ÁREA TEMÁTICA: 11. Administração da informação

ANALYSIS OF BIG DATA ANALYTICS USE INTENTION BY FUTURE BUSINESS MANAGERS

ANÁLISE DA INTENÇÃO DO USO DE BIG DATA ANALYTICS POR FUTUROS GESTORES

Summary

The field related to Big Data Analytics has become relevant for the academic community and also for the market. The objective of this research was to analyze what are the effects of influencing factors on the intention of using Big Data Analytics by future company managers. The sample consisted of 364 business students from a public university in the state of São Paulo. The methodology used was quantitative with the use of Structural Equation Modeling by Partial Least Squares. The research presented a robust model with a high explanatory factor for the intention to use Big Data Analytics (R^2 = 47.8%), in which the factors 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. The results contribute with relevant information about the behavior of future managers in face of a new technology, which has been presented as fundamental in an increasingly competitive environment. Managers can use the results of this study to identify trends and adjustments in the planning, investment and use of technology.

Key words: Big Data Analytics; Technological Adoption; University students; Brazil.

Resumo

O campo relacionado à *Big Data Analytics* tem se tornado relevante para a comunidade acadêmica e também para o mercado. O objetivo dessa pesquisa foi analisar quais são os efeitos de fatores de influência na intenção de uso de *Big Data Analytics* por futuros gestores de empresas. A amostra foi composta por 364 estudantes de Administração de uma universidade pública do Estado de São Paulo. A metodologia utilizada foi quantitativa com a utilização de Modelagem de Equações Estruturais por Mínimos Quadrados Parciais. A pesquisa apresentou um modelo robusto com alto fator explicativo para intenção de uso de *Big Data Analytics* (R^2 = 47,8%), onde os fatores de influência positiva à intenção de uso são expectativa de desempenho, influência social e custo benefício, e o fator de influência negativa é a resistência ao uso. Os resultados contribuem com informações relevantes sobre o comportamento de futuros gestores frente a uma nova tecnologia, que tem se apresentado como fundamental em um ambiente cada vez mais competitivo. Gestores podem utilizar os resultados desse estudo para identificar tendências e adequações no planejamento, investimento e utilização da tecnologia.

Palavras-chaves: *Big Data Analytics*; Adoção Tecnológica; Estudantes Universitários; Brasil.

1. INTRODUÇÃO

Since the beginning of the 21st century, with the popularization of the Internet and the emergence of other technological innovations, the levels of industrial production in the world have grown, aiming to meet needs with an increasing level of demand in an increasingly competitive environment (FREITAS; RECH, 2003; LIMA; PINTO, 2019). As a result, the volume of data produced and shared by organizations, either public or private, has increased immeasurably (AGARWAL *et al.*, 2014).

One of these technologies refers to the use of Big Data Analytics (BDA), which involves the process of extracting value from data, which makes it possible to find specific patterns that can support targeted decision-making (CABRERA-SÁNCHEZ; VILLAREJO-RAMOS, 2019).

Companies that can turn data into real-time information about their customers gain a substantial competitive advantage, which could even lead to reaching market leadership (MCAFEE; BRYNJOLFSSON, 2012; SIVARAJAH *et al.*, 2017). Since technological innovations can affect organizations (PATRAKOSOL; OLSON, 2007) as well as impact their performance and market share (MCAFEE; BRYNJOLFSSON, 2012), research on technological adoption seeks to understand the introduction of these technologies, as well as conduct and procedures, having a critical role in organizations (KARAHANNA; STRAUB; CHERVANY, 1999; VENKATESH; THONG; XU, 2012).

Companies considering the adoption of BDA face several barriers, such as lack of knowledge, fear, resistance to change and the very limitations of technology (YAQOOB *et al.*, 2016). In order to explain and increase the acceptance of individuals in relation to technologies, it is necessary to comprehend the reasons that lead them to either adopt or reject IT (DAVIS; BAGOZZI; WARSHAW, 1989; VENKATESH; THONG; XU, 2012).

