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ORIGINAL ARTICLE

Adoption of business analytics in accounting

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ABSTRACT

The aim of this study is to analyze feasible business analytics (BA) adoption initiatives in accounting and their potential antecedents and effects, according to experts and early adopters. BA solutions help professionals explore data and gain insights for decision making. Although there is a clear relationship between BA and accounting, there is a gap between the theory and its adoption in practice. The research is relevant to academia and the market because it presents the main antecedents, effects, uses, techniques, and data sources, as well as the characteristics of the task, technology, and individual that impact the fit between BA and accounting. The main antecedents of adoption and good practices in early adopter projects using BA are highlighted, reducing the theory-practice gap and bringing new elements to promote its adoption among professionals and organizations. A qualitative-exploratory study was conducted using semi-structured interviews with 20 professionals from different accounting areas. The results highlight the main BA usage initiatives: identifying improper transactions, analyzing larger volumes of data, and performing predictive analyses. Efficiency, quality, and improved decision making were the main effects of using BA. The feasibility of BA initiatives was analyzed using the task-technology fit (TTF) model and the antecedents of adoption were analyzed using the technology-organization-environment (TOE) model, identifying characteristics of the task, technology, and individual as well as technological, organizational, and environmental factors that increase the fit between BA and accounting. The study contributes to highlighting the barriers (regulation and data availability) that affect the adoption of BA and concludes that the purposes of use, the depth of adoption, and the effects differ according to the accounting area, as the main effects of the use of BA primarily impact the accounting area itself, followed by other stakeholders.

Keywords: business analytics, adoption, antecedents, effects, accounting.

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1. INTRODUCTION

Today's business environment is centered on data (Appelbaum et al., 2021), and its growing volume is creating a need for organizations to learn how to use this available information to produce better results (Camm et al., 2020). Davenport (2021) points out that between 20 and 37% of the largest global corporations are adopting some form of artificial intelligence technology, mostly in the form of machine learning, in business analytics (BA) projects to help the companies explore data, uncover patterns and trends, and generate insights for their operations (Deloitte, 2021). For example, accounting scandals such as the recent Americanas case could be minimized by using BA to detect fraud and/or errors (Comissão de Valores Mobiliários [CVM], 2023).

Analytics solutions are transforming markets, especially the accounting environment, due to the nature of the accountant's job of supporting managers through accounting information (Wongsim et al., 2019). For Rikhardsson and Yigitbasioglu (2018), there is a clear relationship between the use of BA and the accounting area, as they share the common mission of facilitating organizational decision making. BA techniques and processes can focus on identifying significant trends and ideas from financial and non-financial data, intelligently presenting and visualizing data, and using it to improve performance (Cockcroft & Russell, 2018).

In "The Future of Analytics in the Finance Function – Global Survey 2020," responses from senior finance and accounting executives indicated that only 14% of accounting and finance functions use BA to derive value from data (FSN – The Modern Finance Forum, 2020). Even with new data-centric businesses and the role of accounting in this context, there is still little evidence of the use of BA by accounting (Schmidt et al., 2020). The study by Schmidt et al. (2020) points to the cost of change as a factor inhibiting adoption, but also indicates that the opinion of colleagues has a positive influence, making it important to understand other aspects that influence adoption.

Considering these aspects, this research aims to analyze feasible BA adoption initiatives in accounting and their potential antecedents and effects. We chose a qualitative and exploratory approach, operationalized through interviews with experts and early adopters of BA. A total of 20 professionals from five different accounting areas were interviewed, totaling almost 30 hours of recording. The data were analyzed using the content analysis technique with hierarchical coding, and the results showed the main feasible initiatives for using BA in the accounting field, its main effects, antecedents of adoption, as well as the characteristics of the task, technology, and professional that contribute to the fit between BA and accounting.

This study helps to fill the gaps related to the adoption of BA in accounting. While research indicates that organizations will continue to invest in the use of BA to gain competitive advantage in the face of technological advances (Deloitte, 2021), a significant number of companies have not yet managed to implement BA (Nam et al., 2019). It is also argued that the accounting area can play a leading role in the current context by providing useful information for decision making (Coyne et al., 2018); however, there is little evidence on whether accounting professionals are actually playing this role (Schmidt et al., 2020). There is a need for more studies that empirically explore the drivers of BA adoption in accounting and its effects (Perkhofer et al., 2019; Rikhardsson & Yigitbasioglu, 2018).

2. BA AND ACCOUNTING

BA is the use of data, statistical analyses, and quantitative and mathematical methods to help managers obtain better information about their operations and make better decisions based on facts (Davenport & Harris, 2017). Davenport (2014) coined the term to represent the main analytical component of business intelligence (BI), differentiating them by how they achieve the primary objective. According to the author, BI relies on reports to support decision makers, while BA focuses on statistical and mathematical analyses.

Holsapple et al. (2014) proposed three dimensions for understanding BA. The first concerns domain, which refers to traditional business disciplines such as accounting. The second concerns orientation and refers to why BA is being used, which can be categorized as descriptive, predictive, or prescriptive. These three types of orientation involve an "analytical journey" (Appelbaum et al., 2017; Nielsen, 2018) in which (i) descriptive seeks to answer questions about what happened and how it unfolded through reports, ad hoc consultations, and interactive visualizations, (ii) predictive aims to understand the future and answer what could happen, using data mining and statistical techniques to discover explanatory and predictive models based on accumulated historical data to calculate probabilities of future events, and (iii) prescriptive seeks to answer what should be done based on the descriptive and predictive analytical results.

The third dimension, called technique, refers to the way in which an analytics task is performed (Holsapple et al., 2014). In terms of the analytics techniques used in the accounting field, Appelbaum et al. (2017) highlight clustering and classification models, data and text mining, and visualization, as well as artificial neural networks, decision trees, regressions, and different statistical techniques. There has been an evolution in the techniques used, since in the past they originated from basic statistical analysis, and today they incorporate techniques derived from machine learning, which learns patterns from existing data to make predictions about future events, and is a subset of artificial intelligence (Appelbaum et al., 2017; Cho et al., 2020). Two technical approaches to analytics are described (Appelbaum et al., 2017; Han et al., 2011): the unsupervised approach (concerning techniques that draw inferences from labeled datasets – training data) and the supervised approach (concerning techniques that draw inferences from unlabeled datasets, where the instances have no specified output or the output value is unknown).

In order to analyze feasible BA initiatives in accounting and the respective determinants of their effects, the task-technology fit (TTF) construct was used. According to Goodhue and Thompson (1995, p. 216), TTF is "the degree to which a technology assists an individual in carrying out their tasks," and the higher the degree, i.e., the fit, the greater the likelihood that the technology will be used, leading to better performance because it better meets the needs of the individual's task. To do this, characteristics of the task, the technology, and the individual are taken into account, so that the combination of task requirements, individual abilities, and technology functionality are the factors that determine the TTF.

