

Business Intelligence Solutions Adoption Model for Peruvians SMEs Based on UTAUT2

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Keywords: Adoption, Business Intelligence, SMEs, UTAUT2, Intention to Use.


Abstract: Small and medium-sized enterprises (SMEs) face significant challenges to grow and make strategic decisions due to their small size and limited resources. This study proposes a model to identify the factors that influence the adoption of Business Intelligence (BI) solutions in Peruvian SMEs, based on the Unified Theory of Acceptance and Use of Technology (UTAUT2). The study methodology is divided into four phases. The first phase consists of analyzing existing technology adoption models to identify critical components that affect BI adoption. In the second phase, the proposed model is developed and survey questions are designed that will measure relevant factors for statistical validation. The third phase involves data collection through surveys targeting SMEs in Peru, followed by analysis to identify significant patterns. The fourth and final phase validates the model using the Partial Least Squares Structural Equation Modeling (PLS-SEM) technique, evaluating the robustness and accuracy of the proposed model. The validation results show that the proposed factors Performance Expectation (PE), Price/Value Ratio (PV) and Competitive Pressure (CP) are the most influential in the intention to use BI solutions by Peruvian SMEs.


1 INTRODUCTION


Small and medium-sized enterprises (SMEs) face a significant problem with respect to their subsistence: only 30% of them manage to survive after 2 years and the main reason is liquidity (Rubio, 2020). The causes vary from operating policies, which do not guarantee survival in the market, often leading companies to bankruptcy (Roever, 2016), internal factors (business understanding, resources, budget, solvency level, liquidity, etc.) and external factors (political, social, environmental, etc.) (Vukšić, Bach & Popovič, 2013), trust in one's own experience when making decisions, ruling out the possibility of opting to improve this process through the incursion of technology (Bhatiasevi & Naglis, 2020) and underestimation of technology, limiting its use to administrative tasks instead of using it for complex business operations (Caseiro & Coelho, 2018).

In their study on the intention to use Business Intelligence in SMEs in Libya using UTAUT2 and

TAM, Alsibhawi, Yahaya & Mohamed (2023) reveals that the effective adoption of this technology depends on factors such as business resources and capabilities. In another study, Kašparová (2023) shows a technology model based on UTAUT2 for BI adoption by adding the habit factor within the constructs of the presented model, which was found to be the most influential according to the results. On the other hand, Zheng & Khalid (2022) conducted a research on ERP and BI adoption in SMEs in Malaysia using UTAUT and TOE, highlighting that ERPBI plays an important role in organizational performance and business continuity, so it is necessary to adopt it among SMEs. In addition, Kwarteng, Ntsiful, Diego & Novák (2023) show a technology model for digitalization adoption in SMEs in Czech Republic and Slovakia, which highlights the competitive pressure factor being the most significant predictor of BI adoption intention in Czech and Slovak SMEs. Fang, Azmi, Yahya, Sarkan, Sjarif & Chuprat (2018) shows their study of mobile BI

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adoption based on UTAUT, with adaptation of TAMMS. The result of the study was that it is important for users the ease of use and whether it is useful to have the information at the reach of a mobile device. However, all these authors have developed studies on the adoption of BI solutions in different countries in Asia and Europe, having that in Peru has not developed a study that evaluates the intention to use this same technology, so this paper is to show the proposed model that illustrates the main potential factors to be influential for the adoption of BI solutions, based on the UTAUT2 model (Venkatesh, Thong, & Xu, 2012). This study will focus on understanding the factors that influence the intention and acceptance of Peruvian SMEs towards the implementation of BI solutions, therefore we will perform (1) Tool selection, (2) Model design, (3) Data collection and analysis and (4) Validation.

The organization of the article is as follows: in Section 2, we will talk about the work related to the proposed solution; in Section 3, about the proposed model, highlighting all the phases of its development; in Section 4, about the validation of the proposed model; in Section 5, about the results of the study and finally Section 6, with the conclusions of the study, as well as the possible future work.

