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Antecedents of big data analytics adoption: an analysis with future managers in a developing country

Gustavo Hermínio Salati Marcondes de Moraes,
Gisela Consolmagno Pelegrini, Laís Porfírio de Marchi and
Gabriela Trindade Pinheiro
School of Applied Sciences, State University of Campinas, Limeira, Brazil, and
Alexandre Cappellozza
Social and Applied Sciences Center,
Mackenzie Presbyterian University, Sao Paulo, Brazil

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Abstract

Purpose – This paper aims to identify the antecedents' factors that positively and negatively influence the intention to use big data analytics (BDA) by future managers of companies.

Design/methodology/approach – The sample comprised 364 business students from a public university in Brazil. The methodology had a quantitative approach, with the use of structural equation modeling.

Findings – This paper presented a robust model with a high explanatory factor for the intention to use BDA, in which the elements of positive influence on the intention to use are expected performance, social influence and cost–benefit, and the negative influence factor is resistance to use.

Research limitations/implications – Research on BDA has improved the understanding of the phenomenon, mostly emphasizing the technical dimensions of BDA and underestimating organizational and human dimensions. This research contributed to the literature by presenting new insights into these organizational and human aspects by presenting influencing factors for future managers. User resistance is a variable that can incorporate technology adoption theories in BDA.

Practical implications – The results present a positive perception of future managers in the decision on financial resources in the acquisition of new technologies and enable managers to improve planning, investment and choice of technologies while presenting insights from the next generation. Issues regarding privacy, security and ethical aspects are key to minimizing user resistance.

Originality/value – This paper fills a significant research gap on the adoption of BDA, presenting the perception of future managers on fundamental aspects of adoption in a developing country. In addition, the research offers a theoretical model with new latent variables for a current and relevant topic.

Keywords Big data analytics, Technological adoption, University students, Brazil, PLS-SEM, UTAUT

Paper type Research paper

1. Introduction

Triggered by technological innovations, industrial production levels have grown, aiming to meet needs with an escalating level of demand in an increasingly competitive environment.

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As a result, the volume of data produced and shared by either public or private organizations has increased considerably (Maroufkhani *et al.*, 2020; Medeiros *et al.*, 2020a, 2020b). In face of this scenario, big data analytics (BDA) emerged. It relates to extracting value from data, enabling finding specific patterns that can support targeted decision-making (Cabrera-Sánchez and Villarejo-Ramos, 2019; Razaghi and Shokouhyar, 2021; Cetindamar *et al.*, 2022).

Similar to gold and oil, Big Data has been considered a valuable and strategic resource since organizations and institutions, in general, have been receiving an immense amount of data and still cannot fully take advantage of it (Alharthi *et al.*, 2017).

In this sense, companies that are able to process data into real-time customer information might gain a substantial competitive advantage, leading them to market leadership (Sivarajah *et al.*, 2017; Medeiros *et al.*, 2020a, 2020b). As technological innovations can affect organizations and impact their performance and market share, research on technological adoption seeks to understand the introduction of these technologies and conduct procedures, having a critical role in organizations (Venkatesh *et al.*, 2012).

Organizations face several challenges when considering the adoption of new technologies such as BDA, e.g. lack of knowledge, fear and resistance to change (Yaqoob *et al.*, 2016). However, to explain and increase individuals' acceptance toward technologies, it is necessary to comprehend the reasons that lead them to either adopt or reject them (Davis *et al.*, 1989; Venkatesh *et al.*, 2012; Gong and Janssen, 2021), what can be done through the use of technology adoption models.

Several models are considered in the adoption of technology, especially concerning Big Data; however, according to Baig *et al.* (2019), the application and adoption of well-known models, such as Unified Theory of Acceptance and Use of Technology (UTAUT), are still overlooked by the research body. Considered mature and widely used (Cabrera-Sánchez and Villarejo-Ramos, 2019), UTAUT presents direct determinant constructs of intention to use behavior, namely:

- performance expectation;
- effort expectancy;
- social influence, and
- facilitating conditions (Venkatesh *et al.*, 2003).

In addition, the model also features some moderators, such as gender, age, the experience of the individual and voluntariness (Venkatesh *et al.*, 2003).

Firms are trying to make the most out of BDA attributes (Gong and Janssen, 2021). BDA adoption and implementation have been a challenge for several organizations, including large ones (Giest, 2017; Gong and Janssen, 2021), which provoked academic and practical interest due to its relevance; however, few authors have researched the adoption of BDA, reinforcing the topic as a research gap (Chen *et al.*, 2012; Cabrera-Sánchez and Villarejo-Ramos, 2019; Gong and Janssen, 2021). Many organizations have not yet been able to exploit the potential and value of big data analytics with their organizational readiness, not having the necessary technological and human resources for correct adoption (El-Haddadeh *et al.*, 2021).

Based on the literature review conducted for this research paper, a gap was identified on following the path of research of BDA adoption, especially if we consider lack of research conducted in Brazil, which highlights the opportunity to comprehend what factors are relevant for future managers regarding BDA adoption in the future.

In this way, the objective of the research is to identify the factors that positively and negatively influence the intention to use BDA by future managers of companies. Thus, we intend to answer the following research question:

RQ1. What are the main factors influencing the intention to use big data analytics?

The research adapted a model established in the technology adoption literature (UTAUT). The sample comprises 364 business students from a public university in Brazil. The methodology used was quantitative using structural equation modeling by partial least squares (PLS-SEM).

The originality of the article lies in filling a significant research gap on the adoption of the BDA, presenting the perception of future managers on fundamental aspects of adoption in a developing country. In addition, the research offers a theoretical model with new latent variables for a current and relevant topic.

The results contribute to the academic literature on BDA by presenting new insights into organizational and human aspects, which are aspects underestimated by research that emphasizes the technical dimension (Gupta and George, 2016; Gong and Janssen, 2021). Additionally, we validate a consistent theoretical model with two new latent variables in a current and relevant context. User resistance is a variable that can incorporate technology adoption theories in BDA.

