive system (Choi, Dooley, & Rungtusanatham, 2001), and this complexity has impacted the increasing amount of data. Considering the use of Big Data in SCM, it is clear that it assists in the decision-making process by providing powerful insights into SCM dynamics (e.g., customer buying patterns, cost analysis, market trends). With the help of robust prescriptive and descriptive analysis (G. Wang et al., 2016), businesses have witnessed many cases of significant performance enhancement (Akter et al., 2016; Gunasekaran et al., 2017).

Technology acceptance models (TAMs) and Unified theory of acceptance and use of technology (UTAUT)

Scholars have studied the diffusion and proliferation of information technology (IT) (Davis, 1989; Wamba, 2018; Morris & Venkatesh, 2000; Venkatesh & Brown, 2001) in terms of individuals' beliefs and behavior toward their adoption and use (Mamonov & Benbunan-Fich, 2017; Youngberg, Olsen, & Hauser, 2009). The technology acceptance model (TAM) is a seminal and influential contribution in technology adoption (Davis, 1989), with its roots in the theory of reasoned action (TRA) (Azjen & Fishbein, 1980). The core of the TAM resides in two latent variables: perceived usefulness (PU) and perceived ease of use (PEOU). More recently, Venkatesh et al. (2003) proposed the consolidation of the acceptance model theories leading previously into the unified theory of acceptance and use of technology (UTAUT).

UTAUT

The UTAUT model (Venkatesh et al., 2003) is a robust and influential approach to understanding technology adoption and use at the individual behavior level. The model has four constructs directly focused on technology's intended use: performance expectancy, effort expectancy, social influence, and facilitating conditions.

Performance expectancy refers to "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, p. 447). Effort expectancy is "the degree of ease associated with the use of the system" (Venkatesh et al., 2003, p. 450). Social influence denotes "the degree to which an individual perceives that important others believe he or she should use the new system" (Venkatesh et al., 2003, p. 451). Finally, facilitating conditions indicates "the degree to which an individual believes that an organizational and technical infrastructure exists to

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support use of the system" (Venkatesh et al., 2003, p. 453). The UTAUT model also has four moderators: gender, age, experience, and voluntariness of use. However, following a previous study (Weerakkody, El-Haddadeh, Al-Sobhi, Shareef, & Dwivedi, 2013), we do not use these moderators in our adapted model (explained in the next section) because this is a preliminary study of BDA adoption in the Brazilian SCM context.

Hypotheses and research model

Supported by the emerging literature on Big Data, SCM, and UTAUT, we adapted a recent model reported in Queiroz and Wamba (2019) to comprehend the Big Data adoption behavior of Brazilian supply chain professionals. We adopted some of the constructs and hypotheses proposed in Queiroz and Wamba´s (2019) model (Figure 1) as these have been adopted and validated by previous studies (Exhibit 1). To these previous constructs reported in Queiroz & Wamba (2019) we added a trust construct, previously validated in the literature (Alalwan, Dwivedi, & Rana, 2017; Gefen, Karahanna, & Straub, 2003). Moreover, the constructs in our model have different relationships than the ones reported in the literature (Queiroz & Wamba, 2019).

Facilitating conditions

Facilitating conditions play a fundamental role in predicting user acceptance and usage behavior (Venkatesh et al., 2003, 2012). In this study, facilitating conditions denotes SCM professionals' knowledge of their organization's capabilities and infrastructure available to support the use of Big Data. Previous studies have reported that facilitating conditions are a good predictor of the behavioral intention of Big Data adoption (Huang, Liu, & Chang, 2012; Sabi, Uzoka, Langmia, & Njeh, 2016). In this study, we theorize that facilitating conditions, besides influencing behavioral intention directly, are critical in professionals' effort expectancy (Dwivedi et al., 2017) and influence their performance expectancy (C. Wang, Jeng, & Huang, 2017). Therefore, we propose the following hypotheses:

> H1a**:** Facilitating conditions positively affects effort expectancy.
>
> H1b**:** Facilitating conditions positively affects performance expectancy.
>
> H1c**:** Facilitating conditions positively affects behavioral intention to adopt Big Data.