2 RELATED WORKS

The field of Business Intelligence (BI) adoption has gained relevance in response to the growing demand for data for business decision making. In this context, previous research is highlighted and will be presented as related work in this study. These works, conducted in different countries, share similar models while incorporating their own constructs, thus offering a global and contextualized view of the challenges and strategies in the implementation of BI and other technologies at the international level.

Rouhani, Ashrafi, Ravasan & Afshari (2018) conducted an empirical research on the factors influencing BI adoption in the banking and finance industry. This research is particularly relevant because of the few previous attempts to identify the factors affecting the adoption of BI systems. Given the rapid proliferation of data in organizations and the critical importance of managerial decision making, it is critical to determine the most appropriate factors for BI adoption, as this significantly influences the decision to implement BI. In addition, a conceptual model based on the TOE framework was proposed and validated using survey data and the PLS technique. The research concluded that the most

influential factors in IT implementation stages are grouped into five categories: individual, organizational, technological, task-related, and environmental characteristics.

Zheng & Khalid (2022) goes into the adoption of ERP-BI systems, which should consider technological, organizational, and environmental (TOE) factors to ensure its continuity and sustainability. Since the study aims to close the current gaps in ERP-BI adoption through a TOE-focused perspective and presents a conceptual framework that describes the dimensions of this theory and its factors. Thus, the article contributes to the understanding of how companies can successfully adopt ERP-BI systems in a constantly changing and competitive business environment, since according to several authors it has been shown that the integration of ERP and BI systems enhances business decision making capabilities. What refers to our study, what is different is that it is only based on measuring the intention to use BI solutions, using UTAUT2.

Bany Mohammad, Al-Okaily, Al-Majali & Masa'deh (2022) examined the relationship between business intelligence capabilities and the performance of SMEs in Jordan, under the TOE framework, taking into account the moderating role of competitive intelligence. The results showed that BI capabilities have a significant influence on business performance and that competitive intelligence positively enhances this relationship. This indicates that SMEs should focus on developing their BI capabilities to improve their competitiveness in the marketplace. However, although this study focused on measuring BI usage intention in Jordanian SMEs, the study we propose is based on the UTAUT2 model, which includes more specific constructs related to software usage and acceptance.

Ahmad, Miskon, Alabdan, & Tlili (2021) a BI system adoption model based on the TOE framework was investigated in the textile industry, extending the original model with an additional dimension (Individual) in addition to the three traditional dimensions (technological, organizational, and environmental). Preliminary findings from the interviews were used to validate the suitability of the proposed model. The research model was then validated through a questionnaire survey and DEMATEL techniques. Analysis of the results indicated that user traits, technological maturity, sustainability, leadership commitment and support, and compatibility were the most significant factors. The determinants of the causal group were shown to have greater influence throughout the model compared to those of the effect group, such as

interpersonal communications and satisfaction with existing systems. In relation to our study, we highlight the use of the TOE framework to measure BI usage intention in the textile industry, highlighting the flexibility of the model to be applied in different industries.

Hmoud, Al-Adwan, Horani, Yaseen & Al Zoubi (2023) made a study based on the Technology-Organization-Environment model, which provides a comprehensive framework for understanding technology adoption processes. By applying the TOE model specifically to the context of BI adoption in Educational Institutions, this study extends the theoretical understanding by incorporating organizational and environmental factors unique to Jordanian HEIs. One of the main contributions of this study is its focus on BI adoption by Educational Institutions in Jordan, filling an important gap in the literature by identifying and analyzing the factors that influence this adoption. The findings show that organizational characteristics, such as top management support, information culture, complexity, and vendor selection, have a positive impact on BI adoption in these institutions. This study is significant in that it uses the context of Jordanian educational institutions to demonstrate that it is possible to measure the intention to use any technology. We use the UTAUT2 model, which is more oriented to measure acceptance with constructs specific to software use.

3 PROPOSED MODEL

The following are the parts of this study: first, the selection of tools was carried out, then the proposed model was designed, followed by data collection and analysis, and finally, the validation of the results.