According to Cabrera-Sánchez and Villarejo-Ramos (2019), technological adoption by companies is crucial. Because of this, several models of technological adoption have been developed, tested and improved over time (CABRERA-SÁNCHEZ; VILLAREJO-RAMOS, 2019).

Considered as a mature and widely used model (CABRERA-SÁNCHEZ; VILLAREJO-RAMOS, 2019), the theory known as UTAUT (Unified Theory of Acceptance and Use of Technology) presents direct determinant constructs of intention to use behavior, namely: a) performance expectation; b) effort expectation; c) social influence and d) facilitating conditions (VENKATESH *et al.*, 2003). In addition, the model also features some moderators, such as gender, age, experience of the individual and voluntariness (ALVEZ; PEREIRA, 2015; VENKATESH *et al.*, 2003).

Broadly researched in the industrial segment, few authors research the adoption of BDA in companies (CABRERA- SÁNCHEZ; VILLAREJO-RAMOS, 2019; CHEN; CHIANG; STOREY, 2012), so, the study of the adoption of BDA is identified as an opportunity by future company managers. Thus, the objective of this article is to verify the main factors that may influence the intention of using Big Data Analytics by future company managers through the use of UTAUT. With this, we intend to answer the following research question: *What are the influencing factors in the intention of using Big Data Analytics by future managers?*

The study was conducted with students of Business Administration from the State University of Campinas (UNICAMP), in the state of São Paulo, Brazil. Brazil is the largest country in South America with about 211 million inhabitants (IBGE, 2021). São Paulo is the state which presents the largest GPD per capita in the country and also the largest population density with more than 46 million people. It presents the best results concerning basic education development (IBGE, 2021) and it is one of the most relevant metropolitan regions in Brazil (FISCHER; SCHAEFFER; QUEIROZ, 2019). São Paulo contributed with 29,87% to the GPD by itself, being the biggest contributor in the country (IBGE, 2021). Concerning the educational system, in 2019, Brazil accounted for 2608 Higher Education Institutions and 25% of enrollments were done in courses offered in São Paulo (INEP, 2021).

This article was structured, besides introduction, as follows: theoretical background (chapter 2), conceptual model and hypotheses (chapter 3), methodological procedures (chapter 4), results analysis (chapter 5) and final remarks (chapter 6).

2. THEORETICAL BACKGROUND

Widely studied, the Unified Theory of Acceptance and Use of Technology (UTAUT) is a comprehensive model used for the study of the adoption of technologies (CABRERA-SÁNCHEZ; VILLAREJO-RAMOS, 2019). For UTAUT, there are critical and contingent factors that can predict the intention to use technologies in organizational contexts and, despite the intense replication of the model and its applicability, new studies on the topic work with the aim of understanding the theory in new contexts, add constructs that can expand its scope and also include predictors for its variables (VENKATESH *et al.*, 2012).

2.1 *Big Data Analytics* and Business Management

Studying BDA through UTAUT, a theory with mature results, requires just revisiting the model and adding constructs that relate to the peculiarities of BDA. Big data, a term derived from the massive amount of data created through the interaction between customers and companies, is used for analyzes that allow an accurate perception of the behavior and trajectories of individuals and, thus, make the consumer experience more assertive (ALOYSIUS *et al.*, 2018).

At the same time that the BDA provides competitive advantage and innovated areas such as marketing, pricing and customer prospecting (CABRERA-SÁNCHEZ; VILLAREJO-RAMOS, 2019), its application is still complex and requires teams with specific knowledge, in addition to a database architecture and substantial processing capacity (SUN *et al.*, 2018). In addition, there is also resistance on the part of consumers to make their personal data available. Many prefer to maintain their privacy instead of having access to more personalized services (ALOYSIUS *et al.*, 2018), and companies are aware of this issue.