Trust

The trust construct has been studied extensively in the business management and management information systems (MIS) fields (Colquitt & Rodell, 2011; K. Wu, Zhao, Zhu, Tan, & Zheng, 2011). Trust is defined as "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, & Schoorman, 1995, p. 712). This definition implies that trust is a willingness to depend on the partner based on integrity, benevolence, and credibility. In this context, Big Data is trustworthy for users. In line with prior works (K. Wu et al., 2011), we hypothesize that:

> H2a**:** Trust positively affects performance expectancy.
>
> H2b**:** Trust positively affects behavioral intention to adopt Big Data.

Social influence

As reported previously, social influence is a good predictor of technology behavioral intention and usage (Venkatesh et al., 2003). In this work, social influence denotes the extent to which SCM professionals believe their colleagues should use Big Data. Previous studies highlight social influence as a predictor of behavioral intention (Batara, Nurmandi, Warsito, & Pribadi, 2017; Oliveira, Faria, Thomas, & Popovič, 2014; Venkatesh et al., 2012). Our study argues that in the SCM context, social influence relationships exert significant influence on trust (A. Chin, Wafa, & Ooi, 2009) and, in turn, on the behavioral intention (Alalwan et al., 2017). Thus, we propose the following hypotheses:

> H3a**:** Social influence positively affects trust.
>
> H3b**:** Social influence positively affects behavioral intention to adopt Big Data.

Effort expectancy

Effort expectancy is related to the system's complexity of operation (Venkatesh et al., 2003). In this study, effort expectancy refers to the ease of use of Big Data systems for an SCM professional. Previous studies discussed the direct effect of effort expectancy in the behavioral intention and usage of a new technology (Batara et al., 2017; Venkatesh et al., 2012; Y. Zhao, Ni, & Zhou, 2018) as well as in the adoption of blockchain in the SCM field (Francisco & Swanson, 2018). Accordingly, this study hypothesizes that:

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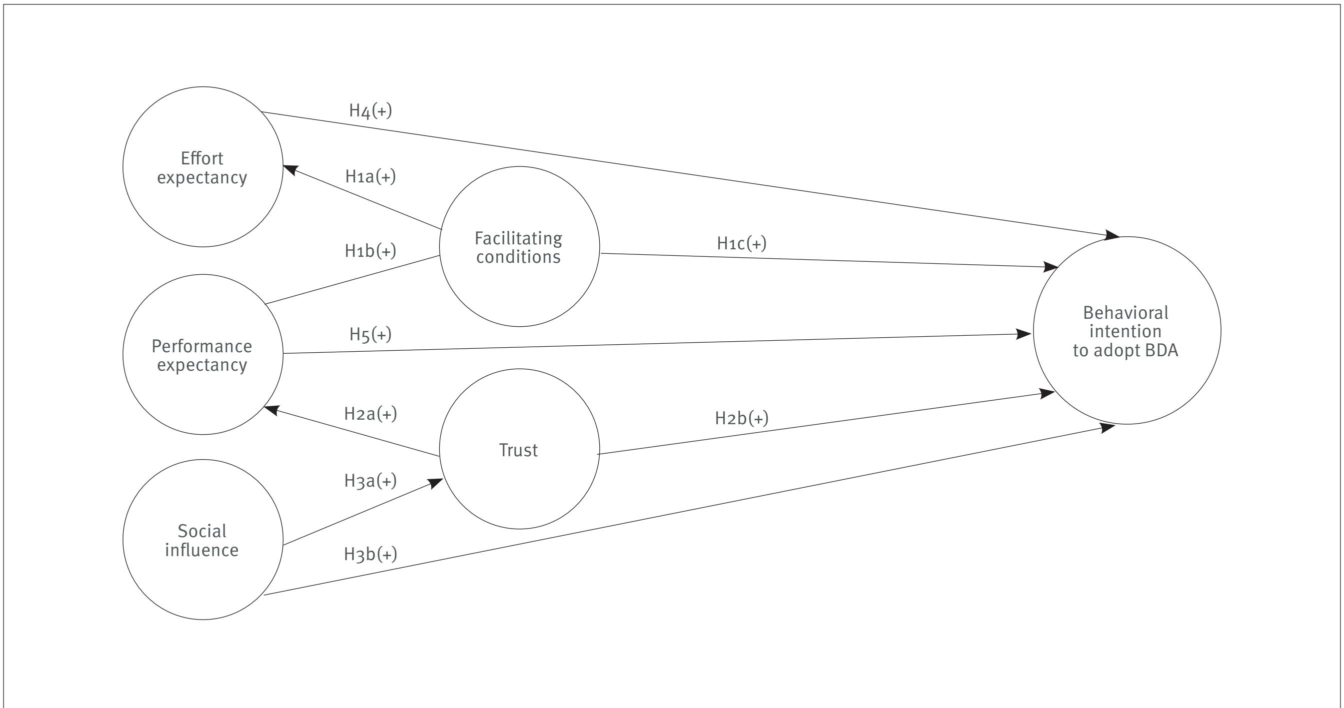
H4: Effort expectancy positively affects behavioral intention to adopt Big Data.