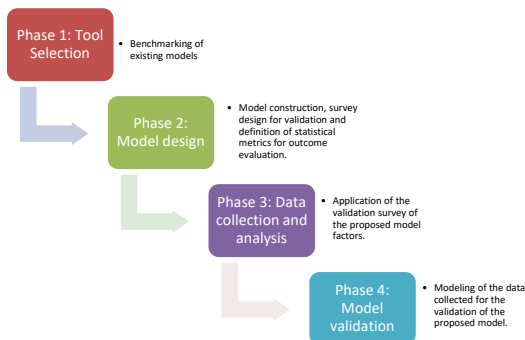


Figure 1: Proposed Methodology.

3.1 Phase 1: Tool Selection

The goal of this phase is to be able to adequately determine the tools that best fit the proposal proposed in this study to be used and applied. To this end, we first conducted a systematic review of the literature and then benchmarked the models used in the articles reviewed. Regarding the review, this allowed us to define the criteria to be taken into account for the evaluation and comparison of the selected models:

- Focus: This aspect refers to the main focus or central issue addressed by each model.
- Key Factors: These are the main factors or constructs that each model considers as determinants of technology adoption.
- Main Application: Indicates in which areas or contexts each technology adoption model is commonly applied.
- Integration of Social Factors: This aspect refers to the consideration of social factors and social influences on technology adoption within each model.

Once the articles were compiled, a benchmarking of the models used in the studies was carried out, highlighting the model approach, the key factors used, the main application of the model used and finally the integration of social factors, which is shown in the following table:

Table 1: Comparative table of adoption models according to comparison criteria.

Criteria	Ortiz-Gutierrez Model	UTAUT	UTAUT2	TAM	TOE
Approach	Integration of previous models and factor augmentation	Integration of 3 old theories to be unified and identify key factors	Integration of previous models and simplification of factors.	Attitude and perception towards technology.	Organizational approach and operational context.
Key Factors	<ul style="list-style-type: none"> • Ease of use • Perceived Utility • Intent to use • Social factors • Competitive Pressure 	<ul style="list-style-type: none"> • Ease of use • Perceived Utility • Intent to use • Flexibility to allow the adoption of any new technology • Social factors 	<ul style="list-style-type: none"> • Ease of use • Perceived Utility • Intent to use • Social factors 	<ul style="list-style-type: none"> • Ease of use • Perceived Utility • Attitude towards use 	<ul style="list-style-type: none"> • Ease of use • Perceived Utility • Intent to use • Social Factors • Organizational Factors
Main Application	Research on technology adoption in SMEs in Peru.	Research on technology adoption, including in various contexts and technologies.	Research on technology adoption, including organizational and consumer contexts	Technology Adoption in Consumer and Business Contexts	Technology Adoption in Organizational Contexts
Integration of Social Factors	Yes	Yes	Yes	No	Yes

From the benchmarking, the UTAUT2 model was chosen, as it provides more value and its approach fits our study. Also, Quicano (2019) demonstrates that the

UTAUT2 model provides superior explanatory power compared to other technology acceptance models. By incorporating additional factors such as hedonic motivation, price value, and habit, UTAUT2 more accurately captures the complexities of user acceptance and usage behavior, outperforming its predecessors in predictive capability. In addition, an additional construct from a peer-reviewed article is incorporated, which contributes significantly to the result of this article.

3.2 Model Design

The objective of this phase is to design the proposed model based on the selected tools. To this end, the model was first built, the survey design was defined and the metrics for the validity of the model were defined. First, the constructs of the model were analyzed, as well as the external construct identified during phase 1. From this, the proposed model was designed, which contemplates some constructs of the UTAUT2 model, adding the identified external construct.