In addition, the technology-organization-environment (TOE) model was the theoretical lens used to analyze the antecedents of early adopters' adoption and was proposed to study the adoption of technological innovations by organizations (Depietro et al., 1990). The model posits three aspects of a company's context that can influence the process by which the company adopts and implements technological innovations (Tornatzky & Fleischer, 1990). The technological context includes the necessary equipment and processes as well as internal and external technologies that are relevant to the company (Tornatzky & Fleischer, 1990). The organizational context is usually defined in terms of descriptive measures such as the size and scope of the company, the management structure, the quality of human resources, and the number of resources available internally. The environmental context refers to the company's external environment – its industry, competitors, access to third-party resources, and government regulations (Tornatzky & Fleischer, 1990).

3. METHODOLOGICAL PROCEDURES

In order to analyze feasible BA adoption initiatives in accounting and their potential antecedents and effects, this research adopted a qualitative and exploratory approach. The research rigor criteria included the triangulation of data sources by interviewing experts and early adopters.

The first profile of analyzed units of analysis consists of experts who have worked or are working in the accounting area, with process-oriented and interpretative technical knowledge of their respective areas of activity. Experts were selected from the sub-areas of auditing, financial accounting, forensic accounting, management accounting, and tax accounting. Experts were considered to be those who had knowledge of BA, regardless of whether they used it or had already participated in an analytics project. The purpose of these interviews was to identify feasible BA initiatives that have been previously mapped in the literature (Appendix A) and the potential effects of their adoption in accounting. The experts were chosen based on their level of knowledge of the subject, their availability, and their proximity to the companies/professionals.

The second profile consists of early adopters. Since BA is a relatively new term and there are few empirical studies in the accounting context, early adopters were defined as those accounting professionals who already had some professional experience with analytics practices in the accounting area, preferably with continuous use of the techniques. The objective was to explore the adoption of BA among early adopters, describing the type of adoption and characterizing the initiative in terms of orientation and technical aspects, as well as investigating the antecedents and effects of its adoption.

In-depth semi-structured interviews were used as the data collection technique. The interview scripts for experts (Appendix B) and early adopters (Appendix C) were developed based on the literature review and validated by a researcher experienced in information systems and accounting. The interviews were conducted between March and July 2021. Twenty professionals from the five accounting sub-areas were interviewed (each area had at least three professionals). Four professionals were both experts and early adopters, another four had expertise in more than one accounting subfield, and two units of analysis consisted of two people each. Appendix D provides more information on the profile of each interviewee. The average professional experience of the respondents is 16 years and 80% of the companies they work for are large and important in their segments. In the results, experts are identified by EX and early adopters by EA.

The interviews were recorded, resulting in almost 30 hours of recordings, which were transcribed for analysis. The data analysis technique adopted was content analysis with hierarchical coding. This technique allows the researcher to make replicable inferences that are valid for the contexts in which they are used (Krippendorff, 2018). As a support tool, NVivo software was used to interpret and code the data with different coding sets. For the initiatives and effects, the coding was data driven. For the analysis of the antecedents of adoption, the coding was theory driven, using the factors of the TOE model *a posteriori*, as the factors were identified from the results analysis. For the determinants of the effects, the coding was hybrid, as the initial codes were defined *a priori* of the data collection, using a theory-driven approach based on the TTF model, and the final categories were defined using a data-driven approach. The codebook used is presented in Appendix E. The appendices are available by requesting the authors.

4. DATA ANALYSIS

4.1 Feasible BA Initiatives According to the Experts

First, the BA initiatives considered feasible for accounting by the experts are presented, based on the initiatives previously studied in the literature. The initiatives were characterized according to the three dimensions of BA: domain, orientation, and technique.

4.1.1 Domain – Usage purposes

Domain refers to business disciplines, such as accounting. The experts' responses identified two groups of purposes for using BA in accounting: 1) initiatives that "automate" tasks; and 2) initiatives that "turbocharge" activities. Among the initiatives that automate activities, initiatives to "identify suspicious transactions" used in forensic accounting were considered feasible: *"the points would be to detect relationships, that'd be quite feasible, I'd say it's 100% applicable"* (EX10-O); and in auditing:

> *there's a tool that I just load the data into and, according to the type of need I have, it gives me the answers, so I can see if there's anything too outside the curve, if there's something that calls my attention to investigate, something that's happening that shouldn't be* (EX3-A).

Initiatives to "identify duplicates" were also confirmed, both in auditing and in the tax area. EX1-A highlights *"using programming for this and, by using programming, if you're automating things, it falls under analytics, the point is that it's a simple approach, it's a supervised approach."* EX2-A confirms this initiative by saying *"this is the item that we can certainly explore through analytics because we can start from a supervised approach."*

The experts see analytics being used for "miscellaneous analysis" activities in tax, management, and financial accounting and auditing, for example: *"it's possible to have a historical analysis of company prices and news, of course very much based on unstructured data"* (EX9-F) and *"to monitor the level of customer satisfaction, which has no form, no predictive approach, which actually fits in with the descriptive analysis"* (EX5-G).

As for the analytics initiatives that turbocharge accounting activities, there is "analysis of a greater volume of data," as EX11-O explains: *"I can do this in a much more artisanal way, but by using an analytics tool, I can do a much broader sweep to cover my entire database instead of covering, for example, a sample."* EX1-A adds that *"for a long time auditing has used these smaller numbers, but it's far from ideal; if you can work and test the completeness of* *the numbers and ensure that everything is being captured by the systems, it's much better."*

Another set of initiatives are those that make it possible to "develop predictive analyses." This purpose was validated by experts from all accounting areas. For EX12-F, *"looking at the risk behavior of small and medium-sized companies based on a set of variables and understanding the direction of the behavior of these variables [...] could trigger an alert."* Finally, the experts analyzed a set of initiatives that they believe are feasible and that would allow the accounting field to "innovate," such as the initiative to *"support the external audit in the planning and risk assessment phase, for example, developing models that make it possible to infer what could and should happen and compare it to what actually happened, helping in the sizing of the audit,"* which, according to EX1-A, *"is a matter of using analytics to create predictive risk assessment models, for example, so I see that there really is a nice application."*

It can be inferred that the experts legitimize the use of BA in the accounting context, not only by making it possible to automate some tasks, but also by enhancing the activity of the accounting professional. With regard to the purpose of use related to the automation of tasks, the validation of two initiatives related to the identification of transactions (suspicious and duplicate) is highlighted. Another highlight concerns the auditing area, which was mentioned in all the initiatives, both those aimed at automation and those aimed at improvement. The results confirm the arguments of the Institute of Internal Auditors (IIA, 2021) about analytical evolution in auditing, related to 100% coverage of the database, exception alerts (based on previously established parameters), and the implementation of continuous monitoring of controls (due to the automation of tasks).