From a practical point of view, the results provide relevant information for managerial decision-making regarding BDA adoption, indicating which variables facilitate and inhibit the use of BDA by future managers. Research shows that user resistance is a negative aspect of using BDA. Thus, although the use of BDA improves corporate performance management, it also implies greater exposure to risks in various organizational aspects (Medeiros *et al.*, 2021). It is essential to establish clear definitions, policies and processes to minimize user resistance to ensure data quality and, most importantly, data protection. Other important factors are performance expectation and social influence. These factors positively impact the use of technology. Thus, managers can make BDA simulators available in real situations to have a clear perception of how technology can help decision-making and raise awareness of the benefits that can be achieved.

Further practical contribution refers to the understanding that investments in technology by organizations are considered as another relevant factor for the sample's intention to use BDA. In practical terms, the positive perception in the decision on financial resources in the acquisition of new technologies may represent the overcoming of one of the main obstacles to the execution of these initiatives in projects of this nature due to the uncertainties that may exist in the implementation of innovative technologies.

This article was structured as follows: theoretical background (Section 2), the conceptual model of the research (Section 3), methodological procedures (Section 4), results from analysis (Section 5) and discussion (Section 6) and conclusion and final remarks (Section 7).

2. Theoretical background

BDA is an emerging technology capable of processing significant volumes of data, which contributes to decision-making processes in several types of organizations. Practitioners and academics evaluate ways to incorporate it into organizations' strategic decisions with its growing relevance. Technological adoption remains a challenge for corporations and managers, as they must deepen adoption models to comprehend such challenges and factors affecting either technological adoption or rejection. Based on the aforementioned, the following sections approach BDA and business management (Section 2.1) and technological adoption models for big data analytics (Section 2.2).

2.1 Big data analytics and business management

Still considered to be new, the term "Big Data" refers to the massive amount of data created through the interaction between customers and companies; it is used for analyses that allow an accurate perception of the behavior and trajectories of individuals and, thus, make the consumer experience more assertive (Aloysius *et al.*, 2018), contributing to improvements on processes (Villarejo-Ramos *et al.*, 2021).

Once dealing with a large amount of data requires more complex and thorough methods than traditional ones, BDA presents features, which aim to treat such volume and variable data, with veracity and velocity, besides showing its value with readable visualizations, to gain speed in processing and also reliability (Erevelles *et al.*, 2016).

According to Furht and Villanustre (2016), Big Data's workflow consists of six steps: data collection, its storage, discovery and cleansing, integration, analysis and delivery. Its contributions relate to the company's growth and competitive advantage by offering essential insights with strong statistical support for interdisciplinary studies in a dynamic environment (Behl, 2022).

Providing competitive advantages and innovation in marketing, pricing and customer prospecting (Baig *et al.*, 2019; Cabrera-Sánchez and Villarejo-Ramos, 2019; Medeiros *et al.*, 2020a, 2020b), its application can be complex, and it represents costs to the organizations once it demands teams with specific knowledge, database architecture, and substantial processing capacity (Sun *et al.*, 2018). In addition, consumers' resistance to make their data available as many prefer to maintain their privacy instead of having access to more personalized services (Aloysius *et al.*, 2018).

Despite several benefits to organizations' decision-making process, BDA carries out several barriers, e.g. infrastructure readiness and infrastructure, complexity, multiple formats of data, cultural barriers and lack of skills (Alharthi *et al.*, 2017; Gong and Janssen, 2021), besides fear of technology, distrust, among others (Yaqoob *et al.*, 2016).

In agreement with our further delineated hypotheses, previous research concluded the influence of managers on the adoption of technology, meaning managerial support is crucial to either moderate or mitigate user resistance (Maroufkhani *et al.*, 2022). Thus, it reinforces the need to evaluate future managers BDA intentions, once it could lead to future impact on technological acceptance.

2.2 Unified theory of acceptance and use of technology

The UTAUT model integrates previous theories and concepts, such as one of the most fundamental behavioral theories of psychology, Fishbein and Ajzen's Theory of Reasoned Action (TRA) (1975), the successor theory, Ajzen's Theory of Planned Behavior (TPB) (Ajzen, 1991), as well as covering the Technology Acceptance Model (TAM) and the Motivational Model (MM) (Venkatesh *et al.*, 2003). The basic concept of UTAUT states that the individual reacts to the use of information technology and, consequently, leads to the behavior itself.

The original UTAUT model presents four constructs that influence behavioral intent, namely, performance expectancy (PE), effort expectancy (EE), social influence (SI) and facilitating conditions (FC). Behavioral Intention, in turn, predicts usage and facilitating conditions directly influence it. Moderating factors such as age, gender, previous experience and voluntary or mandatory use are also considered in the relationships between the constructs (Venkatesh *et al.*, 2003). In this research, the original constructs were used with two others, namely, price value and user resistance, all directly linked to BDA use intention.

UTAUT has been recently used in research on several fields, e.g. education (Yang *et al.*, 2019), demonstrating that cloud technology acceptance was not affected by performance expectancy and facilitating conditions.

Performance expectancy consists of the hopes individuals have by applying technology (Villarejo-Ramos *et al.*, 2021), and it is considered to predict intention best to use (Venkatesh *et al.*, 2003). The literature shows both perspectives, namely, technology acceptance not being directly influenced by performance expectancy (Yang *et al.*, 2019), while another research confirms this positive relationship (Cabrera-Sánchez and Villarejo-Ramos, 2019), and the first hypothesis is formed based on this assumption:

H1. Performance expectancy positively influences the intention to use big data analytics.

According to Cabrera-Sánchez and Villarejo-Ramos (2019), several studies endorse that the degree of adoption of the DBA is associated with the expectation of the complexity of its use. In turn, effort expectancy is related to either ease/difficulty of using the technology; that is, it is proportional to the complexity of the use (Venkatesh *et al.*, 2003). Thus, the following hypothesis is:

H2. Effort expectancy positively influences the intention to use big data analytics.