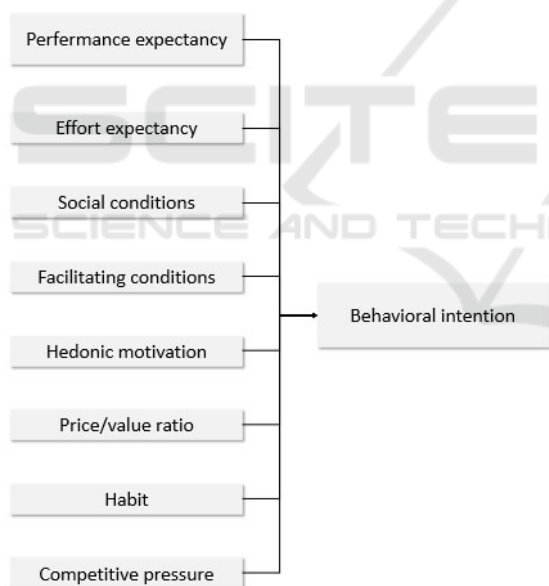


Figure 2: Proposed Model.

The proposed model has the following factors:

- Performance Expectancy: Performance expectancy refers to the individual’s perception of whether using a particular technology will improve his or her job or personal performance.
- Effort Expectancy: Effort expectancy refers to the individual’s perception of the

perceived ease or difficulty of using a particular technology.

- Social Influence: Social influence refers to the individual’s perception of the perceived social pressure to use a particular technology.
- Facilitating Conditions: Facilitating conditions refer to additional resources that can help make the adoption of a technology easier and more successful.
- Hedonic Motivation: Hedonic motivation refers to the degree to which a person perceives that using a particular technology will provide pleasure, fun, or entertainment.
- Price/Value Ratio: Price/value ratio refers to an individual’s perception of whether the cost of acquiring and using a technology is justified by the benefits and value it provides.
- Habit: Habit refers to the degree to which an individual has a habit or routine of using a particular technology.
- Competitive Pressure: refers to the forces and challenges organizations face to remain competitive in a dynamic and changing environment.

For the validation of the model, a questionnaire with questions that are directly related to each construct will be carried out. Below is the table with the questions for each construct:

Table 2: Questionnaire for the validation of the model.

Construct	ID	Question
Performance Expectancy (Venkatesh, Thong, & Xu, 2012)	ED1	Digitization would be useful in my work.
	ED2	Using digitized processes allows me and the company to perform tasks efficiently and quickly.
	ED3	The use of digitized processes and services increases productivity
	ED5	Digitalization impacts profits and performance in the company
	ED6	My good digital skills increase my chances of getting a raise
	Effort Expectancy (Venkatesh, Thong, & Xu, 2012)	EE1
EE2		It would be easy for me to acquire digital skills to work in the digitized work environment
EE3		You would find a digitized work environment easy to use
EE4		Learning how to operate processes in a digitized way is easy for me

Table 2: Questionnaire for the validation of the model (cont.).

Facilitating conditions (Venkatesh, Thong, & Xu, 2012)	CF1	The company has the resources to use more digitized processes and services.
	CF2	The company has the necessary knowledge to use more digitized processes and services
	CF3	Modern digitalization techniques are not compatible with other digitized processes and services in the company
	CF4	A specific person (or group) is available to help if difficulties arise with digitalization in the company.
Social Influence (Venkatesh, Thong, & Xu, 2012)	IS1	The people who are important to me think that I should use digitization tools in my work.
	IS2	My work environment (colleagues, bosses, etc.) thinks I should use digitization tools.
Motivation (Venkatesh, Thong, & Xu, 2012)	ME1	Using digitizing tools is fun
	ME2	Using digitization tools is nice
Price/Value Ratio (Venkatesh, Thong, & Xu, 2012)	PV1	Digitization tools are good value for money.
	SS2	Digitization tools offer good value for money.
Habit (Venkatesh, Thong, & Xu, 2012)	HA1	Using digitization tools has become a habit for me.
	HA2	I feel like I'm in the habit of using digitizing tools.
Competitive pressure (Kwarteng et al., 2023)	CP1	My company plans to invest more in digitalization in the future.
	CP2	Business partners who are important to the company think that the company should be more digitized.
Behavioral intention (Venkatesh, Thong, & Xu, 2012)	IU1	My company intends to digitize its business processes to a greater extent.
	IU2	My company predicts that it will introduce more digitalization in the near future.
	IU3	My company plans to invest in more digitalization in the future.