Even so, BDA is a technology that collects data from registration and payment sources (ALOYSIUS *et al.*, 2018) and that aims to bring incremental value to the business through prospecting customers, whether in a new segment or increasing the current volume, as well as by improving sales and reducing costs, at the same time that it brings to the customer the perception of commitment, satisfaction, association of the company with its values, therefore, it develops consumer loyalty with the brand (INMAN; NIKOLOVA, 2017).

Within a decision context to use BDA in a company is the role of strategy and business intelligence managers (SUN *et al.*, 2018), and the acceptance or rejection on the topic can be measured since the formation of these managers. Therefore, analyzing the tendency to use BDA in students whose training indicates them as probable future managers of companies delivers data on the inclinations regarding the acceptance of the use of this specific technology, adding elements so that the BDA is disseminated as a useful tool.

2.2 Technological Adoption Models for Big Data Analytics

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) (1991), as well as covering the Technology Acceptance Model (TAM) and the Motivational Model (MM) (VENKATESH *et al.*, 2003). The basic concept of UTAUT is the individual reactions to the intention to use information technology and, consequently, lead to the behavior itself.

The original UTAUT model has four constructs that influence behavioral intent, namely performance expectancy, effort expectations, social influence and facilitating conditions. Intention, in turn, predicts usage behavior, and facilitating conditions also 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) and, for this research, the original constructs were used with the addition of two others: price value and user resistance, all of them directly linked to the intention to use the BDA.

Performance Expectancy (PE) is defined as the degree of belief that the individual has about the use of technology to help him improve his performance, and is considered the best predictor of intention to use (VENKATESH *et al.*, 2003). Subsequent studies confirm this positive relationship (CABRERA-SÁNCHEZ; VILLAREJO-RAMOS, 2019), and the first hypothesis is formed based on this assumption:

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

Effort Expectancy (EE), in turn, is associated with the ease / difficulty of using the technology, that is, it is proportional to the complexity of the use (VENKATESH *et al.*, 2003). 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. Thus, the following hypothesis is:

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

Facilitating Conditions (FC) are the environment, the organizational infrastructure that promotes the use of technology, so that the technological organizational environment is designed to remove barriers and facilitate adherence to technology (VENKATESH *et al.*, 2003), having a significant effect about the intention to use a new technology (CABRERA-SÁNCHEZ; VILLAREJO-RAMOS, 2019; VENKATESH *et al.*, 2012), and even about the behavior of using the technology (AJZEN, 1991). Therefore, the proposed hypothesis is:

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

Social Influence (SI) is associated with the perception of importance that others give to the individual whether he uses the technology itself or not, in the way that 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 the use of the BDA is also under the influence of his colleagues and peers. Therefore, we propose the following hypothesis:

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

Price value (PV), despite not being considered in the original UTAUT by Venkatesh *et al.* (2013), was incorporated into the UTAUT extended model, as it is an important construct when the financial part is an analysis factor in the decision to adopt 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 real 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 important factor to be considered. We then propose the hypothesis:

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

Oppositions to the implementation of technologies, as well as other negative reactions, are considered resistance to use. The use of certain information technologies can generate major changes in the organization's social and technical systems (GIBSON, 2003). User resistance is a natural reaction in response to changes, especially in the moment prior to the implementation of the system, which is a critical construct for the success of the project (KIM; KANKANHALLI, 2009; MARKUS, 2004). 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 (BEAUDRY; PINSONNEAULT, 2005; HSIEH, 2015; KIM; PAN 2006; KIM; KANKANHALLI, 2009). In particular, user resistance before implementing IS (that is, when the system is being implemented for the first time) is widespread and critical to the success of the project (KIM; KANKANHALLI, 2009; MARKUS, 2004). 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 (UI), 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 (CABRERA-SÁNCHEZ; VILLAREJO-RAMOS, 2019; FISHBEIN; AJZEN, 1975; VENKATESH *et al.*, 2003, 2012). The relationship between the constructs is presented as the conceptual model in the following section.