Facilitating conditions are the environment, i.e. the organizational infrastructure that promotes the use of technology, considering the corporate environment must be designed to remove barriers and encourage adherence to technology (Venkatesh *et al.*, 2003). It has a significant effect on the intention to use new technology (Venkatesh *et al.*, 2012; Cabrera-Sánchez and Villarejo-Ramos, 2019) and even about the usage of the technology itself (Ajzen, 1991). Therefore, the proposed hypothesis is:

H3. Facilitate conditions positively influence the intention to use big data analytics.

Social influence is associated with the perception of importance that others give to the individual whether he uses the technology. The individual is seen as a result of having used the technology (Venkatesh *et al.*, 2003, 2012). In the organizational environment, the manager's choice about using the BDA is also influenced by his colleagues and peers. Therefore, we propose the following hypothesis:

H4. Social influence positively influences the intention to use big data analytics.

Despite not being considered in the original UTAUT by Venkatesh *et al.* (2003, 2012), price value was incorporated into its extended model, as it is a critical construct when the financial part consists in a factor in the decision to adopt the technology. This latent variable is based on the conceptualization of marketing in which the cost of the service is associated with the quality of the experience. Thus, the cost structure of the technology and the delivery that its application promises to have a tangible impact on the decision for its use (Venkatesh *et al.*, 2012). Thus, it is understood that in this model, the perception of the price value of the application of BDA is an essential factor to be considered. We, then, propose the hypothesis:

H5. Price value positively influences the intention to use big data analytics.

Resistance to use regards to users or managers' adverse reactions toward implementing such technologies. Certain information technologies can generate significant changes in the organization's social and technical systems; thus, user resistance is a natural reaction to changes, especially before implementing the system, which is a critical construct for the project's success (Markus, 2004; Kim and Kankanhalli, 2009). Strong user resistance can lead to a negative influence on the intention to use the technology, causing delays in implementation, budget overruns and, mainly, underutilization of the new system (Kim and Kankanhalli, 2009). Furthermore, before implementing it, it can be critical to the project's success (Markus, 2004; Kim and Kankanhalli, 2009). Thus, the sixth hypothesis presented is:

H6. User resistance negatively influences the intention to use big data analytics.

The six hypotheses proposed, therefore, lead to intention to use (IU), which in turn have a direct and strong connection with the use of technologies according to models of technological acceptance in contexts similar to the BDA (Fishbein and Ajzen, 1975; Venkatesh *et al.*, 2003; Venkatesh *et al.*, 2012; Cabrera-Sánchez and Villarejo-Ramos, 2019). The relationship between the constructs is presented as the conceptual model in the following section.

3. Conceptual model of the research

The literature review on big data analytics and technology adoption led to the formulation of hypotheses based on UTAUT with the addition of two new latent variables. The conceptual research model is presented in Figure 1, representing the research objective to identify the factors that positively and negatively influence the intention to use BDA by future managers of companies.

Table 1 presents the research hypotheses.

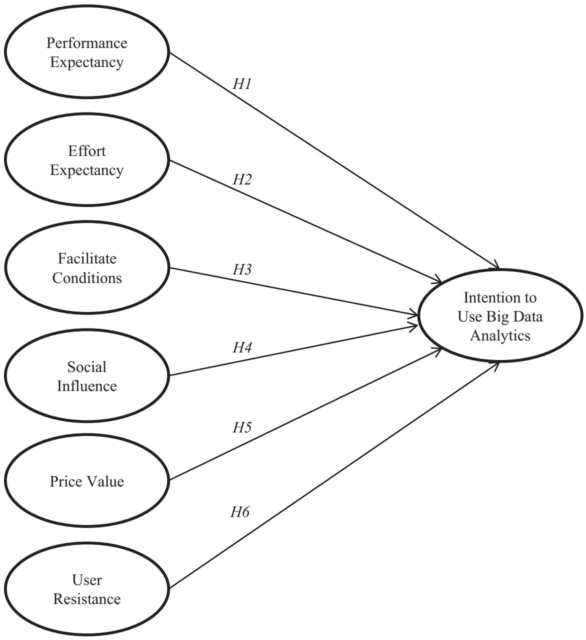


Figure 1.
Conceptual model of the research

Hypotheses	Description	References
H1	Performance expectancy positively influences the intention to use big data analytics	Venkatesh *et al.* (2003), Venkatesh *et al.* (2012), Cabrera-Sánchez and Villarejo-Ramos (2019)
H2	Effort expectancy positively influences the intention to use big data analytics	Venkatesh *et al.* (2003), Venkatesh *et al.* (2012), Cabrera-Sánchez and Villarejo-Ramos (2019)
H3	Facilitate conditions positively influence the intention to use big data analytics	Venkatesh *et al.* (2003), Venkatesh *et al.* (2012), Cabrera-Sánchez and Villarejo-Ramos (2019)
H4	Social influence positively influences the intention to use big data analytics	Venkatesh *et al.* (2003), Venkatesh *et al.* (2012)
H5	Price value positively influences the intention to use big data analytics	Venkatesh *et al.* (2012)
H6	User resistance negatively influences the intention to use big data analytics	Kim and Kankanhalli (2009), Markus (2004)

Table 1.
Research hypotheses

4. Methodology

The research was carried out through a quantitative methodology, using multivariate data analysis using SEM-PLS. The use of SEM-PLS has grown significantly in the applied social sciences, including research in information systems (Ringle *et al.*, 2012). The method allows estimating complex models, with several constructs, indicator variables and structural paths, and a causal-predictive approach, which emphasizes forecasting in the estimation of statistical models, whose structures are designed to provide causal explanations (Hair *et al.*, 2022).

Before starting the research, the research protocols containing the project, preliminary questionnaire, authorization from the university director, and declarations of commitment of the researchers were submitted for evaluation and approval by the research ethics committee through Plataforma Brazil.

After approval by the ethics committee, a pre-test was carried out with experts and potential survey respondents. Validation with specialists confirmed the face validity and adequacy of the questionnaire to the proposed objective. All three experts interviewed had a doctorate for at least five years and worked in information technology at their universities. The questionnaires underwent minor adjustments in the adapted questions to improve the respondents' understanding. The validation with possible respondents served to verify the understanding of the questions, and no adjustment was necessary. The final questionnaire is presented in Table 2.