Despite this, Appelbaum et al. (2021) point out that many tools used by auditors have not yet internalized modern analytics techniques, and it is important to understand the challenges and consequences of implementing BA (Perkhofer et al., 2019; Rikhardsson & Yigitbasioglu, 2018). It is also relevant to train auditors in more advanced analytics techniques and tools to add value to the business with tasks that require human judgment (Appelbaum et al., 2021), contributing to BA initiatives related to the second purpose group (turbocharging accounting activities with innovation and predictive analytics). These inferences can be extended to other areas.

4.1.2 Analysis orientation

With regard to the dimension of analysis orientation, the experts attributed that: 1) a large part of the initiatives are "descriptive"; 2) some are "descriptive-predictive"; 3) others are "predictive"; and 4) few were classified as "prescriptive." In other words, from the point of view of using feasible BA initiatives to automate and improve accounting tasks, the analysis orientations are mainly aimed at describing the data and predicting what might happen.

The initiatives classified as having a descriptive orientation had the following justifications: the need to *"understand the details of the information"* (EX2-T) and *"find out what's going on"* (EX3-A), with *"much greater use of dashboards, indicators, and results from other analytics products"* (EX6-A). Initiatives for "Raising suspicious transactions, such as graphs comparing employee travel expenses" (I14) were one of the examples from this group.

For the group of descriptive-predictive initiatives, the experts explain that these are analytics tasks that start by exploring data from the past (to understand it) and then create models to make predictions. Evidence of this practice can be seen in: *"first it'd be descriptive, where you minimally have to look at the past to identify values that have occurred [...] after descriptive, you move towards predictive, so to speak, because it was able to learn and then start to suggest"* (ESX7-T) and *"I could use the same technique with the investigative view, so in this case it's necessarily descriptive, but in the case of detection, I'm trying to look ahead, it's undoubtedly a combination of descriptive and predictive."* Initiatives such as "Tracking rates and other changes in tax legislation" (I92) are examples from this group.

Another group of initiatives was classified as predictive. The experts highlighted the use of analytics techniques to make predictions based on historical data and by training models, and the necessary role of the accounting professional to analyze the results of these models in order to complete the accounting task.

> *I'll probably run statistics, compare statistics on something and infer that this transaction is fraudulent or not, so I'd say it's predictive because I'm indicating to the auditor what might be fraudulent and he makes a decision afterwards* (EX6-A).

Some examples of initiatives are "Modeling an organization's quarterly net income for X number of years and using the model to predict quarterly net income for X number of years thereafter" (I03).

Finally, some initiatives were classified as prescriptive. For the experts, prescriptive models are models *"where practically the machine, the algorithm, makes the decision alone"* (EX6-A). In this sense, for example, EX12-F explains the initiative of "Enabling an early warning system for financial difficulties" as prescriptive because

> *it'll use a prediction of the future to sound an alarm and say "take some action to mitigate this risk that is being predicted for the future," it's not an alarm for something that's already happened, it's an alarm that the risk of an event happening in the future has increased.*

EX12-F points out that when *"we talk about predictive and prescriptive analysis, we can't forget that we start with descriptive analysis."* Therefore, descriptive analysis is the preliminary basis for predictive and prescriptive analyses, highlighting their evolutionary characteristics (Nielsen, 2018). In the accounting field, the use of descriptive and predictive analyses prevails.

4.1.3 Technical analytics approaches

In terms of technical approaches, the experts classified feasible BA initiatives as 1) "supervised," 2) "unsupervised," 3) "hybrid," or 4) "not applicable." To justify the use of the supervised approach, the experts highlighted the need for a cause-and-effect relationship, models with variables predefined in the literature, and rules to follow. As for the use of the unsupervised approach, the arguments were: the need for initial exploration of the data, not having "labeled" data in advance, and dealing with complex and/or low-frequency events.

For some initiatives, the experts pointed out that the approach could be hybrid, as both approaches can be used. EX1-A explains that *"the approach can be supervised and unsupervised [...] because most models start with something predefined, a simple regression, to try to create a prediction, and then you can also work on more complex machine learning things."* Finally, some initiatives were identified as having a non-applicable approach. EX1-A explains and justifies this as follows:

> *I'd feel more comfortable talking about supervised and unsupervised for what I think you can use regression or machine learning for [...] If I'm doing a difference of means test, it doesn't make sense to call it supervised or unsupervised, I'm not trying to predict, I'm not trying to explain a relationship, I'm just comparing [...] I'll separate supervised and unsupervised when I'm really doing a classificatory or predictive, explanatory analysis.*

It can be inferred that the possible techniques for use in BA initiatives are not limited to the supervised or unsupervised approach. Consequently, the main techniques mentioned were machine learning and regression. The experts characterize machine learning as a broad set of techniques and algorithms with potential for use in various BA initiatives in the accounting field. One example is its use in auditing to support fraud detection: *"there are several algorithms you can use for machine learning, there's regression tree, there's random forest, there's artificial neural networks, there's recurrent neural networks, there's a multitude of techniques"* (EX1-A). Regression and its variants were also mentioned as useful techniques for various analytics initiatives, especially in management accounting, helping to identify correlations such as cost components of price, quality, and time versus revenue based on online customer satisfaction and response, etc. Other techniques were also mentioned, such as clustering, classification, grouping, neural networks, statistics, combination by similarity, and graphical visualizations.

Regarding algorithms, some experts preferred not to comment because they were unfamiliar with them. Many analytics tools available on the market come with encapsulated algorithms, so the user of the tool does not know exactly which one is being used (Appelbaum et al., 2021). Another point was made by EX1-F when saying that *"neural networks are a class, you have different types of neural networks, there are recurrent, non-recurrent, I only know two or three, but I know there are hundreds."* The most frequently cited classes of algorithms include neural networks, statistical algorithms, clustering algorithms, semantic and sentiment analysis algorithms, and decision trees.

Finally, the data sources used were analyzed. Among the internal-structured sources, the following stand out: enterprise resource planning (ERP), legacy systems, financial information from spreadsheets, customer data obtained from customer relationship management (CRM), purchasing system databases, product registers, etc. As examples of unstructured internal sources, the experts cited the use of emails and various process documents. Information from banks and regulatory bodies, such as invoices, market indicators, sales in the segment in which they operate, and competitors, are mentioned as external-structured sources. Unstructured external sources included social media data to verify the behavior of related agents. It can be concluded that structured data are the most used, mostly from internal sources, from ERP and legacy systems. Figure 1 summarizes the results of the analysis of feasible BA initiatives according to the experts.