3. RESEARCH CONCEPTUAL MODEL AND HYPOTHESES

From the development of the literature review and the formulation of the hypotheses, a conceptual model of the research was elaborated (Figure 1). The conceptual model represents the objective of the research, which aims to analyze the influences of managerial support for corporate entrepreneurship, autonomy and the perception of reward in the innovative behavior of the Brazilian university professor. Visual representation facilitates the understanding of the proposed theoretical model (WHETTEN, 1989).

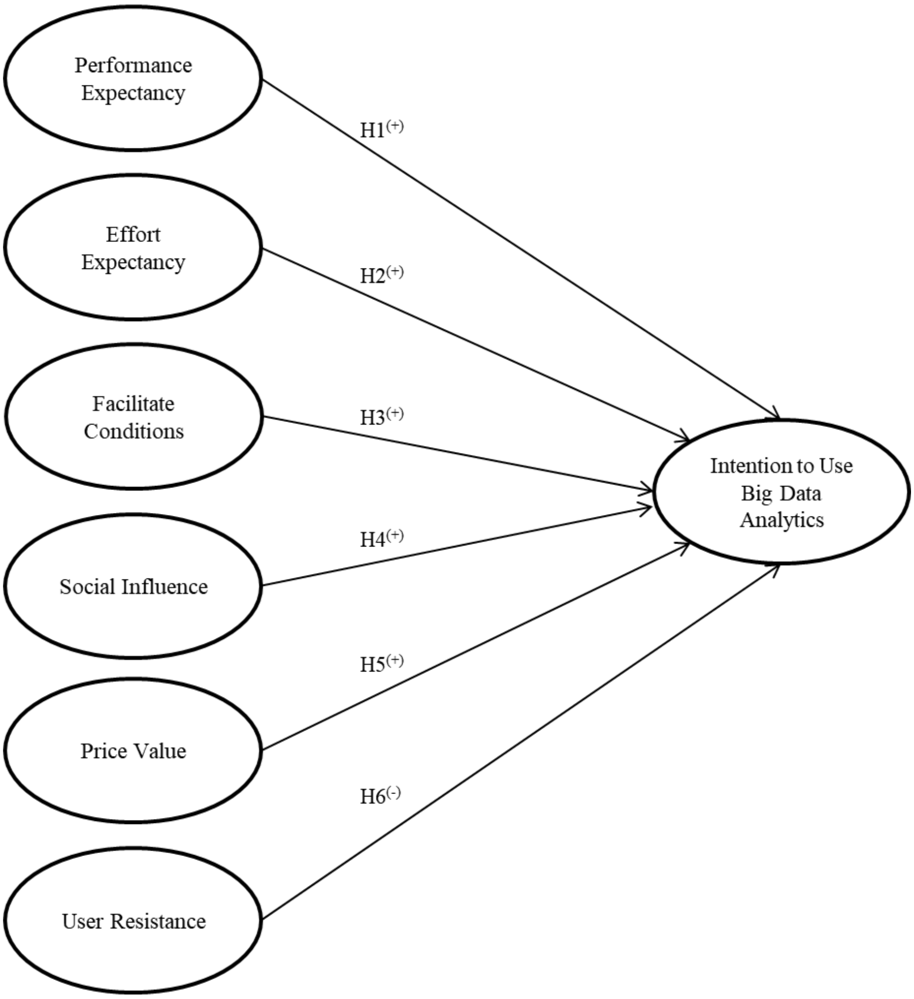

Figure 1. Research Conceptual Model

Table I shows the research hypotheses.