The indicators of performance expectancy, effort expectancy, facilitating conditions, social influence, price value and intention to use were based on the extended UTAUT model by Venkatesh *et al.* (2012) and presented by Cabrera-Sánchez and Villarejo-Ramos (2019). User resistance indicators were based on Bhattacherjee and Hikmet (2007) and Cabrera-Sánchez and Villarejo-Ramos (2019). The questions used a five-point Likert scale (from "Totally Disagree" to "Totally Agree"), following the original scales proposed by the authors.

The interviews were carried out with Business Administration students from a public university in the state of São Paulo, which caused a sampling bias that needs to be considered. However, to minimize bias, we reinforced the importance of this public university and obtained responses from more than 30% of the university's Business

Questions	Mean	SD	Min	Max	N
Facilitate conditions					
CF1. I have enough resources to use big data analytics software	3.335	1.591	1	7	364
CF2. I have enough knowledge to use big data analytics software	2.970	1.507	1	7	364
CF3. The use of big data software is similar to user technologies I use	3.838	1.456	1	7	364
CF4. I can get help from others if I have difficulties in using big data analytics software	4.451	1.634	1	7	364
Performance expectancy					
ED1. I think the use of big data analytics software useful in the day-to-day of the company manager	6.107	1.001	1	7	364
ED2. Using a big data analytics software can improve the performance of business managers	6.349	0.786	3	7	364
ED3. Using a big data analytics software can help business managers get things done faster	6.255	0.876	3	7	364
ED4. I think the use of a big data analytics software can improve the performance of the company manager	6.269	0.904	2	7	364
Effort expectancy					
EE1. Learning to use big data analytics is not difficult	3.810	1.338	1	7	364
EE2. The interaction with big data analytics is understandable	4.302	1.368	1	7	364
EE3. I think it is easy to become skilled in big data analytics	3.475	1.318	1	7	364
EE4. It is easy for me to become skilled in using big data analytics software	4.266	1.474	1	7	364
Social influence					
IS1. People who are important to me think managers should use big data analytics software	5.080	1.453	1	7	364
IS2. People who influence my behavior think that managers should use big data analytics software	5.000	1.404	1	7	364
IS3. People whose opinion I value prefer that managers use big data analytics programs	5.118	1.357	1	7	364
Price value					
CB1. The price of big data analytics software is reasonable	4.338	1.164	1	7	364
CB2. I consider big data analytics software to be a good investment for companies	6.220	0.902	2	7	364
CB3. At the current price, big data analytics software provides a good return	4.783	1.092	2	7	364
User resistance					
RU1. I don't want the use of big data analytics software to change the way I lead	3.442	1.710	1	7	364
RU2. I don't want the use of big data analytics software to change the way I make decisions	2.937	1.556	1	7	364
RU3. I don't want the use of big data analytics software to change the way I interact with other people in my work	4.451	1.804	1	7	364
RU4. Overall, I don't want the use of big data analytics to change the way I work	3.330	1.633	1	7	364
Use intention					
UI1. I plan to use big data analytics software in the future	5.857	1.187	1	7	364
UI2. In the future, I intend to use programs for big data analytics	5.832	1.166	1	7	364
IU3. I plan to use big data analytics software often	5.107	1.380	1	7	364
UI4. I plan to use big data analytics software in the job market	5.701	1.209	1	7	364

Note: The questionnaire used a five-point Likert scale, from "Totally Disagree" to "Totally Agree"

Table 2.
Descriptive statistics

Administration students. Sao Paulo is the state that presents the largest GPD per capita in the country and also the most significant population density with more than 46 million people. It shows the best results concerning basic education development (IBGE, 2021), one of Brazil's most relevant metropolitan regions. Sao Paulo contributed 29.87% to the GPD by itself, being the most significant contributor in the country (IBGE, 2021). Concerning the educational system, in 2019, Brazil accounted for 2608 Higher Education Institutions. Sao Paulo had one-fourth of enrollments in courses offered (INEP, 2021).

The university appears as the second-best in the country in the Times Higher Education World University Rankings 2021 (THE, 2021) and in the Quacquarelli Symonds (QS) World University Rankings 2021 (Symonds, 2021). Thus, it is among the best in Brazil. Regarding the Business Administration course, its students constitute the largest group in the sample of the GUESS report (24.7% of all students) and the scenario of undergraduate courses in Brazil (14.5% of all courses), being the most representative field of knowledge (Sieger *et al.*, 2018; INEP, 2021). In addition, all Business Administration students have Information Technology Administration courses on their curriculum, which address the topic of BDA.

As a form of control, an initial question was added about the student's intention to become a business manager in the future. If not, the questionnaire was ended and excluded from the final sample. The total sample comprised 364 responses from students enrolled in Business Administration.

Data collection was carried out virtually between October and November 2020. An invitation to participate in the research was sent to the students' institutional email, with the research presentation and a link to the digital questionnaire. The educational institution has 960 business administration students, and the sample obtained a response rate of 32.60% of the total, with 364 students.

The software G* Power was used to evaluate the minimum sample size, that is 98 respondents. Thus, the sample of 364 respondents reached the minimum desired size.

5. Results analysis

This section includes the analysis of the measurement models and the structural model. Before the analysis, the data treatment was performed to analyze missing data, normality and outliers. No adjustment or deletion of data was necessary. Table 2 presents the model's indicators and their descriptive statistics.

To evaluate the proposed measurement model, the convergent validity, the discriminant validity and the reliability of the indicators were verified (Hair *et al.*, 2022). The indicators required for these assessments are presented in Table 3, and all are within the established (Hair *et al.*, 2022). No indicators needed to be removed at this stage of the analysis.

For the structural model's validation, the variance inflation factor was initially verified, and all values were within those established by Hair *et al.* (2022). Subsequently, the significance of the indicators and the student's *t*-test were assessed using the bootstrapping technique. Table 5 shows the values of the coefficients between the constructs and their respective Student's *t*-tests.

According to the results (Table 4), all the study hypotheses were confirmed, except for *H2* and *H3*, which concern the expectation of effort and the facilitating conditions that positively influence the intention to use BDA.