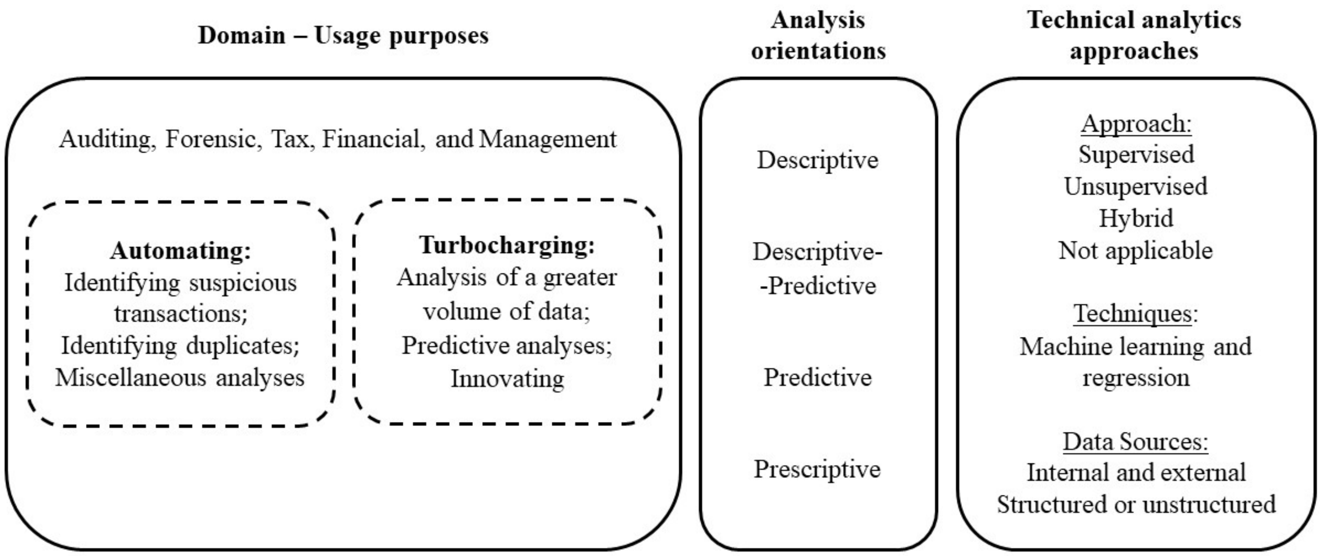

Figure 1 *Systematization of the business analytics (BA) dimensions according to the experts*
Source: *Prepared by the authors.*

It can be inferred that the experts interviewed validate the use of BA in accounting for two main purposes: to automate and to turbocharge accounting tasks, with the objectives of describing the data and predicting what might happen. To this end, different approaches and techniques are adopted, generically grouped as machine learning and regression, and the main data sources are those that already exist in organizations in a structured way.

4.2 Summary of BA Usage Cases According to the Early Adopters

This section analyzes the cases of BA usage by early adopters. First, the objectives of the initiatives are examined. From an in-depth analysis of the interviews, it can be inferred that the main purposes for which early adopters use BA are in line with what was highlighted by the experts, classifying the initiatives as a means of "automating" (related to the word "time") and "turbocharging" (related to the word "better").

As far as automating is concerned, the predominant use is for "various analyses," as highlighted by EA3-A, *"various accounting analyses that are performed on these data, revenue data, expenditure data, both budget and asset, payroll data, line items,"* and by EA9-G, *"profitability monitoring more focused on project management by client."* There is also use for "detecting suspicious transactions," as exemplified by EA7-O: *"monitoring sensitive transactions or transactions with third parties to identify patterns."* For the early adopters, a purpose of use not present in the experts' analysis was evidenced, the use of BA for "providing information to third parties," as EA4-G points out: *"automating as much as possible what is popular, spreadsheets for example [...] we're in this quest to automate via analytics."* The fact that this purpose of use appeared only among the early adopters can be explained by the fact that it is more related to the use of BI and not BA, and it can be inferred that among early adopters the difference between BI and BA is not clear.

As for turbocharging, there is an observed use for "analyzing large volumes of data" in order to *"identify within all the volume of data we receive where the focal points for onsite or remote audits would be"* (EA3-A), "developing predictive analyses" *"for provisioning and then using various predictive algorithms based on the behavior of that operation"* (EA8-F), and "innovating," as in EA1-T's narrative when pointing out that *"two products were created for the tax area."* Table 1 shows the adoption cases from this research. Most of the initiatives are descriptive, and those with more advanced predictive initiatives are highlighted in bold. Other information about technical analytics approaches is also highlighted.

Table 1
Early adopter (EA) initiatives

	Initiative	Target audience	Frequency of use	Approach, technique, algorithm
EA1-T	Conference routines in the tax area that consolidate information from various legacy systems and indicate records for analysis; tax and transfer pricing metrics dashboards with a general and detailed view of all inbound and outbound operations from all business units.	External stakeholders, business areas: commercial, supply chain and procurement, industry bodies	Online with daily updates	Visualization, clustering, statistical techniques using Python and R
EA2-T	A tool that analyzes purchase order history and indicates what the tax code should be for a given item being purchased; a model to optimize income tax and social security contribution projections for the next 12 months.	Tax compliance, tax area	Monthly and quarterly	Supervised, regression, heat map, decision tree, visualization, time series
EA3-A	Dashboards used to analyze accounting accounts for revenues, data on both budget and asset expenses and payroll and line items; tool for detecting anomalies based on historical analysis of spending behavior; issue alerts for auditors to perform their analysis.	Internal auditors, government bodies, society	Online with daily and monthly updates	Descriptive statistics, visualization
EA4-G	Dashboards used directly for various analyses, such as contract profitability analysis, and also as an intermediate consolidated database for other analyses and reports.	Accounting and commercial areas, managers, directors, and superintendents	Online with monthly updates	Descriptive statistics, visualization
EA5-F	Dashboards for monitoring accounting process statistics and volume and tax analysis.	Business and corporate/ back-office areas	Online with monthly updates	Visualization
EA6-O	Identifying hidden relationships between organizations, legal entities, and individuals based on the supplier register.	External stakeholder, external audit	On demand	Supervised, descriptive statistics, classification, clustering, text mining
EA7-O	In the area of compliance, monitoring sensitive transactions or transactions with third parties to identify patterns; identifying companies with some similarity by cross-referencing supplier and customer records with proprietary databases, selecting potential records for in-depth investigation.	Compliance, internal auditing or risk management, legal and forensic areas	Monthly, quarterly, biannual, or annual updates and on demand	Clustering, classification, visualization, fuzzy matching, e-discovery tool
EA8-F	Monitoring the evolution of the general and detailed portfolio; forecasting profits and losses, and measuring risks based on historical data.	Commercial area, accounting area, and management	Online and on demand	Supervised, regression, decision tree
EA9-F	Preparation of financial statements.	Accounting area	Annual	Visualization
EA9-G	Disclosure of results to partners and monitoring of profitability with a focus on project management by client.	Managers and coordinators	Weekly and monthly	Visualization
EA10-F	Control of the accounting area's activities and a dashboard that shows the outliers of divergences between related parties and allows the monitoring of legal balances.	Accounting area	Monthly	Visualization

Note: *Initiatives highlighted in bold have a more advanced predictive orientation.*
Source: *Prepared by the authors.*

Many initiatives are targeted at the accounting area itself, confirming The Modern Finance Forum's report that a large number of usage initiatives have not yet crossed the boundaries of their own departments (FSN, 2020). In terms of "frequency of use," there is a predominance of daily and monthly use, indicating that these solutions are systematized and used in organizations, as indicated by Goodhue and Thompson (1995). As for "techniques," the most used are visualization, descriptive statistics, classification, regression, and decision trees.