Performance expectancy

In this work, performance expectancy denotes the level to which an SCM professional perceives that Big Data will improve his productivity and performance. With Big Data application, organizations can analyze different types of data employing powerful statistics and machine learning techniques (Kune, Konugurthi, Agarwal, Chillarige, & Buyya, 2016). This implies considerable time savings and productivity improvement for organizations, therefore helping enhance its performance (Gunasekaran et al., 2017; Wamba et al., 2017). Thus, we propose that:

H5: Performance expectancy positively affects behavioral intention to adopt Big Data.

Figure 1. **Conceptual model**



METHODOLOGY

Sample and data collection

A survey instrument based on Queiroz and Wamba (2019) was used to test our proposed hypotheses. The web-based questionnaire was grounded on constructs and scales that have been validated by previous studies (Venkatesh et al., 2003, 2012; Gefen et al., 2003). The Queiroz and Wamba (2019) model was developed based on previous studies; their constructs were adapted from recent studies on TAMs (Alalwan et al., 2017; Venkatesh et al., 2003, 2012). As our main objective was to identify the intention to adopt Big Data, we adapted the Queiroz and Wamba (2019) survey instrument. All constructs were measured using a seven-point Likert scale [1 (strongly disagree) to 7 (strongly agree)] (Wamba et al., 2017). Before data collection, a pilot test was performed with five senior academics and five senior SCM professionals. Data were collected through the LinkedIn social network (Gupta & George, 2016; Queiroz & Telles, 2018). After the pilot, we sent the questionnaire to 600 Brazilian supply chain professionals with experience in Big Data. The survey was conducted in August 2018, and a total of 152 questionnaires were received, representing a response rate of 25.33%. Exhibit 1 shows the constructs and their respective items. We validated the questionnaire by employing outer loadings (Hair et al., 2017), Cronbach's alpha, composite reliability, average variance extracted (Hair et al., 2017; Nunnally, 1978; Riffai, Grant, & Edgar, 2012), and discriminant validity.

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Exhibit 1. **Measurement items**

Construct	Label	Items	Sources
Performance expectancy (PE)	PE1	I find big data useful in my daily life.	(Alalwan et al., 2017; Venkatesh et al., 2003, 2012; Queiroz & Wamba, 2019)
	PE2	Using big data increases my chances of completing tasks that are important to me.	
	PE3	Using big data helps me accomplish tasks more quickly.	
	PE4	Using big data increases my productivity.	
Effort expectancy (EE)	EE1	Learning how to use big data is easy for me.	(Alalwan et al., 2017; Venkatesh et al., 2003, 2012; Queiroz & Wamba, 2019)
	EE2	My interaction with big data is clear and understandable.	
	EE3	I find big data easy to use.	
	EE4	It is easy for me to become skilful at using big data.	
Social influence (SI)	SI1	People who are important to me think I should use big data.	(Alalwan et al., 2017; Venkatesh et al., 2003, 2012; Queiroz & Wamba, 2019)
	SI2	People who influence my behaviour think I should use big data.	
	SI3	People whose opinions that I value prefer I use big data.	
Facilitating conditions (FC)	FC1	I have the resources necessary to use big data.	(Alalwan et al., 2017; Venkatesh et al., 2003, 2012; Queiroz & Wamba, 2019)
	FC2	I have the knowledge necessary to use big data.	
	FC3	Big data is compatible with other technologies I use.	
	FC4	I can get help from others when I have difficulties using big data.	
Behavioral intention to use (BI)	BI1	I intend to use big data in the future.	(Alalwan et al., 2017; Venkatesh et al., 2003, 2012; Queiroz & Wamba, 2019)
	BI2	I expect to use big data in the future	
	BI3	I plan to use big data in future.	
Trust (TR)	TR1	I believe that big data is trustworthy.	(Alalwan et al., 2017; Gefen et al., 2003)
	TR2	I have trust in big data.	
	TR3	I do not doubt the honesty of big data.	
	TR4	I feel assured that legal and technological structures adequately protect me from problems on big data.	
	TR5	Big data has the ability to fulfil its task.	