Results point to a determination coefficient considered high (R^2 = 0.451 and R^2 adjusted = 0.441) for the intention to use BDA. In addition, for SEM models, Q^2 values greater than zero indicate the predictive relevance of the path model. In the case of this study, Q^2 = 0.324, and the values are considered adequate (Hair *et al.*, 2022). The complete model which resulted from the empirical research is presented in Figure 2.

Table 3. Measurement model evaluation

Constructs	FC	PE	EE	SI	PV	UR	IU
Facilitating conditions (FC)	*0.732*						
Performance expectancy (PE)	0.146	*0.773*					
Effort expectancy (EE)	0.689	0.224	*0.767*				
Social influence (SI)	0.344	0.397	0.319	*0.871*			
Price value (PV)	0.237	0.566	0.281	0.455	0.865		
User resistance (UR)	0.234	0.528	0.228	0.313	0.471	*0.709*	
Intention to use (IU)	0.210	−0.275	0.077	−0.095	−0.301	−0.139	*0.775*
Alpha de Cronbach	0.707	0.774	0.768	0.841	0.887	0.616	0.788
rho_A	0.724	0.784	0.781	0.856	0.893	0.844	0.845
Confiabilidade Composta	0.820	0.855	0.851	0.904	0.922	0.744	0.855
Variância Média Extraída	0.536	0.597	0.589	0.758	0.748	0.502	0.600

Note: The values in italics diagonally are the square root of the extracted average variance

Table 4. Structural model coefficients

Relationshiops	Average	SD	T-Value	*p-value*
Performance expectancy → Intention to use	0.305	0.054	5.675	0.000
Effort expectancy → Intention to use	0.075	0.058	1.220	0.223
Facilitating conditions → Intention to use	0.075	0.067	1.003	0.316
Social influence → Intention to use	0.205	0.058	3.634	0.000
Price value → Intention to use	0.189	0.059	3.119	0.002
User resistance → Intention to use	−0.197	0.040	4.730	0.000

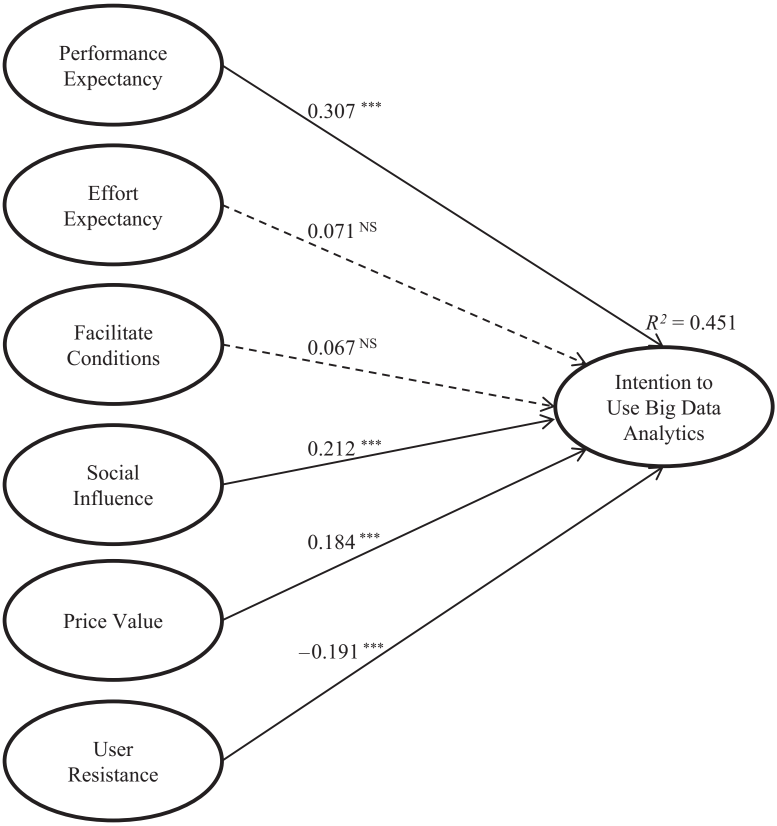
Table 5. Hypothesis results

Hypotheses	Description	Result
H1	Performance expectancy positively influences the intention to use big data analytics	Confirmed
H2	Effort expectancy positively influences the intention to use big data analytics	Not confirmed
H3	Facilitate conditions positively influence the intention to use big data analytics	Not confirmed
H4	Social influence positively influences the intention to use big data analytics	Confirmed
H5	Price value positively influences the intention to use big data analytics	Confirmed
H6	User resistance negatively influences the intention to use big data analytics	Confirmed

6. Discussion

This study presented and tested a research model that considers six possible predictive variables for the intention to use BDA. It also showed a robust model with a high explanatory value for the intention to use BDA ($R^2 = 45.1\%$). The research provides relevant information on the behavior of future managers of companies, presenting relevant implications for the theories of big data and technology adoption. In addition, it offers practical contributions for corporate managers to develop organizational policies.

The factors that positively influence the intention to use BDA are, from highest to lowest intensity: performance expectancy, social influence and cost–benefit. Regarding the negative impact, resistance to use is a relevant factor.



Notes: * = significance at 5%; ** = significance at 1%; *** = significance at 0.1%; NS = not significant

Figure 2. Complete empirical model

Performance expectancy, which showed the most significant positive influence, analyzes the manager's perception of how much technology can improve his performance, helping him make decisions and perform tasks more quickly, being useful in the manager's day-to-day. The result corroborates previous research, in which the performance expectancy was also one of the most influential factors in behavioral intention (Venkatesh *et al.*, 2003; Cabrera-Sánchez and Villarejo-Ramos, 2019). However, in Cabrera-Sánchez and Villarejo-Ramos (2019), facilitating conditions were the most significant influences. The present study's hypothesis of facilitating conditions was not confirmed, perhaps due to differences in the respondents' profiles. This result reinforces the importance of technological relevance to the manager, i.e. how technology can benefit managerial decisions on several grounds (marketing, strategy, financially, among others).

Social influence, the second most relevant factor regarding positive impact, analyzes how important the opinion of essential individuals to the respondent is for the intention to use it, also corroborated by previous research (Kim and Kankanhalli, 2009; Cabrera-Sánchez and Villarejo-Ramos, 2019).