The "visualization" and "presentation of data" were aspects highlighted by many respondents, for example: *"communication isn't what we say, but what others understand [...] we take the data, evaluate which graph would look best, and the agreement is that all this is visual and simple"* (EA1-T). EA7-O states that data visualization and presentation in the forensic context *"is a means, but it can be an end; [...] we use it at both ends, it's a great communication tool, but it also brings a lot of insight for the process itself, in the exploratory phase."* This confirms the findings of Cockcroft and Russell (2018), who show that the intelligent presentation of data is one of the characteristics of the use of BA in the accounting field. The most used ways of presenting the results by the respondents are graphs, Excel tables, and reports, provided through dashboards that allow facilities such as the use of filters and drilldowns.

In terms of "data sources," the most commonly used are internal and structured sources, with data obtained mainly from company systems such as ERP and legacy systems, confirming the experts' indication. The highlight concerns the adopters from the forensic area, as both emphasize the use of external data to cross-check with internal data, both structured and unstructured. For EA7-O, *"the greatest richness in the analysis in a forensic context is when I can combine internal and external data."*

It is worth noting that in most of the organizations where BA adoption cases were analyzed, the analytics journey had already lasted between 1 and 4 months and approximately 2 years. Based on the experience of the early adopters, there are some elements that can contribute to leveraging analytics projects in the accounting context. The first element is the training of people, due to the knowledge required both to work on the development of analytics products and to consume the results in order to better analyze them. The adopters comment on knowledge of technology and statistics and competence to handle data analytically, as well as knowledge of basic accounting concepts for business areas to interpret the results of the analyses (EA2-T, EA3-A, EA4-G, EA5-F, EA7-O, EA8-F, EA9-G, EA10-F).

Another point highlighted is the fact that having people with knowledge of analytics on the accounting team, whether they are accounting professionals or multidisciplinary teams, is a factor that ensures greater speed and assertiveness in analytics projects (EA1-T, EA2-T, EA5-F, EA7-O, EA8-F, EA9-G). It is inferred that accounting professionals who want to develop skills in the use of analytics will be able to take up positions on teams developing these products, helping to accelerate the adoption of BA. Finally, EA1-T and EA9-G comment that after showing the initial results of the analytical effort, they were able to obtain more resources to continue moving forward due to the support of the business areas. Figure 2 summarizes the results of the analysis of the early adopters' usage cases.

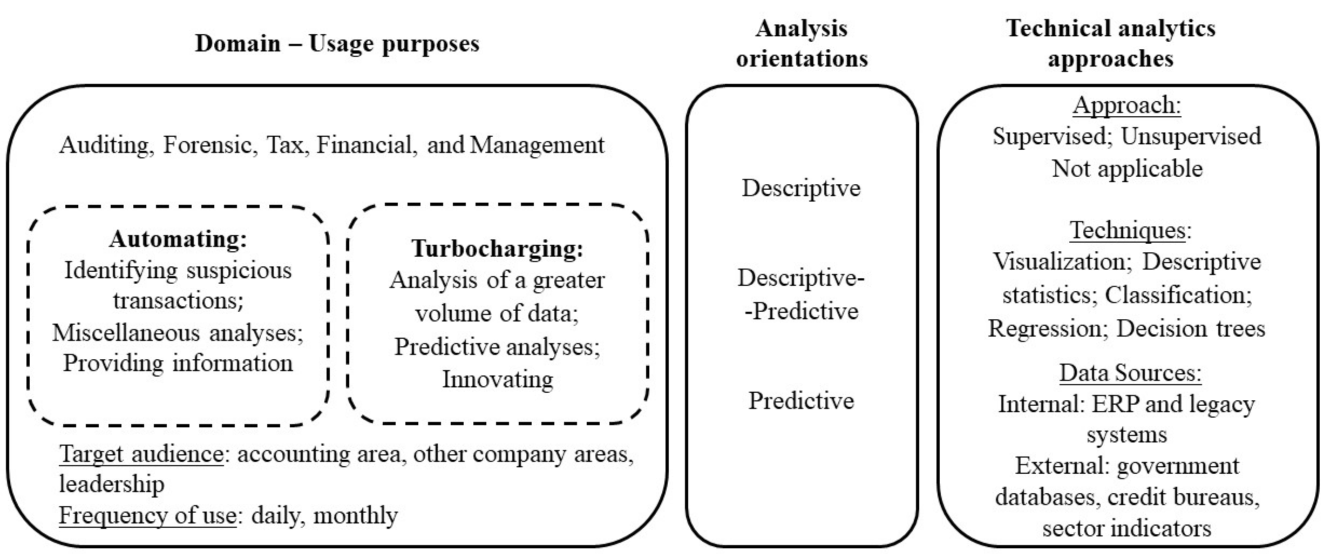

Figure 2 *Summary of business analytics (BA) usage cases according to the early adopters*
ERP = enterprise resource planning
Source: *Prepared by the authors.*

Figure 2 shows that the early adopters interviewed in this study, from the auditing, forensic, tax, financial, and management accounting sub-areas, systematically use BA in accounting – daily and monthly – for two main purposes: to automate and to turbocharge activities, highlighting the purpose of use for providing accounting information, with the main objective of describing the data to different internal audiences. To this end, various approaches and techniques are adopted, with the main sources of data being those that already exist in the organizations in a structured form, mainly ERP and legacy systems data, and structured external sources, collected from public government databases and databases with sector indicators.

Compared to the results for the initiatives analyzed as feasible by the experts, the early adopters also highlighted information provision as a purpose of use. In terms of analysis orientation, the use of prescriptive analysis was not observed, although the experts indicated that this level of analysis can be achieved. And in the technical dimension, the use of unstructured data sources was not observed. From this comparison, it can be inferred that the early adopters are still in the early stages of exploring the potential for adoption, given the experts' opinion of what is feasible.

4.3 Main Effects of BA Initiatives on Accounting

Table 2 shows the effects of BA on accounting as highlighted by the respondents.