This survey includes questions related to each construct, so that respondents can give their opinion and find out which one has the greatest influence on their ability to adopt BI solutions. The answers are based on a Likert scale, so as not to limit them to only “yes” or “no”. This will be developed in a Microsoft Forms questionnaire, since it will be via mail that the selected SMEs will be able to complete the survey.

As for the validation metrics, we have Cronbach's alpha, which is the degree of reliability that reflects a given content domain of what is measured (George &

Mallery, 1995). This value must pass 0.7 to have acceptable reliability. For hypothesis testing, we have the following metrics: Convergent Validity, which must be greater than 0.70 to be acceptable; Discriminant Validity (X2) which must be less than 0.05 and Average Variance Extracted (AVE) which must be greater than or equal to 0.50 [18]. For the fit of the measurement model, we have the normalized Chi-square (CMIN/DF) which should be $1 < X^2/df < 5$; Goodness of fit (GFI) which should be greater than 0.9; Comparative Fit (CFI) greater than 0.9 and Root mean square error of approximation (RMSEA) < 0.08 (Gutarra, 2012).

3.3 Data Collection and Analysis

For this phase, the goal is to define the sample to which the survey of phase 2 will be applied, and then, once applied, to collect the data and analyze them before the validation of the proposed model.

For the selection of companies for the sample, the government's open databases will be searched in order to collect the largest number of candidate companies, and by means of a simple sampling, the sample to be taken to apply the survey will be defined. These companies will be validated with respect to their business segment, since they must belong to the SME segment. Then, once the survey has been applied to the selected sample, the data from the responses will be collected and cleaned, in order to have a clean data set ready to be processed.

Finally, a descriptive analysis of the results of the survey will be made, with the objective of rescuing insights from the SMEs, to be taken into account when drawing conclusions regarding the model calibrated after the modeling.

3.4 Phase 4: Model Validation

The objective of this phase is to validate the proposed model based on the surveys applied to the selected companies. For this purpose, the variables will be modeled using the PLS-SEM method (Structural Equation Modeling).

The use of the PLS-SEM method is based on its ability to handle complex models, even with small samples and data that do not meet normality assumptions. It is less restrictive than other techniques, such as Covariance-Based Structural Equation Modeling (CB-SEM), and is particularly useful for exploratory and predictive research. Hair et al. (2019) mentions that PLS-SEM is a flexible and powerful tool that allows for the simultaneous evaluation of multiple relationships between latent

variables in contexts where other techniques might fail.

Once all the survey results are available, structural equation modeling is performed to analyze the relationships of the variables (the constructs) and to see which are the most influential factors for the intention to use. PLS-SEM is a statistical technique used to analyze the relationships between latent (unobservable) variables in a model.

With this, we would finally have the model adjusted to the context of Peruvian SMEs, showing the survey questions with their respective weights, which will reveal the construct that most influences SMEs in their intention to adopt BI solutions. In addition, it can be discussed whether the UTAUT2 model is the most efficient to use in the context of Peruvian SMEs or not, being able to recommend other constructs to enrich such theory and thus improve the literature of this type of study.

4 VALIDATION

For the validation of the proposed model, the following phases were carried out: (1) survey design, (2) selection of participating companies, (3) sending the survey, (4) data collection and analysis, and (5) evaluation of the model.

For the survey design, questions related to each construct of the model were asked using a Likert scale (from 1 to 5) (see table 2). For the selection of participating companies, a total of 130 companies in the SME sector from all regions of Peru were selected. On the other hand, to send the survey, it is in a Windows Forms form, which is sent by e-mail to the selected companies. Once all the responses are received, they are collected and loaded into the IBM SPSS Statistics software, in order to group them so that they can be loaded into the SmartPLS modeling software.

Finally, once the information has been uploaded to the modeling software, hypothesis testing is performed with the constructs of the model. The model will be validated with statistical metrics.

