# Factors Affecting the Big Data Adoption as a Marketing Tool in SMEs

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**Abstract.** The change brought by Big Data about the way to analyze the data is revolutionary. The technology related to Big Data supposes a before and after in the form of obtaining valuable information for the companies since it allows to manage a large volume of data, practically in real time and obtain a great volume of information that gives companies great competitive advantages. The objective of this work is evaluating the factors that affect the acceptance of this new technology by small and medium enterprises. To that end, the technology acceptance model called Unified Theory of Technology Adoption and Use of Technology (UTAUT) was adapted to the Big Data context to which an inhibitor was added: resistance to the use of new technologies. The structural model was assessed using Partial Least Squares (PLS) with an adequate global adjustment. Among the results, it stands out that a good infrastructure is more relevant for the use of Big Data than the difficulty of its use, accepting that it is necessary to make an effort in its implementation.

**Keywords:** Big data · Intention to use · UTAUT · Acceptance of technologies · Resistance to use · Partial least squares

## 1 Introduction

Talking about marketing and looking for a definition consistent with the digital era entails citing the American Marketing Association (AMA): "Marketing is the activity, set of institutions, and processes for creating, communicating, delivering, and exchanging offerings that have value for customers, clients, partners, and society at large" [1]. The previous statement is not only correct and indicative, but fully


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applicable to the Big Data era in which the clients and partners and the community look for the generation of value in each and every process the companies execute [2].

The term Big Data began to be disseminated in the technological context by scientists and industry executives to the year 2008. At present, it not only represents a huge amount, variety, and volume of information, but the theme of "fashion" that daily appears in newspapers and magazines. Likewise, the economic sectors, the most important companies, and consultants try to show their possible applications and generate frequent reports in this regard [3].

In this digital age in a changing economic environment, Companies must investigate the tastes of customers, conduct market research, and know the actions of the competition with the main objective of launching products and services that generate higher revenues. In other words, the information is every day more relevant for companies to make decisions. Organizations not only need to collect data, but also look for the appropriate way to analyze them to conceive daily actions based on statistics and trends. However, companies currently lack the capacity to use Big Data and data analytics [4, 5].

With this study, the researchers intend to obtain data on the factors that affect the adoption and use of this new technology in small and medium enterprises (SMEs), as well as to understand the possible problems for its implementation in order to give pertinent recommendations to professionals that make decisions.

## 2 Theoretical Review

The adoption of a technology is decisive for its success. From the Theory of Planned Behavior-TPB to the widely used Technology Acceptance Model-TAM, many models of technology acceptance have been developed and tested. But the model proposed by the Unified Theory of Technology Adoption and Use of Technology, or UTAUT integrates different models and previous theories that have been proposed to analyze the acceptance of a technology [6].

The determinants of the model are [7]: (1) the Performance Expectancy (PE), defined as the degree to which using a technology offers benefits in the development of certain activities; (2) Effort Expectancy (EE), which measures the degree of ease associated with the use of technology; (3) Social Influence (SI) or how consumers perceive that friends and family believe that they should use a technology; and (4) Facilitating Conditions (FC), consumer´s perceptions that resources and support are available to develop a behavior. The model proposes a direct influence of the first three determinants on the intention to use (Behavior Intention, BI). Facilitating conditions influence the use of new technology (Usage Behavior, UB).

As stated by [8], the value of this model is in its capacity to identify the main determinants of adoption, and allows to include and consider the effect of different moderators that affect in the influence of the key constructs of the model.

To the constructs of the UTAUT model, Resistance to Use (RE) is added since, in the adoption of new technologies and information systems, there is an adverse reaction or opposition to change or implementation of new technologies [6]. In this context, resistance is defined as the opposition to change associated with the implementation of a new technology or information system.

The hypotheses of this research emerge from the last premises based on the extension of the UTAUT model for the case of acceptance and use of Big Data by companies, which are explained below:

Performance Expectancy (PE) refers to the perception of the performance that the technology will have. Within the UTAUT, this is one of the most influential constructs in the intention to use. Several works, in addition to the original work itself, sustain this positive relationship [6].

Effort Expectancy (EE) refers to how easy it is to learn and use what this new technology will be. According to UTAUT, Big Data will be used more or less depending on how easy or difficult it is. Other studies reinforce the meaning and weight of this relationship that confirm [9] the effect of the expected effort on the intention to use.

The measure of Social Influence (SI) in the original proposal of [10], and extended in the UTAUT2 [11] has been used to measure the effect of the influence perceived by the users regarding what others -friends, family- think with respect to the use of a technology. In a business environment, it is also important what leaders and colleagues think.