Table 2
Main effects of business analytics (BA) initiatives on accounting

Evidence of the effects	Effects
"I can do this more efficiently, for example, by combining an unsupervised technique where I can review a database of a million emails and, from the 10,000 I've reviewed, I can project to the rest of the database which emails or which of those 990,000 would have a high probability of being relevant, I can substantially direct my effort and be much more efficient and accurate in my review." (EX11-O)	Experts and early adopters from all the accounting areas studied highlighted "efficiency" as the main effect. The words productivity, time, process, agility, bigger, and better stood out.
"Better efficiency in directing resources to increase sales in a specific region and optimize operational resources." (EX5-G)	
"It's optimizing the process, so in a way, we can do it with more productivity, ask less of the team, and improve the speed of taking that credit. It improves the process and takes that credit faster." (EA2-T)	
"It's accuracy, accuracy in classification, so you can predict for the organization that's calculating, you can predict a scenario more accurately, have actions, so to speak, to minimize unpredictability." (EX12-F)	Experts and early adopters from all the accounting areas studied highlighted the effect of "quality." The words greater accuracy, coverage, precision, and security stood out.
"The most sensitive thing, the first thing is the accuracy of the data, right, reliability, agility in getting the data, right; I focus on reliability because I generally don't know what the percentage is, but the vast majority of errors that occur that result in fines from the tax authorities are due to data errors." (EX8-T)	
"There's an improvement in the quality of information, knowing how much we're going to grow, how much we're going to lose, and then being able to invest better." (EA8-F)	
"Effects, here, is a support for corporate decision making, because with the result of this analysis, the company will know that it has to take some action plan to improve." (EX3-A)	Experts and early adopters from all the accounting areas studied highlighted "improved decision-making" as one of the effects, derived from better conditions for planning and managing the business based on reliable and easily accessible information.
"I think there are n possibilities when it comes to forecasting, but the main ones are these: it improves decision making in the company." (EX5-G)	
"There's another front that helps me make decisions, calling the sales department, for example, and saying: look, we're going to change the pricing policy for this item, this item, this item, and the return for the company is going to be this, we're going to optimize the tax chain by this much, etc." (EA1-T)	
"The best decision making, really, if we think about optimizing financial gain, I'm going to buy, I'm going to sell, I'm going to negotiate based on the model's response, right, if it's falling I'm going to buy, well, for that kind of decision making, for gain." (EX12-F)	With the exception of the forensic area, experts and early adopters highlighted "increased profitability" as one of the effects, with the financial and management areas being the most prominent.
"The economic gain in the capital market is because with these techniques the auditor can audit better, can do his job better, and that protects the market in general, resulting in better quality accounting information." (EX1-A)	
"We can increase the company's profitability and really increase the people doing what they should be doing." (EA9-G)	
"Greater control over transactions, over operations, over sensitive interactions, according to the company's vision of risk." (EX11-O)	Compliance is one of the effects present in the research. It is strongly related to the forensic, auditing, and tax areas. The main words associated with it are fraud, control, supplier, and detection.
"We can often stop a tender that's overpriced or something like that before it happens, because we already get the data on a daily basis, we can detect it by generating alerts." (EA3-A)	
"The company doesn't like positive surprises or negative surprises, it likes predictability, which in a country like Brazil is complicated; it likes to be in compliance [...] So this analytics front seeks to bring a little more tax coherence to our table." (EA1-T)	
"Basically, you're going to have a more rounded company, I'd say, you're going to detect fraud, you're going to improve controls, you're going to inhibit fraud." (EX10-O)	"Effectiveness" is one of the effects highlighted by experts.
"I think that the effect is to strengthen the internal control structure [...] you improve your control so that it doesn't happen again next time." (EX1-A)	

Table 2
Cont.

Evidence of the effects	Effects
"We could bring new business to the company, new possibilities, open up customers, launch new products." (EX2-A)	Experts believe that some initiatives have the effect of "anticipating market trends."
"Bringing in new customer perspectives that can shape new products and bringing in new ideas that can add to the company's portfolio." (EX5-G)	
"An understanding of the market perhaps in that sense, a greater understanding [...] of the market that we operate in, you know, niche markets that we operate in to promote new business and opportunities." (EX9-F)	

Source: *Prepared by the authors.*

From a more macro perspective of the effects, the following were highlighted: efficiency, quality, improved decision making, increased profitability, compliance, effectiveness, and anticipation of market trends. Other considerations were made that complement the effects. The first is the fact that during the implementation of an analytics initiative, or even at the end of it, insights and data emerge for new analyses, as ESP6-A explains: *"I see insight generation as: I'm going to generate new hypotheses, new analytics products."* EA1-T adds that

> *there are results that we expect, and there are reflections and provocations that arise that we didn't even expect; [...] today we work a lot with financial data, [...] but we're going into a second wave where we're going to start comparing these data with operational indicators from other areas.*

Another indirect effect is that it gives the organization the ability to know its processes and data better: *"in most cases, in deployments, it leads to greater knowledge of the data itself"* (EX9-F). EA1-T provides an example:

> *some questions in the OECD [Organization for Economic Cooperation and Development] questionnaire asked for information that we had quickly, [...] and I saw a lot of people saying "I'll need about 3 or 4 days to get that," so that gave me a message that we were at a stage, if not the most advanced, in the early adopter group.*

Improving the customer journey was an effect commented on by EA7-O: *"especially for those companies that are service providers, the use of visualization mechanisms facilitates the process of communicating findings and helps tell the story in a more understandable way."* EX1-A complements this with the narrative that as the accounting professional contributes new insights to the business, they become more valuable. It can be inferred that the use of analytics can help to promote the accounting professional.

Some experts highlighted the behavior-changing effect that monitoring initiatives to detect suspicious transactions can have:

> *"if academia starts analyzing companies' disclosures, looking for the tone of the text using the machine learning algorithm, what's to stop the company from hiring a researcher to run its statements through an algorithm before taking them to the market and embellishing its financial statement?"* (EX1-A).

It highlights both positive changes, such as a reduction in fraud due to the inhibition caused by the use of analytics, and negative ones, such as the use of the same intelligence to hide suspicious transactions and deceive monitoring.

4.4 Main Drivers of BA Adoption in Accounting

The main elements determining the effect of the use of analytics in accounting, the initiatives considered feasible by the experts, and the initiatives adopted by the early adopters were grouped according to the TTF model (Goodhue & Thompson, 1995). The characteristics of the "task," according to the respondents, center on three aspects. The first is the fact that the accounting task is "highly regulated and complex" if performed manually, as it can lead to human error. The second characteristic of the task is that it is "repetitive" and the last is that it involves working with "large volumes of data."

Regarding the characteristics of "technology," the "technological evolution" itself stands out, as evidenced by the existence of tools that encapsulate various analytics techniques and facilitate the use by professionals (EX3-A, EX8-T, EA7-O, EA10-F) of models, statistical algorithms, and machine learning used in predictive analysis (EX1-A, EX5-G, EX7-T, EA2-T), and by the hardware, which offers greater processing and analysis capacity (EA3-A, EA7-O). Another aspect is "data availability." The respondents emphasize the importance of having access to data in sufficient quantity, quality, and timeliness to perform better analyses. Finally, there is the issue of "data preparation." According to EX1-A, *"data preparation is a very strong point, like if you don't have good data, or if you don't have things that help tell the story you're trying to predict, it gets complicated [...]."* EA4-G and EA9-G add the aspect of data standardization when they report on activities to create and format a data warehouse with unified rules and to create a data taxonomy prior to implementation.