All 130 SMEs responded to the survey. It was sent to the managers of each company to get an overview of their views on the adoption of BI in their businesses. The survey was available for one week after the emails were sent. After the survey deadline, the data was collected, initially exported to an Excel format, then loaded into SPSS to be formatted properly before being uploaded without issues to SmartPLS. Since all the questions were mandatory, there were no unanswered questions.

5 RESULTS

After processing the survey data and adjusting the model to acceptable thresholds for the metrics, we have that the final observable variables of the model (which would be the valid hypotheses of the influence of intention to use BI solutions) are: Performance Expectation (PE), Price/Value Ratio (PV) and Competitive Pressure (CP).

Table 3: Hypothesis test results.

Hypothesis	Estimate	S.E	C.R.	P-Value	Results
H1 (PE->BI)	0,343	0.083	3.996	0.001	Pass
H6 (PV->BI)	0,462	0.088	4.126	0.001	Pass
H8 (PC->BI)	1,045	0.079	12.874	0.001	Pass

The factors pass based on their strong and statistically significant metrics. For each hypothesis, the high Critical Ratios (C.R.) and low P-Values (all below 0.05) indicate robust relationships between the variables. The path coefficients (Estimates) show positive and substantial effects, with perceived cost (PC) having the strongest influence, as reflected by its high estimate (1.045). These metrics confirm that performance expectancy (PE), price/value ratio (PV), and competitive pressure (CP) significantly affect behavioral intention (BI), validating the hypotheses and demonstrating that the relationships are not due to chance.

Table 4: Model fit indices.

Model fit indices		Final SEM	
Index	Threshold	Index	Fulfillment
Normalized Chi-square	>1 y <5	2,96	Pass
GFI	>0,9	0,92	Pass
CFI	>0,9	0,96	Pass
RMSEA	<0,08	0,078	Pass

Such variables have factor loadings greater than 0.7 (acceptable level), as well as their variances are greater than 0.5. With this, it can be concluded that the model already has a conforming and validated structure.

6 CONCLUSIONS

The present study allowed us to explore the factors influencing the intention to use Business Intelligence (BI) solutions in small and medium-sized enterprises

(SMEs) in Peru, based on a survey. Information was collected from 130 SMEs across Peru to validate the UTAUT2 model.

Through detailed analysis, three main constructs were identified that exert significant influence on this intention: Performance Expectancy (PE), Price/Value Ratio (PV), and Competitive Pressure (CP). Thus, it is found that in the UTAUT2 model, only PE and PV are valid in the analyzed context, as well as CP. However, while Performance Expectancy is recognized as a critical factor for SMEs across various countries, including the Czech Republic (Kašparová, 2023), additional factors such as PV and CP may gain prominence depending on the specific market in which these SMEs operate. This suggests that while PE remains universally important, the impact of other constructs can vary significantly based on the unique characteristics of different geographical and cultural contexts.

Together, these findings provided valuable insights for both SMEs considering the adoption of BI solutions and for the providers of these technologies. For SMEs, it is crucial to assess how BI solutions can integrate and enhance their operations effectively. For providers, understanding these motivations can help develop more effective marketing and sales strategies, aligning their offerings with the specific needs and concerns of SMEs.

Future studies could further explore how other factors, such as staff training and technical support, influence the adoption of BI solutions or other essential solutions for the optimization and growth of SMEs. Specifically, it would be valuable to conduct an analysis focused on the retail sector, given its dynamism and high competitiveness, to better understand how SMEs in this industry perceive and utilize BI technologies.

It is important to note that the findings of this study are based on the context of Peruvian SMEs. Due to differences in economic, social, and technological contexts between countries, the results may not be generalizable to SMEs in other regions. The specific conditions of each market can influence the identified technology acceptance factors.

ACKNOWLEDGMENTS

We would like to express our most sincere gratitude to the School of Systems and Computer Engineering of the Peruvian University of Applied Sciences for providing us with the necessary tools and environment for the development of this research. To

our advisors, for their invaluable guidance, patience and support throughout this project. Finally, to the other individuals who were involved in the development of the project, for their constant encouragement, understanding and unconditional support, without whom this achievement would not have been possible.

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