Resistance to Use (RU) has been understood as opposition or negative reaction to the implementation of a new technology. As [12] points out, the use of many new technologies has failed because of the opposition of users to their implementation. And although the resistance to use is well studied in the literature [13–15], there are very few studies that use it, integrating it in the UTAUT model. However, there are precedents of resistance to use with the intention to use.

Facilitating Conditions (FC) highlight the ease of access to the resources needed to use a new technology, as well as the support and subsequent support. In a later work, the UTAUT2 [11], found that this construct has a significant effect on the intention to use a technology. Also, more recent studies have contrasted this positive effect on the intention to use [13].

In agreement with both the Theory of Planned Behavior TPB and so with the original UTAUT, it can be observed that facilitating conditions positively affect the use of a new technology. Subsequent studies [16] and [17] have contrasted this hypothesis.

From the widely used proposal of [18] of the Technology Acceptance Model (TAM) to predict and evaluate the acceptance and use of technologies, up to the proposed UATUT model [3] that predicted moderating effects on the antecedents of the intention to use the technologies, going through the Theory of Reasoned Action (TRA) [5], a direct relationship between the intention of behavior and the use of technologies is observed. In this case, it is unquestionable that the behavior intention of the Big Data user, positively and negatively influenced by the variables proposed in the model, favorably affects the final use of the service.

This influence has been contrasted in many contexts such as, for example, the adoption of Internet banking in Portugal [19], purchase of airline tickets in Spain [20], use of electronic document management systems [21], or adoption of ERPs in India [22].

Figure 1 presents the proposed model based on the hypotheses stated above.

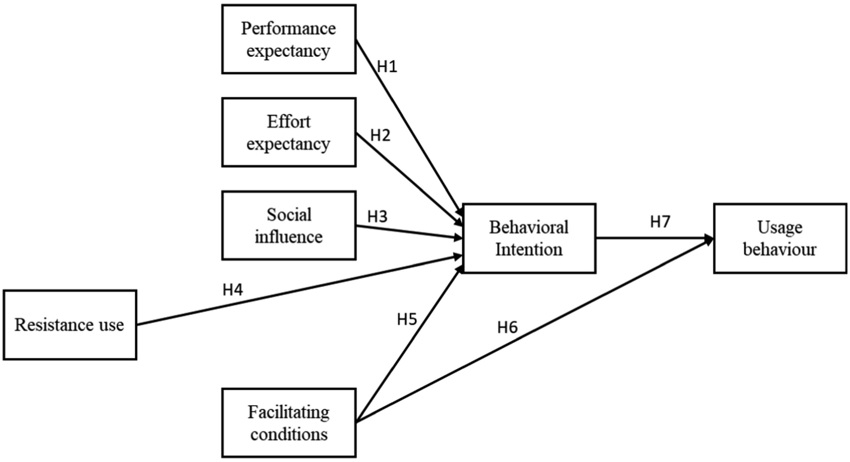


**Fig. 1.** Big data acceptance in companies

# 3 Materials and Methods

## 3.1 Database

The sample used in this work comes from managers responsible for an area such as HR, Financial, Marketing, and Sales of the different SMEs. The data was collected during the months of September and October 2018 through a survey carried out by Internet. To eliminate possible ambiguities in the questionnaire, it was previously reviewed, as a pre-test, with 5 volunteer managers and other researchers. The number of valid surveys was 564 and can be classified according to their turnover and sector of activity, as shown in Table 1a and b.

**Table 1.** Companies in the sample according to turnover and sector.

(a)

| Sector | (Empty) | Less than 2 Million $ | Between 2 and 10 Million $ | Between 10 and 43 Million $ | More than 43 Million $ | Total |
|---|---|---|---|---|---|---|
| Farming | 2 | 10 | 14 | 14 | 1 | 41 |
| Commerce and distribution | | 20 | 8 | 12 | 18 | 58 |
| Communications | 1 | 35 | 4 | 45 | 51 | 136 |
| Building | | 15 | | 1 | 14 | 30 |
| Education | | 12 | 3 | | 20 | 35 |
| Energy and Mining | | 10 | | 1 | | 11 |
| Financial | | 10 | | | 42 | 52 |

(*continued*)

**Table 1.** (*continued*)

| (b) | | | | | | |
|---|---|---|---|---|---|---|
| Sector | (Empty) | Less than 2 Million $ | Between 2 and 10 Million $ | Between 10 and 43 Million $ | More than 43 Million $ | Total |
| Industrial | | 36 | 4 | 2 | 15 | 57 |
| Others | 1 | 14 | 14 | 12 | 18 | 59 |
| Sanitary | | 8 | 1 | | 20 | 29 |
| Services | | 14 | 19 | 7 | 14 | 54 |
| (Empty) | 1 | | 1 | | | 2 |
| Total | 5 | 184 | 68 | 94 | 213 | 564 |

### 3.2 Methods

PLS has been used to analyze the reliability and validity of measurement scales and assess the structural model [23, 24]. Specifically, the SmartPLS 3 software package was used [25]. It was also previously checked that there were no errors due to measurement bias or Common Method Bias (CMB). For this, the indications of [26] and [27] were followed and a new latent variable called CMB variable was added as dependent of the previous ones of the model, measured with a previously unused indicator. All Variance Inflation Factors (VIF) obtained by this method should be less than 3 to confirm that the sample does not have a CMB. Compliance with the requirements is shown in Table 2.