The characteristics of the profile of the "individual" who carried out the tasks highlighted in this research are essentially based on the "knowledge of analytics" that the accounting professional must have of its main techniques, statistics, available tools, and possibilities of use in the face of a business problem or a need to be met. Another characteristic highlighted is the capacity for "critical analysis," as stated by EX12-F: *"it's using this information, being able to understand these cause-effect relationships, the human factor."* Added to this is "knowledge of the business" and other related areas, according to EX5-G: "*a professional accounting profile focused on financial planning, alignment of strategies with executives.*" Some experts also point out the importance of the accounting professional knowing how to "present the results" of the analyses, as EX11-O mentions: *"the professional's vision of how to communicate the result of their work, or how to communicate their findings or their vision in the case, is the main determining factor."* Finally, EX3-A, EA1-T, and EA10-F highlight the professional's behavioral issue of "accepting the use of new technology" as a determining factor in its use and effects.

According to the early adopters, the main determinant was the task, due to the already mentioned issues of large volumes of data and repeatability, which make manual execution time-consuming and highly susceptible to human error. As a second determinant, the characteristics of the professionals were highlighted, both technical skills, such as knowledge of analytics and statistics, and behavioral skills, to promote the initiatives. The last determinant is the effect of technology, highlighting technological evolution. In addition, the survey of early adopters identified the elements that motivated the adoption of initiatives, analyzed in the light of the TOE model (Depietro et al., 1990) (Table 3).

Table 3
Technology-organization-environment (TOE) antecedents for early adopters (EA)

	Antecedents of adoption	Evidence
TECHNOLOGICAL FACTORS	Technological competence: infrastructure that facilitates adoption and experts, i.e., people who have the knowledge to perform the tasks (Zhu & Kraemer, 2005).	*"It makes all the difference to have two people on the tax team who have a lot of expertise in technology, it's certainly also a differentiator."* (EA2-T)
		"Each superintendency has a data science team assigned to it, which speeds up deliveries and provides a better understanding of the business area." (EA5-F)
		"It was done by the accounting team, but with advice from the data team, which is a productive team in the company; and when we have any doubts, we call them too, but the implementation was all done by the team itself." (EA9-G)
	Relative advantage: defined as "the degree to which an innovation is perceived as better than the idea it replaces" (Sun et al., 2016).	*"Increased productivity. The teams are getting leaner and there's a need for rapid delivery."* (EA4-G)
	Observability: technology features are perceived as beneficial after observing how other organizations use them.	*"So we started discussing this and we visited the ... cube here to evaluate new fronts; we benchmarked with other companies and then we realized that we were on the right track."* (EA1-T)
ORGANIZATIONAL FACTORS	Management support, or management commitment, is the degree to which a company's management invests in technological innovation (Cohen & Sayag, 2010); it is explained as "the degree to which management understands the importance of technology and the extent to which it is involved in related initiatives" (Park et al., 2015).	*"And then, without the support of our head office here, and this very good relationship we have with the head office, we would hardly be able to do it, because it's a project that takes time, it's something new for the area, and even in the market there isn't much benchmarking."* (EA2-T)
		"Initially, it was even a stimulus that came from the organization's own management for us to start investing in these new data analysis technologies." (EA3-A)
	Effectiveness of change: this is "the extent to which members of the organization are psychologically and behaviorally prepared to implement organizational change" (Weiner et al., 2008).	*"What motivated the initial adoption was the issue of visibility. We were able to get the information from the sector and that thing of everyone working together for the company's results."* (EA9-G)
	Decision-making culture, e.g., evidence-based, decision-making standards.	*"There's a strategic driver in the organization, which is data-driving decision making; as a result, each superintendency has a data science team assigned to it."* (EA5-F)

Antecedents of adoption		Evidence
ENVIRONMENTAL FACTORS	External pressure: these are "the influences of the external environment" (Verma et al., 2017), regulatory pressures, competitive pressures (Lin, 2014), encouragement from professional bodies.	*"In terms of good practices and thinking about how the market has adopted these solutions, has adopted these tools, has thought about this issue in order to continue or remain competitive in the future, so we need to adopt these practices."* (EA8-F)
		"[Our country] is today the country that's most at the forefront of this tax transformation initiative, not because we're better, not because we're faster, but because it's a very complex country in the tax area; we saw this as an opportunity to make it less complex." (EA1-T)
	External support: defined as the "availability of support for implementing and using an information system" (Premkumar & Roberts, 1999); readiness of the commercial partner.	*"About two years ago, we started working together with a supplier, which we signed a mentoring contract with, and then we developed these tools internally with them in the organization to speed things up and to really be able to analyze all the data."* (EA3-A)
		"We'd need external support, for example, a Big Four, a ..., in short, companies that work in this area." (EA1-T)

Source: *Prepared by the authors.*

Based on Table 3, "technological competence" stands out, as most of the organizations studied have professionals with the technical skills required for implementation on their accounting or IT teams. Another highlight is "top management support," which acts as a lever for the projects, especially in the case of medium and long-term exploratory projects. Among the environmental factors, "external pressure" stands out; both competitive pressure, due to competition, and pressure due to the complexity of tax legislation, putting pressure on organizations to look for technological alternatives to carry out their activities. It can be inferred that, once the technological competences are available and there is support from senior management and/or external pressure, initiatives to adopt BA in accounting are prioritized based on the characteristics of the task to be performed. Figure 3 consolidates the elements identified in this section.