Price value was presented as the third most significant and positive influence. It consists of how the benefits of using technology outweigh its monetary cost. This construct was not presented in the original UTAUT (Venkatesh *et al.*, 2003), but it was incorporated into the extended UTAUT model (Venkatesh *et al.*, 2012). This construct had not been tested in the context of the BDA previously, which brings originality to this research.

Resistance to use has negatively influenced the intention to use and concerns opposite or adverse reactions to implementing new technology. Few studies have addressed this construct in adoption models, but the results were similar to those found in this research (Cabrera-Sánchez and Villarejo-Ramos, 2019), demonstrating the importance of cultural change acceptance and also that managers should be open to new ways to make decisions, interact with people and, especially, to get the most out of technological benefits.

Some considerations can be made concerning the hypotheses which were not confirmed, related to the effort expectation and facilitating conditions. Effort expectation refers to the ease of learning and use of technology, and facilitating conditions refer to having the necessary resources (Venkatesh *et al.*, 2003). As the responding public consisted of students from the Business Administration course, they are generally young people with high use of technology, which may have influenced the non-confirmation of these hypotheses. It is possible that in different sample analysis, especially among an older sample, the results could be different. The results obtained are essential, i.e. planning actions, training, and BDA projects in companies.

Considering the state of the art of research on the topic, the article innovates on the following fronts:

- We validate a consistent theoretical model with two new latent variables in a current and relevant issue (BDA) in a little explored context.
- We offer an in-depth investigation into the perception of future managers, who, in general, were born in a period of greater technological interaction, showing knowledge and interest in BDA and a good perception of price for technology.
- We demonstrate that resistance to use is the most relevant issue regarding technological adoption.

BDA's technical capabilities are tangible, but in the organizational dimension, insights are often intangible and relate to the organization's collaboration and strategy (Klievink *et al.*, 2017).

Regarding research contributions to the academic literature in the area, although research on BDA has improved the understanding of the phenomenon, it mostly emphasizes technical dimensions of BDA, and it underestimates the organizational and human dimensions (Gupta and George, 2016; Gong and Janssen, 2021). Our research contributed to the literature by presenting new insights into these organizational and human aspects by presenting influencing factors for future managers.

Still considering theoretical contributions, it is observed that effort expectation and facilitating conditions were not relevant to the intention to use BDA. However, they were confirmed as significant for adopting technologies in Venkatesh *et al.* (2012) study.

This result indicates that, although the model describes a set of relevant factors to the use of technologies, their importance can change depending on the sample group selected for the study developed. It is understood that, in this study, the respondents consider BDA as a future technology that must be present in their future jobs and, therefore, the relationship between facilitating conditions and effort expectation would not be subject to analysis in the respondents' perception.

Regarding managerial implications, results indicate which variables facilitate and inhibit BDA by future managers. Thus, managers can consider these aspects in decisions involving BDA's adoption. In addition, the results can generate economic and commercial impacts on firms, reinforcing the importance of managers' understanding of the benefits of technology adoption to improve organizational communication to elucidate the system's functionalities, increasing the use of the BDA aiming for the best organizational performance, as pointed out in recent research as well (Maroufkhani *et al.*, 2022). This action can be done, for instance, with training actions to enable simulations in managerial decision-making situations.

In addition, it is necessary to make the user aware of the company's care concerning privacy, security and ethical aspects in using the BDA, as these factors can reduce resistance to use. According to the results obtained in this paper, resistance to use stands out as one factor that reduces the intention to use. Thus, managers must be aware that the implementation of BDA systems can impact users' routines and strengthen communication processes during technological transitions, as well as invest in proper training and onboarding programs.

In addition, the role of leadership as a motivating force for technological innovations also plays a fundamental role in adopting these tools. The study results show social influence as the second most relevant factor for the intention to use these technological resources in organizations, which can also be corroborated by recent research (Maroufkhani *et al.*, 2022).

Practical contributions can also regard to the understanding that investment in technology by organizations is considered as another relevant factor for the sample's intention to use BDA. According to the study results, it shows that BDA solutions are considered a proper investment decision. In practical terms, the positive perception in the decision on financial resources in the acquisition of new technologies may represent the overcoming of one of the main obstacles to the execution of these initiatives in projects of this nature due to the uncertainties that may exist in the implementation of innovative technologies.

Contributions can cover three fronts: more robust understanding of the benefits of technology (performance expectation), more people using and adopting technology on a day-to-day basis, influencing colleagues (social influence), and encouraging the creation of a culture geared to use in the company (user resistance).

Another guideline that can be considered for companies that do not yet use BDA software is to present and make available free software so that managers have the first contact and analyze the possibilities for improvements that its use can generate. This initiative helps explore options and prices of the most suitable paid software for the organization. The same strategy can be used by companies that sell BDA software. This action would help provide a clearer understanding of the relationship between benefits and cost related to price value.

Furthermore, practical implications can be drawn for the university environment, where managers can use these results to plan initiatives using information technology, whether in teaching, research, or extension activities, highlighting its benefits and enabling future managers who study at that institution to better their knowledge on the matter.

7. Conclusion and final remarks

The digital transformation taking place in companies and the emergence of the BDA generate opportunities to improve the analytical resources necessary to manage information effectively to improve the managerial decision-making capacity from the adoption of the BDA (Seddon *et al.*, 2017). Companies of all sizes face difficulties in adopting and implementing the BDA due to the technological and human demands necessary for the correct adoption (Gong and Janssen, 2021). Among barriers and obstacles to the effective use of BDA, we can mention the outdated IT infrastructure, the complexity and chaos inherent to a large amount of information, the quality of data selection, the concern with security and privacy and the lack of data science skills in organizations (Medeiros *et al.*, 2021). Thus, creating a culture and organizational vision focused on using BDA is necessary. This research contributes to filling a research gap regarding the adoption of BDA, by presenting in-depth information about the factors that companies positively and negatively influence the intention to use BDA by future managers. The results help overcome some challenges and barriers in using the BDA.