Table I.
Research hypothese

Hyphoteses	Description
H1	Performance expectancy positively influences the intention to use big data analytics
H2	Effort expectancy positively influences the intention to use big data analytics
H3	Facilitate conditions positively influence the intention to use big data analytics
H4	Social influence positively influences the intention to use big data analytics
H5	Price value positively influences the intention to use big data analytics
H6	User resistance negatively influences the intention to use big data analytics

4. METHODOLOGY

The research was carried out through a quantitative methodology, employing multivariate data analysis with the use of Structural Equation Modeling by Partial Least Squares (SEM-PLS). The use of SEM-PLS has grown significantly in the applied social sciences, including research in the area of information systems (RINGLE *et al.*, 2012). The method allows estimating complex models, with several constructs, indicator variables and structural paths, in addition to being a causal-predictive approach, which emphasizes forecasting in the estimation of statistical models, whose structures are designed to provide causal explanations (HAIR *et al.*, 2019).

In order to assess the effectiveness of the questionnaire, a pre-test with possible respondents was first performed, and no adjustment to the questions was necessary. In addition, the questionnaire was analyzed by three experts, in order to assess the validity of the content presented (NETEMEYER; BEARDEN; SHARMA, 2003).

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 closed and excluded from the final sample. The total sample obtained 364 responses from students who were studying Business Administration at UNICAMP. The collection took place virtually; the electronic questionnaire was sent to the students' institutional e-mail in the second semester of 2020. UNICAMP has 960 business students, and the sample received a response of 32.60% of the total.

UNICAMP is among the best university in the country in the international rankings. In the Times Higher Education World University Rankings 2021, UNICAMP appears in second place (between 401 and 500 in the world), and in Quacquarelli Symonds (QS) World University Rankings in 2021, it also appears in second place (233rd in the world). Regarding the Business Administration course, its students constitute the largest group in the sample of the GUESSS 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 (INEP, 2021; SIEGER; FUEGLISTALLER; ZELLWEGER; BRAUN, 2018). In addition, all UNICAMP Business Administration students have Information Technology Administration courses on their curriculum, which address the topic of Big Data Analytics.

To evaluate the sample size of each stage of the study and the statistical power of the analyzes, the software G * Power 3.1 was used (FAUL *et al.*, 2009). Considering six predictive variables of the intention to use BDA construct, with a significance level of 5%, statistical power of 0.8 and average effect size ($f^2 = 0.15$, which is equivalent to $R^2 = 13\%$), obtained it is assumed that the minimum sample size is equal to 98 respondents. Thus, the sample of 364 respondents reached the minimum desired size.

5. RESULTS ANALYSIS

This section included the analysis of the measurement models and the structural model. The performance expectancy, effort expectancy, facilitating conditions, social influence, price value and intention to use indicators were based on the extended model of the UTAUT presented by Cabrera-Sánchez & Villarejo-Ramos (2019). The indicators of user resistance were based on Hsieh (2015) and presented by Cabrera-Sánchez & Villarejo-Ramos (2019). The questions used a 5-point Likert scale (1: Strongly Disagree; 2: Disagree; 3: Not Sure; 4: Agree; 5: Strongly Agree), following the original scales proposed by the authors. Table 2 presents the model's indicators and their descriptive statistics.

Table II.
Descritive Statistics

Questions	Mean	Standard Deviation	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 are 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

To evaluate the proposed measurement model, the convergent validity, the discriminant validity and the reliability of the indicators were verified (HAIR *et al.*, 2019). The indicators required for these assessments (composite reliability, rho_A, Cronbach's alpha, average variance extracted and correlation of the indicators) are presented in Table III, and all are within the established (HAIR *et al.*, 2019).

Table III
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 bold diagonally are the square root of the extracted average variance.

For the validation of the structural model, initially the variance inflation factor was verified, and all values were within those established by Hair *et al.* (2019). Subsequently, the significance of the indicators and the Student's t-test were assessed using the bootstrapping technique. Table IV shows the values of the coefficients between the constructs and their respective Student's t tests. According to the results, all the hypotheses of the study were confirmed, except for hypotheses 2 and 3, which concern, respectively, the expectation of effort and the facilitating conditions that positively influence the intention to use BDA.