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RESULTS AND ANALYSIS

Partial least squares structural equation modeling (PLS-SEM) (Ringle, Wende, & Becker, 2015; Shim, Lee, & Kim, 2018; Sun & Teng, 2017) was applied to analyze the research model. PLS-SEM is a powerful approach for analyzing simple and robust models in business management (Hair, Sarstedt, Hopkins, & Kuppelwieser, 2014; Hair, Hult, Ringle, & Sarstedt, 2017), and has gained the attention of SCM scholars (Autry, Williams, & Golicic, 2014; Grawe, Daugherty, & Ralston, 2015; Han, Wang, & Naim, 2017; Yadlapalli, Rahman, & Gunasekaran, 2018). Its main advantages are its flexibility in working with small samples (e.g., 100 respondents) and its formative and reflective constructs (Hair et al., 2017).

Table 1 reports the characteristics of the respondents. Male respondents comprised almost 90% of the total. Regarding age distribution, most respondents (52.63%) were aged 34-41 years. A total of 55.26% respondents had a postgraduate/MBA—the highest education level in our sample—followed by 39.47% holding bachelor degrees and 5.26% holding a master of science degree. Considering the experience at their respective organizations, 50% respondents had worked there for 2-5 years, followed by 21.05% having worked for 6-10 years and 18.42% working for less than one year. Finally, 46.05% of the sample comprised logistics analysts, followed by 26.32% transportation managers, 18.42% operations managers, and 9.21% supply chain managers.

We analyzed the research model with SmartPLS 3.0 (Hair et al., 2017; Ringle et al., 2015). First, the model was assessed by its loadings, Cronbach's alpha, composite reliability, average variance extracted, and discriminant validity.

Measurement model

All outer loadings highlighted in Table 2 exceeded the 0.70 threshold recommended in the literature (Hair et al., 2017). Table 3 shows the main measures for construct reliability and internal consistency of items. In this study, both Cronbach's alpha value and composite reliability were above the 0.70 threshold, and all average variance extracted values were above the 0.50 threshold (Hair et al., 2017; Nunnally, 1978; Riffai, Grant, & Edgar, 2012). Therefore, all constructs in the model have their utilization validated. Table 4 presents the discriminant validity results. In this case, the square root of the average variance extracted for each construct should be greater than the correlations between the constructs (Fornell & Larcker, 1981; Henseler, Ringle, & Sinkovics, 2009). Our results are higher than the 0.70 threshold (Fornell & Larcker, 1981), confirming that all constructs show discrimination (Ahmad & Khalid, 2017; Martins, Oliveira, & Popovič, 2014).

Table 1. **Demographic profile of respondents (n=152)**

Gender	n	%
Male	136	89.5
Female	16	10.5
Age		
26-33	40	26.32
34-41	80	52.63
42-49	12	7.89
50+	20	13.16
Highest education level		
Bachelor degree	60	39.47
Postgraduate/MBA	84	55.26
Master of Science (MSc)	8	5.26
Number of years spent working in the organization		
Less than one year	28	18.42
2-5 years	76	50.00
6-10 years	32	21.05
11-15 years	16	10.53
Occupation		
Logistics analyst	70	46.05
Operations manager	28	18.42
Transportation manager	40	26.32
Supply chain manager	14	9.21

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Table 2. **Factor loadings**

	BI	EE	FC	PE	SI	TR
BI1	0.887					
BI2	0.916					
BI3	0.900					
EE1		0.945				
EE2		0.906				
EE3		0.947				
EE4		0.900				
FC1			0.789			
FC2			0.884			
FC3			0.719			
FC4			0.800			
PE1				0.764		
PE2				0.803		
PE3				0.914		
PE4				0.899		
SI1					0.953	
SI2					0.983	
SI3					0.967	
TR1						0.964
TR2						0.944
TR3						0.918
TR4						0.937
TR5						0.913

Note: BI = Behavioral intention
EE = Effort expectancy
FC = Facilitating conditions
PE = Performance expectancy
SI = Social influence
TR = Trust.