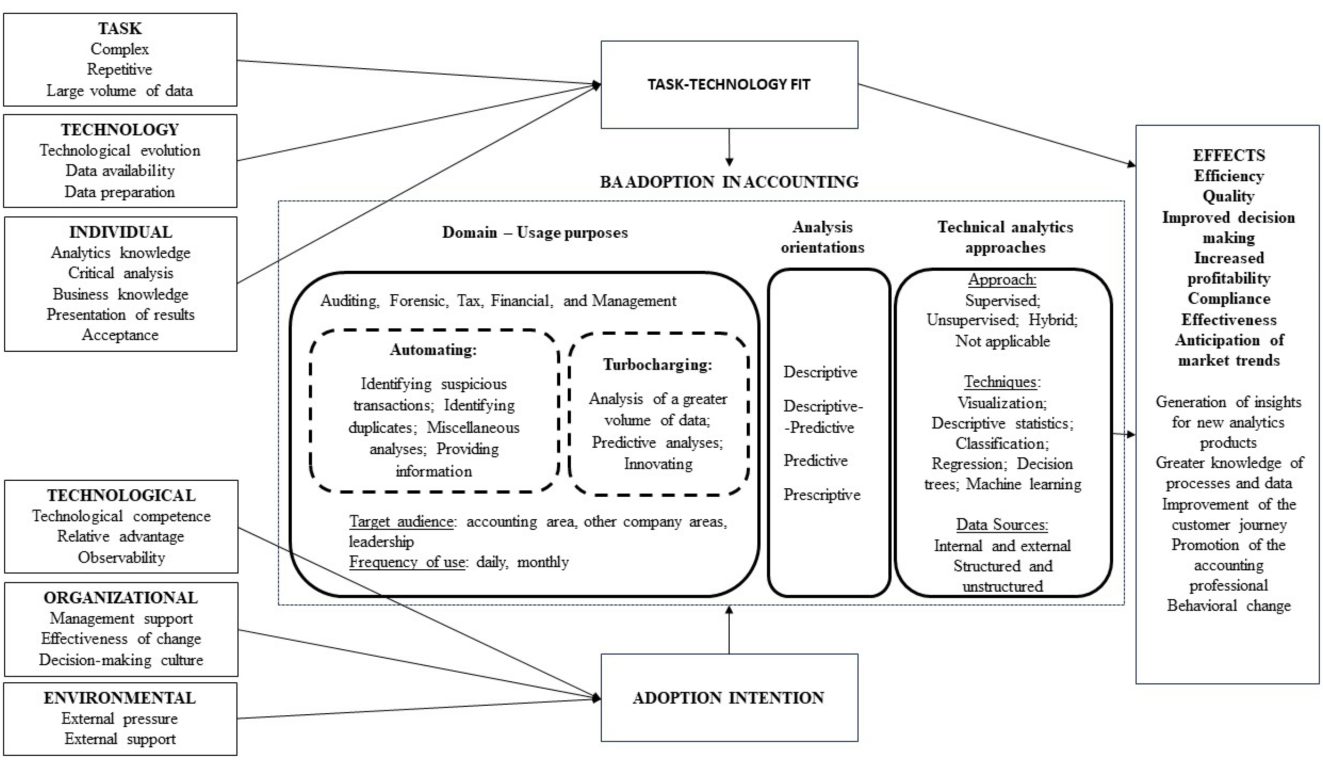

Figure 3 *Main drivers of business analytics (BA) adoption in accounting and its effects*
Source: *Prepared by the authors.*

The adoption of BA in accounting aims to automate and turbocharge tasks, and its analysis objectives are to describe and predict scenarios. A variety of data mining approaches are employed, using machine learning and regression techniques, with the main source of data being structured and internal sources (ERP and legacy systems). The early adopters interviewed were motivated to adopt at least one element from the technological, organizational, or environmental contexts of the TOE model. Therefore, the model explains the antecedents of the intention to adopt BA in these organizations, since all the motivations were categorized in one of its constructs, with technological competence, top management support, and external pressure standing out. This confirms the findings of Schmidt et al. (2020) that stakeholder opinion positively influences adoption.

The initiatives considered valid for use were analyzed in the light of the TTF model. Different characteristics of the task and technology were examined, as well as various characteristics of the professional profile, including technology skills and motivation, in line with the characteristics presented by Goodhue and Thompson (1995). According to the experts and early adopters, the main effects were efficiency and quality. There was no conflict between the effects suggested by the experts and the actual effects experienced by the adopters. Thus, the TTF model explains the elements responsible for the fit between BA and accounting, since characteristics of the task, technology, and individual that generate the fit were identified; and the fit, in turn, precedes the actual use, helping to explain the determinants of the effect of BA on accounting. The use of BA in accounting has implications for both professionals and organizations.

Also categorized according to the TTF model were the reasons given by the experts for the initiatives that were considered unfeasible, constituting barriers to adoption. Regulatory aspects, complexity, and cost-benefit were identified as task characteristics. Data availability was identified as a technological factor, and training as an individual characteristic.

5. CONCLUDING REMARKS

This research achieved its objective by analyzing feasible BA adoption initiatives in accounting and its potential antecedents and effects, according to experts and early adopters. The most evident effects of BA adoption were efficiency, quality, improved decision making, and compliance. The study also identified the main characteristics of the task (a large volume of data and repeatability), technology (technological evolution), and the individual (knowledge of analytics and statistics and behavioral competences) that positively and negatively affect the fit between the use of BA and the accounting area, and the main antecedents of adoption in the light of the TOE model, such as technological competence (technological context), management support (organizational context), and external pressure and support (environmental context).

Another important result was the evidence that BA in accounting is used to automate and/or accelerate a portion of the accounting professional's tasks through different techniques and data sources, freeing the accounting professional to focus on another portion of tasks of greater complexity and added value that require human intervention, increasing the use of accounting information by other business areas and stakeholders, and contributing more significantly to the decision-making process.

Theoretical contributions include: (i) that the purposes of use, depth of adoption, and effects differ by accounting area, such as initiatives involving automation with a greater volume of data in the field of auditing and forensic accounting, and initiatives with descriptive and predictive models in tax accounting; (ii) that the main effects of using BA in accounting first affect the accounting area itself and then extend to other stakeholders. Barriers affecting the adoption of BA in accounting were also identified, with emphasis on regulatory aspects of activities (task) and lack of data availability to run some models (technology), complementing Schmidt et al. (2020), who highlighted cost as a barrier.

In terms of practical contributions, the results for the early adopters in terms of the main antecedents of adoption – support from senior management and technological competence – are highlighted. In addition, there are the good practices and lessons learned from the early adopters' projects, where analytics and business knowledge were fundamental to the success of their initiatives, often provided by multidisciplinary teams. Another finding was the importance of data availability to apply more advanced techniques and raise the level of analytics products, as well as time to learn during implementation projects. In addition, all the participants emphasized the importance of the accounting professional being able to take on different roles in analytics projects and how analytics can promote the accounting function in organizations, which is consistent with the authors Appelbaum et al. (2017) and Rikhardsson and Yigitbasioglu (2018). It should be noted that what was found to be feasible is in line with the current stage of knowledge of the professionals interviewed and the technologies available at the moment, but there is still more to be explored with increased use as a result of more knowledge on the part of the accountant and more resources available, which would contribute to the sustainability of the accountant's career (Wanderley, 2021). These results serve as guidelines for managers who want to achieve better results from adoption, as they form a synthesis of good practices for the adoption of BA in accounting.

In view of the results of this research, and especially due to the evidence of the beneficial effects produced by the use of analytics tools in the accounting area, some opportunities for future studies are suggested. Among them is a qualitative and quantitative evaluation of the use of predictive and prescriptive analytics for new effects and/or improvement of the effects already identified, especially with regard to supporting organizational decision making. Another suggestion is to apply this study to BA adopters in contexts that have different levels of tax system complexity, in order to compare the purposes of use, drivers of fit and effects, and possible differences in the results obtained.

For professionals and companies interested in helping to increase the use of BA in accounting, it is suggested that the training of accounting professionals in technology, data analysis tools, and statistics be expanded, with the aim of increasing the sponsorship of initiatives and adoption, accelerating implementation projects, and maximizing the effects. Finally, studies are suggested on how to expand the adoption of BA in accounting in small and medium-sized organizations so that smaller organizations can also benefit from its effects.

As a limitation, the techniques and algorithms identified by the experts as useful for accounting initiatives were not discussed in greater depth, so studies are suggested to promote the use of predictive and prescriptive analytics through more advanced and heterogeneous techniques, and to increase the diversity of data sources, combining internal and external, structured and unstructured sources. The qualitative nature of this research should also be noted, as it does not allow its results to be generalized.

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