Table IV.
Structural Model Coefficients

Relationshiops	Average	Standard deviation	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

To assess the coefficient of determination (R^2), the study by Cohen (1988) and Faul *et al.et al.* (2009). According to the analyses, the complete model presented a determination coefficient considered high 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, the values are considered adequate (HAIR *et al.*, 2019). Table V shows the values of R^2, adjusted R^2 and Q^2 of the model.

Table V.
Values of R^2, R^2 adjusted and Q^2

Construct	R^2	Adjusted R^2	Q^2
Intention to Use	0.451	0.441	0.324

The complete model which resulted from the empirical research is presented in Figure 2

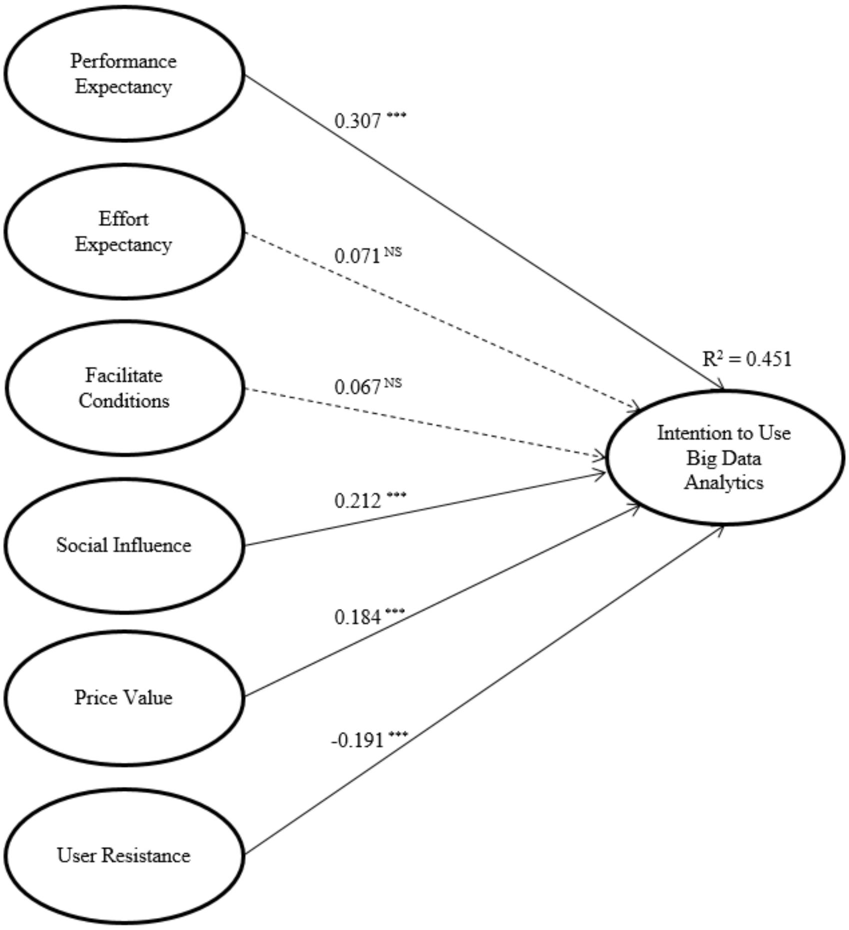

Figure 2. Complete Empirical Model
Note: * = significance at 5%; ** = significance at 1%; *** = significance at 0.1%; NS = not significant.

6. FINAL REMARKS

This study presented and tested a research model that considers six possible predictive variables for the intention to use BDA. It also presented a robust model with high explanatory value for the intention to use BDA (R2 = 45.1%). The research provides relevant information on the behavior of future company managers, presenting theoretical and managerial implications for the management of information systems and organizational policies.

Research innovation is on two fronts: a) to investigate the perception of future managers who, in general, were born in a time of greater technological interaction, know BDA and have a good perception of price for technology; b) expand UTAUT with two important constructs to analyze the perception of future behavior in relation to the BDA, which are price value and resistance to use.