Table 3. **Reliability measures**

Construct	Cronbach's alpha	Composite reliability	Average variance extracted
BI	0.881	0.926	0.808
EE	0.942	0.959	0.853
FC	0.806	0.873	0.637
PE	0.864	0.908	0.715
SI	0.965	0.977	0.934
TR	0.963	0.971	0.871

Table 4. **Discriminant validity**

Construct	BI	EE	FC	PE	SI	TR
BI	**0.901**					
EE	0.527	**0.925**				
FC	0.614	0.577	**0.800**			
PE	0.314	0.238	0.620	**0.847**		
SI	0.399	0.390	0.508	0.421	**0.968**	
TR	0.511	0.456	0.580	0.640	0.715	**0.935**

Structural model

Table 5 and 6 present the results of our structural model. Table 5 highlights the path coefficients statistics.The findings indicated that FC has a significant positive effect on EE (β = 0.578, p < 0.001). Thus, H1a is supported. H1b hypothesized that FC has a significant positive effect on PE. The results (β = 0.380, p < 0.001) support H1b. H1c theorized that FC has a significant positive effect on BI. This hypothesis was also supported (β = 0.490, p < 0.001). Next, H2a argued that TR has a significant positive effect on PE. Our results (β = 0.413, p < 0.001) support this hypothesis. Then, H2b argued that TR has a significant positive effect on BI. The results supported H2b (β = 0.327, p < 0.05). H3a theorized that SI has a significant positive effect on TR. The results supported H3a (β = 0.710, p < 0.001). The rest of the hypotheses had unexpected results. H3b theorized that SI has a significant positive effect on BI. Surprisingly, the relationship was found to be negative and non-significant. Therefore, H3b was not supported (β = -0.073, p = 0.519). H4 argued that EE has a significant positive effect on BI. This hypothesis was not supported either (β = 0.166, p < 0.1). Next, H5 theorized that PE has a significant positive effect on BI. Surprisingly, the results (β = -0.214, p < 0.05) showed a negative significant effect on BI. Thus, H5 was not supported.Table 6 demonstrates the variance of the model: 46% variance in BI; 33.30% in EE; 49.80% in PE; and finally, 50.30% in TR. In line with the literature (W. W. Chin, 1998), all r-squares of the model exceeded the 0.20 threshold (Martins et al., 2014).

Table 5. **Path coefficients**

Path	Beta	Standard deviation	t-statistics	p-value	Result
FC -> EE	0.578	0.053	10.921*	0.000	Supported
FC -> PE	0.380	0.064	5.875*	0.000	Supported
FC -> BI	0.490	0.097	5.016*	0.000	Supported
TR -> PE	0.413	0.080	5.301*	0.000	Supported
TR -> BI	0.327	0.112	2.987**	0.003	Supported
SI -> TR	0.710	0.047	15.17*	0.000	Supported
SI -> BI	-0.073	0.097	0.646	0.519	Rejected
EE -> BI	0.166	0.090	1.86	0.063	Rejected
PE -> BI	-0.214	0.099	2.184**	0.029	Rejected

Note: *p < 0.001; **p < 0.05.

Table 6. **R^2 results (dependent variables)**

Construct	R^2	R^2 adjusted
BI	0.477	0.460
EE	0.337	0.333
PE	0.504	0.498
R	0.506	0.503

DISCUSSION AND IMPLICATIONS

The main objective of this study was to gain an in-depth understanding of the intention of Big Data adoption in the Brazilian supply chain context. In light of the lack of Brazil-based studies on cutting-edge technologies (Queiroz and Telles, 2018), this work contributes to advancing the literature on BDA, SCM, and TAMs. The results offer significant managerial and theoretical implications as well as valuable directions to adapt and extend the adopted model.

Managerial implications

We believe the main findings of this study provide important implications for managers and practitioners interested in gaining deeper insights about BDA in SCM and their adoption enablers. In line with the literature that regards Big Data as an essential tool to improve supply chain performance (Gunasekaran et al., 2017; Hazen, Skipper, Ezell, & Boone, 2016; G. Wang et al., 2016), our study first showed that Big Data can be a suitable tool to help SCM managers gain insights and thus support their decision-making process. Second, facilitating conditions exert a high influence on Big Data adoption. This implies that managers have to pay sufficient attention to IT infrastructure, internet speed, and integration with other systems, among other considerations (Sabi et al., 2016; Venkatesh et al., 2003).