**Table 2.** VIF extracted from the constructs to check the CMB

| | Variable CMB |
|---|---|
| Behavioral intention | 2,351 |
| Effort expectancy | 1,621 |
| Facilitating conditions | 2,027 |
| Performance expectancy | 1,971 |
| Resistance to use | 1,611 |
| Social influence | 1,710 |
| Variable CMB | |

## 4 Results

The measurement scales, mostly coming from the original model of [3] have been adapted to Big Data, according to different works, as shown in Table 3. The Resistance to Use variable was measured using the scale proposed by [28].

**Table 3.** Measurement scales for the sample SMEs

| Construct | Scale |
|---|---|
| Performance expectancy | PE1: I believe that Big Data is useful to carry out the tasks of our company. PE2: I believe that with Big Data we could do the tasks of our company more quickly. PE3: I believe that with Big Data we could increase the productivity of our company. PE4: I believe that Big Data would improve the performance of our company. PE5: I believe that with Big Data you can obtain more information from our customers. PE6: I believe that with Big Data the quality of the information used in our company will be increased. PE7: I believe that with Big Data we will obtain new valuable information from our clients |
| Effort expectancy | EE1: Big Data would be clear and understandable to the people of our company. EE2: It would be easy for our company to become familiar with Big Data. EE3: For our company, it would be easy to use Big Data. EE4: I believe that with Big Data we could increase the productivity of our company. EE5: Generating valuable data using Big Data would be easy for our company |
| Social influence | SI1: The companies that influence ours use Big Data. SI2: Our reference companies use Big Data. SI3: The companies in our environment that use Big Data have more prestige than those that do not use it. SI4: The companies in our environment that use Big Data are innovative. SI5: Using Big Data is a status symbol in our environment |
| Facilitating conditions | FC1: Our company has the resources necessary to use Big Data. FC2: Our company has the knowledge necessary to use Big Data. FC3: Big Data is not compatible with other systems of our company. FC4: Our company has an available person (or group) for assistance with any difficulties that might arise |
| Resistance to use | RU1: We do not want to use Big Data to change the way we analyze our data. RU2: We do not want to use Big Data to change the way we make our decisions RU3: We do not want to use Big Data to change the way we interact with other people in our work. RU4: Above all, we do not want to use Big Data to change our current way of working |
| Behavioral intention | BI1: We intend to use Big Data in the coming months. BI2: We predict that we will use Big Data in the coming months. BI3: We plan to use Big Data in the coming months. BI4: We intend to obtain new and valuable data thanks to Big Data in the coming months |
| Usage behavior | UB: What is the current use of Big Data in your company? (i) We have never used. (ii) Once a year. (iii) Once in 6 months. (iii) Once in 3 months. (v) Once a month. (vi) Once a week. (vii) Once every 3–4 days. (vii) Once every 2–3 days. (ix) Daily |

The next step was to analyze the reliability of the constructs using composed reliability and Cronbach's alpha indicators. In all cases, the indicators are greater than 0.7 as suggested by [22]. In addition, the convergent validity was ensured by analyzing the Average Variance Extracted (AVE). In this case, all the indicators offered levels above the proposed 0.5 [24]. These indicators are listed in Table 4 to verify that all constructs, including the Enabling Conditions construct, meet all the requirements.

**Table 4.** Composite reliability and convergent validity.

| | Cronbach's alpha | Rho_A | Composite reliability | Average Variance Extracted (AVE) |
|---|---|---|---|---|
| Behavioral intention | 0,979 | 0,978 | 0,998 | 0,948 |
| Effort expectancy | 0,873 | 0,925 | 0,914 | 0,659 |
| Facilitating conditions | 0,847 | 0,849 | 0,921 | 0,745 |
| Performance expectancy | 0,948 | 0,971 | 0,971 | 0,772 |
| Resistance to use | 0,951 | 0,978 | 0,987 | 0,861 |
| Social influence | 0,868 | 0,845 | 0,885 | 0,647 |
| Usage behavior | 1,000 | 1,000 | 1,000 | 1,000 |

The discriminant validity is assessed through the method of Heterotrait-Monotrait ratio (HTMT) [29] checking that, in all cases, levels below 0.9 were obtained, see Table 5.