The factors that positively influence the intention to use BDA are, in order from highest to lowest intensity: expected performance, social influence and cost benefit. Regarding the negative influence, resistance to use is a relevant factor to be considered.

Performance expectancy, the factor with the greatest positive influence, analyzes the manager's perception of how much the use of technology can improve his performance, helping him to make decisions and perform tasks more quickly, being useful in the day-to-day of the manager. The result corroborates other studies, in which the expectation of performance was also one of the most influential in behavioral intention (BRÜNINK, 2016; CABRERA-SÁNCHEZ; VILLAREJO-RAMOS, 2019; CHAUHAN; JAISWAL, 2016; YU, 2012; VENKATESH *et al.*, 2003). However, in Cabrera-Sánchez and Villarejo-Ramos (2019), facilitating conditions were the factor of greatest influence, and in the present study, the hypothesis of facilitating conditions was not even confirmed, perhaps due to the difference in the respondent's profile. This result reinforces the importance of the manager being clear on how he can benefit from the technology.

Social influence, the second biggest factor of positive influence, analyzes how important the opinion of important people to the respondent is for the intention to use it. The result is similar to previous research (AL-GAHTANI *et al.*, 2007; BRÜNINK, 2016; CABRERA-SÁNCHEZ; VILLAREJO-RAMOS, 2019; CHAUHAN; JAISWAL, 2016; GUPTA; HUANG; NIRANJAN, 2010; KIM *et al.*, 2007; LEE; SONG, 2013).

Price value was presented as the third factor with the greatest positive influence. It consists in the perception of how much the benefits of using a technology are perceived to be greater than the 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 yet been tested in the context of the BDA, HOWEVER, RESULTS SHOW SIMILARITIES TO STUDIES WHICH USE OTHER TECHNOLOGIES (KWATENG, 2019; MORAES *et al.*, 2020; TAMILMANI, 2018).

In respect to resistance to use, it has presented a negative influence in the intention to use, and concerns opposition or negative reactions to the implementation of a new technology. Few studies have addressed this construct in adoption models, but the results were similar to those found (CABRERA-SÁNCHEZ; VILLAREJO-RAMOS, 2019; HSIEH, 2015; NORZAIDI *et al.*, 2008). This demonstrates the cultural importance in the company on the use of information technology, as the manager should not be afraid of having to change the way he makes decisions, interacts with people and how he works, to get the most out of the technology.

In regard to effort expectation and facilitating conditions concern, respectively, the ease of learning and the use of technology and having the necessary resources for use (VENKATESH *et al.*, 2003), as the present research was carried out with students of the Business Administration course who, in general, are young and technological, this may have influenced the non-confirmation of these hypotheses. These results are important when planning efforts, training and BDA projects in companies.

Concerning managerial implications, results reinforce the importance of the managers understanding on the benefits of technological adoption, thus, they can improve organizational communication in order to elucidate the functionalities of the system. This action can be done, for example, with training actions that simulate managers' daily work routines and situations that offer opportunities for improvement in decision making with more accurate information. Contributions can cover three fronts: greater 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).

For companies that still have not adopted a BDA software, to present and make free software available for managers to have a first contact and analyze the possibilities for improvement, in addition to demonstrating the options and prices of the most appropriate paid software for the organization. This action would assist into providing a clearer understanding concerning the relationship between benefits and cost (price value).

Regarding research limitations, this article can address some aspects. Firstly, the study collected information with a single cross-section in the 2nd semester of 2020, and it may not represent the respondent's opinion over time; secondly, the collection period was during the coronavirus pandemic, and this may have impacted the perception of the future manager; lastly, the sample comprised students from a single course and educational institution.

Future research can be suggested on the following fronts: studying different courses and educational institutions; test differences according to the respondent's gender, age and region; longitudinal studies, analyzing differences in perception over time.

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