Surprisingly, despite the literature reporting performance expectancy as a good predictor of behavioral intention towards technology adoption (Dwivedi et al., 2017; Farooq et al., 2017; Venkatesh et al., 2003; Weerakkody et al., 2013), in this study, performance expectancy was not found to be a good predictor of the behavioral intention to use Big Data among Brazilian SCM professionals. This finding indicates a challenge for managers because it can be a significant barrier to the adoption of Big Data technologies. It also opens up research directions for scholars and practitioners to investigate. On the other hand, social influence as a predictor of trust is a high influencer (A. Chin et al., 2009). However, based on our results, it can realize that social influence did not affect behavioral intention to adopt Big Data, thus, regarding more investigation to support decision-makers is needed.

Theoretical implications, limitations, and future research

From the theoretical perspective, this study makes critical contributions to the field of logistics in SCM. First, by integrating the literature on BDA, SCM, and UTAUT, we validated a strong theoretical model. We adapted and applied a previously developed model for use with Brazilian SCM professionals, and the results validated it. The theoretical model explained 46% of behavioral intention, outperforming the 20% threshold in the literature (W. W. Chin, 1998; Martins et al., 2014). As previously mentioned, since our results regarding discriminant validity are consistent with those in the literature, they support our hypothesized structural paths. In other words, the model actually measures the behavioral intention to adopt Big Data by SCM professionals.

Our findings reveal that facilitating conditions are a good predictor of the behavioral intention to use Big Data. Future research could focus on an in-depth understanding of the enablers of facilitating conditions, as well as its barriers. In the proposed model, in line with a prior study (Alalwan et al., 2017), trust was a good predictor of performance expectancy and behavior intention. On the other hand, social influence was not found to be a good predictor of behavioral intention, following the results reported in Alalwan et al. (2017). This finding suggests the need for further investigation of the role of social influence in Big Data adoption and other technologies that are emerging in the SCM field.

This study suffers from some limitations. We believe that, first, a moderator variable could be incorporated into the model (Venkatesh et al., 2003, 2012) to capture the nuances and differences in the sample, such as industry, gender, and experience. Second, because of the scarcity of Brazilian studies on Big Data adoption, our findings cannot be compared with other similar works in this context. However, it opens up opportunities for scholars and practitioners to apply the validated model and to adapt it to other contexts. Third, the adopted model was tested in an emerging economy; because of this, the results cannot be generalized globally. Consequently, obtaining more empirical evidence by applying the adopted model in other countries could be an exciting stream for future research.

Finally, this study was one of the first attempt to understand the behavioral intention to adopt Big Data by Brazilian SCM professionals. There is an urgent need and opportunities for additional investigations on this and other cutting-edge technologies (e.g., blockchain, internet of things, 3D printing, etc.), regarding the relationship, as also compare the hypotheses of this model into other contexts.

CONCLUSION

The purpose of this study was to gain an in-depth understanding of Big Data behavior intention among Brazilian SCM professionals and to adjust and apply a model that captures the constructs of adoption behavior. In this regard, our study contributes to a more thorough understanding of the intention to adopt BDA in the Brazilian SCM field.

The contributions of this study are threefold. First, supported by a strong theoretical literature (Akter et al., 2016; Alalwan et al., 2017; Davis, 1989; Venkatesh et al., 2003, 2012; Queiroz & Wamba, 2019) we adapted and applied a model to understand behavioral intention concerning Brazilian SCM professionals. Second, our findings provide strong implications for theory and practice. For instance, one implication is that only facilitating conditions, and trust were good predictors of behavioral intention. Contrary to findings of previous studies (Venkatesh et al., 2003, 2012), social influence was not a predictor of behavioral intention, but this result is in line with the recent findings reported by Alalwan et al. (2017). Third, both performance expectancy and effort expectancy were not good predictors of behavioral intention. This interesting finding opens up opportunities to further exploration of this behavior. Finally, our study contributes to fill a gap in the Brazilian empirical literature on Big Data in SCM, while simultaenously motivates logistics and SCM scholars to advance this stream of research.

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