Despite its implications, this research does not go out without limitations. First, the study collected information with a single cross-section in the second semester of 2020, and it may not represent the respondents' opinion over time; second, the collection period was during the coronavirus pandemic, and this may have impacted the perception of the future manager; third, the sample consisted of students from the Business Administration course at an educational institution, which can result in a critical bias; lastly, the research did not test for common method bias, which can have adverse effects on results.

Future research can be suggested on the following fronts:

- studying different undergraduate courses and educational institutions;
- test differences according to the respondent's gender, age and region; and
- longitudinal studies, besides analyzing differences in students' perception over time.

References

Ajzen, I. (1991), "The theory of planned behavior", *Organizational Behavior and Human Decision Processes*, Vol. 50 No. 2, pp. 179-211, doi: 10.1016/0749-5978(91)90020-T.

Alharthi, A., Krotov, V. and Bowman, M. (2017), "Addressing barriers to big data", *Business Horizons*, Vol. 60 No. 3, pp. 285-292, doi: 10.1016/j.bushor.2017.01.002.

Aloysius, J.A., Hoehle, H., Goodarzi, S. and Venkatesh, V., (2018), "Big data initiatives in retail environments: linking service process perceptions to shopping outcomes", *Annals of Operations Research*, Vol. 270 Nos 1/2, pp. 25-51, doi: 10.1007/s10479-016-2276-3.

Baig, M.I., Shuib, L. and Yadegaridehkordi, E. (2019), "Big data adoption: state of the art and research challenges", *Information Processing and Management*, Vol. 56 No. 6, p. 102095, doi: 10.1016/j.ipm.2019.102095.

Behl, A. (2022), "Antecedents to firm performance and competitiveness using the lens of big data analytics: a cross-cultural study", *Management Decision*, Vol. 60 No. 2, pp. 368-398, doi: 10.1108/MD-01-2020-0121.

Bhattacherjee, A. and Hikmet, N. (2007), "Physicians' resistance toward healthcare information technology: a theoretical model and empirical test", *European Journal of Information Systems*, Vol. 16 No. 6, pp. 725-737, doi: 10.1057/palgrave.ejis.3000717.

Cabrera-Sánchez, J.-P. and Villarejo-Ramos, Á.F. (2019), "Factors affecting the adoption of big data analytics in companies", *Revista de Administração de Empresas*, Vol. 59 No. 6, pp. 415-429, doi: 10.1590/S0034-759020190607.

Cetindamar, D., Shdifat, B. and Erfani, E. (2022), "Understanding big data analytics capability and sustainable supply chains", *Information Systems Management*, Vol. 39 No. 1, pp. 19-33, doi: 10.1080/10580530.2021.1900464.

Chen, C.-C., Shih, H.S., Shyur, H.J. and Wu, K.S. (2012), “A business strategy selection of green supply chain management via an analytic network process”, *Computers and Mathematics with Applications*, Vol. 64 No. 8, pp. 2544-2557, doi: 10.1016/j.camwa.2012.06.013.

Davis, F.D., Bagozzi, R.P. and Warshaw, P.R. (1989), “User acceptance of computer technology: a comparison of two theoretical models”, *Management Science*, Vol. 35 No. 8, pp. 982-1003.

El-Haddadeh, R., Osmani, M., Hindi, N. and Fadlalla, A. (2021), “Value creation for realising the sustainable development goals: fostering organisational adoption of big data analytics”, *Journal of Business Research*, Vol. 131, pp. 402-410, doi: 10.1016/j.jbusres.2020.10.066.

Erevelles, S., Fukawa, N. and Swayne, L. (2016), “Big data consumer analytics and the transformation of marketing”, *Journal of Business Research*, Vol. 69 No. 2, pp. 897-904, doi: 10.1016/j.jbusres.2015.07.001.

Fishbein, M. and Ajzen, I. (1975), *Belief, Attitude, Intention and Behaviour: An Introduction to Theory and Research*, Addison-Wesley, Reading, MA.

Furht, B. and Villanustre, F. (2016), *Big Data Technologies and Applications*, Springer International Publishing, Cham, doi: 10.1007/978-3-319-44550-2.

Giest, S. (2017), “Big data for policymaking: fad or fasttrack?”, *Policy Sciences*, Vol. 50 No. 3, pp. 367-382, doi: 10.1007/s11077-017-9293-1.

Gong, Y. and Janssen, M. (2021), “Roles and capabilities of enterprise architecture in big data analytics technology adoption and implementation”, *Journal of Theoretical and Applied Electronic Commerce Research*, Vol. 16 No. 1, pp. 37-51, doi: 10.4067/S0718-18762021000100104.

Gupta, M. and George, J.F. (2016), “Toward the development of a big data analytics capability”, *Information and Management*, Vol. 53 No. 8, pp. 1049-1064, doi: 10.1016/j.im.2016.07.004.

Hair, J.F., Hult, G.T., Ringle, C.M. and Sarstedt, M. (2022), *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*, 3rd ed. Thousand Oaks, CA: Sage.

IBGE (2021), “Panorama” IBGE, Rio de Janeiro available at: https://cidades.ibge.gov.br/brasil/panorama (accessed 16 March 2022).

INEP (2021), “Higher education assessments – INEP”, available at: www.gov.br/inep/pt-br/areas-de-atuacao/pesquisas-estatisticas-e-indicadores/censo-da-educacao-superior/resultados (accessed 16 March 2022).

Kim, H.W. and Kankanhalli, A. (2009), “Investigating user resistance to information systems implementation: a status quo bias perspective”, *MIS Quarterly*, Vol. 33 No. 3, p. 567, doi: 10.2307/20650309.

Klievink, B., Romijn, B.J., Cunningham, S. and de Bruijn, H. (2017), “Big data in the public sector: uncertainties and readiness”, *Information Systems Frontiers*, Vol. 19 No. 2, pp. 267-283, doi: 10.1007/s10796-016-9686-2.

Markus, M.L. (2004), “Technochange management: using IT to drive organizational change”, *Journal of Information Technology*, Vol. 19 No. 1, pp. 4-20, doi: 10.1057/palgrave.jit.2000002.