**Table 5.** Discriminant validity (Heterotrait-Monotrait Ratio-HTMT)

| | Behavioral intention | Effort expectancy | Facilitating conditions | Performance expectancy | Resistance to use | Social influence | Usage behavior |
|---|---|---|---|---|---|---|---|
| Behavioral intention | | | | | | | |
| Effort expectancy | 0,322 | | | | | | |
| Facilitating conditions | 0,678 | 0,556 | | | | | |
| Performance expectancy | 0,600 | 0,485 | 0,422 | | | | |
| Resistance to use | 0,539 | 0,275 | 0,448 | 0,569 | | | |
| Social influence | 0,529 | 0,558 | 0,569 | 0,489 | 0,258 | | |
| Usage behavior | 0,679 | 0,311 | 0,723 | 0,442 | 0,441 | 0,585 | |

Finally, Fig. 2 shows the values for each of the loads and the path of the model. Also, the $R^2$ of the constructs of second order is checked: Behavioral intention and use in Table 6.

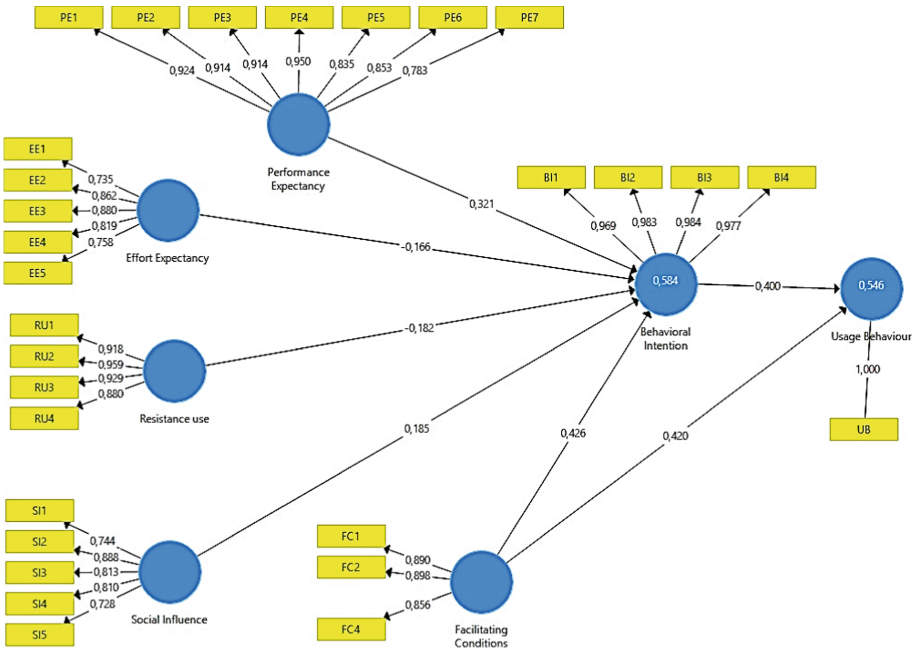


**Fig. 2.** Results of the model

**Table 6.** $R^2$ of the model

| | R squared | R squared |
|---|---|---|
| Behavioral intention | 0,574 | 0,555 |
| Usage behavior | 0,556 | 0,548 |

The results indicate that the proposed hypotheses are accepted with a high level of significance. So, in order of influence, it is observed how the Enabling Conditions is the construct that contributes the most to the Intention and Use, followed by the Expectations of Result. It was also found that the relationship between the Intention and Use were meaningful to the highest demands.

## 5 Conclusions

It was observed that the Intention to Use of Big Data on the part of SMEs is determined: (1) by the perception of getting good results with the use of this technology (Performance Expectancy); (2) by the positive effect posed in this technology that others consider important to use (Social Influence); and (3) mainly due to the fact that the company provides the support and resources to promote their use (Facilitating Conditions).

On the other hand, it is observed that the intention to use is negatively affected by the Resistance to Use new technologies in any organization although their influence is less than the previous relationships. Although the use of Big Data is perceived as difficult (Effort Expectancy), its influence is very low, with little significance over the intention to use. This could be explained by the fact that Big Data is perceived as a technology that presupposes a difficulty in its use and that this does not affect the intention to use.

It was possible to contrast a great positive influence of the enabling conditions on the use of new technology, providing more load even than the intention to use. Therefore, after the comparison of the model, it is concluded that the assumptions made in the proposed expansion of the UTAUT model have been accepted, which can be used to the design of a model that brings some improvement to the original.

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