Maroufkhani, P., Iranmanesh, M. and Ghobakhloo, M. (2022), “Determinants of big data analytics adoption in small and medium-sized enterprises (SMEs)”, *Industrial Management and Data Systems*, doi: 10.1108/imds-11-2021-0695.

Maroufkhani, P., Tseng, M.L., Iranmanesh, M., Ismail, W.K.W. and Khalid, H. (2020), “big data analytics adoption: determinants and performances among small to medium-sized enterprises”, *International Journal of Information Management*, Vol. 54, p. 102190, doi: 10.1016/j.ijinfomgt.2020.102190.

Medeiros, M.M., de, Hoppen, N. and Maçada, A.C.G. (2020a), “Data science for business: benefits, challenges and opportunities”, *The Bottom Line*, Vol. 33 No. 2, pp. 149-163, doi: 10.1108/BL-12-2019-0132.

Medeiros, M.M., de, Maçada, A.C.G. and Freitas Junior, J.C. (2020b), "The effect of data strategy on competitive advantage", *The Bottom Line*, Vol. 33 No. 2, pp. 201-216, doi: 10.1108/BL-12-2019-0131.

Medeiros, M.M., Maçada, A.C.G. and Hoppen, N. (2021), "The role of big data stewardship and analytics as enablers of corporate performance management", *RAM. Revista de Administração Mackenzie*, Vol. 22 No. 6, doi: 10.1590/1678-6971/eramd210063.

Razaghi, S. and Shokouhyar, S. (2021), "Impacts of big data analytics management capabilities and supply chain integration on global sourcing: a survey on firm performance", *The Bottom Line*, Vol. 34 No. 2, pp. 198-223, doi: 10.1108/BL-11-2020-0071.

Ringle, C.M., Sarstedt, M. and Straub, D.W. (2012), "Editor's comments: a critical look at the use of PLS-SEM in 'MIS quarterly", *MIS Quarterly*, Vol. 36 No. 1, pp. 3, doi: 10.2307/41410402.

Seddon, P.B., Constantinidis, D., Tamm, T. and Dod, H. (2017), "How does business analytics contribute to business value?", *Information Systems Journal*, Vol. 27 No. 3, pp. 237-269, doi: 10.1111/isj.12101.

Sieger, P. Fueglistaller, U. Zellweger, T. and Braun, I. (2018), "Global student entrepreneurship 2018: insights from 54 countries", available at: www.guesssurvey.org/resources/PDF_InterReports/GUESSS_Global_2018.pdf (accessed 16 March 2022).

Sivarajah, U., Kamal, M.M., Irani, Z. and Weerakkody, V. (2017), "Critical analysis of big data challenges and analytical methods", *Journal of Business Research*, Vol. 70, pp. 263-286, doi: 10.1016/j.jbusres.2016.08.001.

Sun, Z., Sun, L. and Strang, K. (2018), "Big data analytics services for enhancing business intelligence", *Journal of Computer Information Systems*, Vol. 58 No. 2, pp. 162-169, doi: 10.1080/08874417.2016.1220239.

Symonds, Q. (2021), "Quacquarelli Symonds (QS) world university rankings 2021", available at: www.topuniversities.com/university-rankings/world-university-rankings/2021, (accessed16 March 2022).

THE (2021), "World education ranking 2021", available at: www.timeshighereducation.com/world-university-rankings/2021/world-ranking#!/page/0/length/25/sort_by/rank/sort_order/asc/cols/stats (accessed16 March 2022).

Venkatesh, V., Thong, J.Y. and Xu, X. (2012), "Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology", *MIS Quarterly*, Vol. 36 No. 1, p. 157, doi: 10.2307/41410412.

Venkatesh, V., Morris, M.G., Davis, G.B. and Davis, F.D. (2003), "User acceptance of information technology: toward a unified view", *MIS Quarterly*, Vol. 27 No. 3, p. 425, doi: 10.2307/30036540.

Villarejo-Ramos, Á.F., Cabrera-Sánchez, J.P., Lara-Rubio, J. and Liébana-Cabanillas, F. (2021), "Predicting big data adoption in companies with an explanatory and predictive model", *Frontiers in Psychology*, Vol. 12, doi: 10.3389/fpsyg.2021.651398.

Yang, H.H., Feng, L. and MacLeod, J. (2019), "Understanding college students' acceptance of cloud classrooms in flipped instruction: integrating UTAUT and connected classroom climate", *Journal of Educational Computing Research*, Vol. 56 No. 8, pp. 1258-1276, doi: 10.1177/0735633117746084.

Yaqoob, I., Hashem, I.A., Gani, A., Mokhtar, S., Ahmed, E., Anuar, N.B. and Vasilakos, A.V. (2016), "Big data: from beginning to future", *International Journal of Information Management*, Vol. 36 No. 6, pp. 1231-1247, doi: 10.1016/j.ijinfomgt.2016.07.009.

About the authors

Gustavo Hermínio Salati Marcondes de Moraes is an Associate Professor at the School of Applied Science (FCA), University of Campinas. Professor Moraes holds his Ph.D. (2013) and MSc (2010) in

Business Administration from Sao Paulo School of Business Administration, Getulio Vargas Foundation (FGV/EAESP). Gustavo Hermínio Salati Marcondes de Moraes is the corresponding author and can be contacted at: salati@unicamp.br

Gisela Consolmagno Pelegrini is a Ph.D. Candidate in Business Administration at the School of Applied Sciences, University of Campinas. Professor Pelegrini holds a MSc in Business Administration in 2020.

Laís Porfírio de Marchi is a graduate student in Business Administration from the School of Applied Sciences at the University of Campinas.

Gabriela Trindade Pinheiro is a Ph.D. Candidate in Business Administration at the School of Applied Sciences, University of Campinas. Professor Pinheiro holds a MSc in Business Administration in 2020.

Alexandre Cappellozza is an Associate Professor at the Mackenzie Presbyterian University. Professor Cappelloza holds his Ph.D. (2013) in Business Administration from Sao Paulo School of Business Administration, Getulio Vargas Foundation (FGV/EAESP).