Adoption of Intelligent Information Systems: An Approach to the Colombian Context

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Abstract: Enterprise Information Systems (EIS) are widely used to support operational and tactical processes of companies and have begun, in recent years, to be used at the strategic level to support decision-making processes. To do so, new systems, known as intelligent EIS, integrate data analytics modules to provide the necessary information and reports to make informed decisions. There are certain influencing factors for the adoption of such systems, however, from a first analysis of the academic literature, it was found that research works in the domain are very scarce and even more, there are no research works on the subject in Colombia. Consequently, this article aims at identifying the relevant factors for the adoption of intelligent EIS based on an analysis of the academic literature, and then structuring a focus group activity with 5 experts on the subject to obtain a first approach to the adoption of this kind of systems for the Colombian context. As a preliminary result, we found that in the Colombian industry the most important influencing factors include cost and IT capabilities which differs from main factors identified in the revision of the international scholar literature.

1 INTRODUCTION

There is a wide variety of technological tools that aims at providing support to the companies' business processes. Some of the most important support tools are Enterprise Information Systems (EIS) and data analytics modules, which have become very popular in recent years due to the large amount of data produced by both companies and customers (el Kadiri et al., 2016).

The use of EIS can bring great benefits to companies due to the high impact they have on business processes at both operational and tactical levels. Usually, systems such as Enterprise Resource Planning (ERP) or Customer Relationship Management (CRM) contribute to register transactional data generated in business processes such as financial accounting, purchasing, operations or sales, and in the realization of descriptive reports of the company's situation based on historical information (Kenneth C. Laudon & Jane P. Laudon, 2014).

On the other hand, data analytics tools allow a characterization of both customers and the business based on historical information (Sharda et al., 2015). By analysing the company's historical data, it is viable to know its current situation, i.e., it is possible to identify the failures that are occurring, as well as the processes that are working correctly. In this manner, the company's historical data can be used to develop a predictive analysis, with which the company can have an idea about the possible scenarios that may arise both internally and in relation to customers, and thus be able to identify new business opportunities. In this way, data analytics makes it possible to determine the changes that should be made in business processes in order to improve the company's situation. (Sharda et al., 2015)

In recent years, data analytics components have begun to be integrated to EIS in order to support processes at the strategic level, all thanks to advances in analytics and business intelligence (Kenneth C. Laudon & Jane P. Laudon, 2014). This allows companies to profit of transactional data registered in EIS for several strategic processes such as decision-making, recommendations and analysis of customer behaviour. To this end, today analytics can be integrated to EIS through embedded modules that collect all the information stored in the EIS and

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perform more accurate business analysis and reports (Z. Sun et al., 2017). Other possibility is when the organisation has analytics tools external to the transactional EIS, in which case, the EIS collects data from the different processes, and then there is an external integration with the analytics tool (Sharda et al., 2015). It is used when the EIS and the analytics tools were implemented by different vendors or at different times.

This new configuration of systems are called intelligent EIS (Jenab et al., 2019), since they take advantage of the organisation's information in internal sources and combine them with external information to make business analysis using techniques such as artificial intelligence, analytics and business intelligence (Jenab et al., 2019). Companies can also have analytics tools external to the transactional enterprise systems, in which case, the enterprise system collects data from the different processes, and these are transferred to the analytics tool to be analysed.

The adoption of intelligent EIS brings great advantages for businesses, as a correct data analysis helps to identify new opportunities and, consequently, create value. However, there is little research literature found on the factors influencing the adoption of such systems, and to understand if they are implemented and adopted through embedded analytics modules, or by implementing and integrating external analytics tools. Moreover, in Colombia, the documentation on the adoption of technological tools including EIS and analytic applications is quite scarce and, so far, there are no academic publications that analyse such aspects.

To fulfil this lack we carry out a review of the international research literature that aims at determining the most significant factors in the adoption of intelligent EIS and the type of impact they have. Then we undertake a qualitative analysis for the Colombian context from a focus group from experts in the domain.

This paper is structured as follows: section 2 analyses the research literature in the domain. Section 3 describes the characteristics of the focus group and synthesize the main results of this activity. Section 4 compares and discusses the results of both activities to draw conclusions for the Colombian context. Finally, section 5 describes conclusions.

2 LITERATURE REVIEW

The process of conducting the literature review is divided into three main stages: (i) Planning: it focuses on identifying the articles' selection criteria and defining a framework with review questions for the evaluation of the articles. (ii) Realization: it consists in searching and selecting academic articles based on the fulfilment of the selection criteria and the possibility of answering the review questions. (iii) Synthesis and analysis: the review questions are applied to each of the selected academic articles and answered according to the information obtained.

2.1 Planning

For the selection of the most relevant academic articles, a set of criteria is defined, which are: adoption of an intelligent business system or an analytics tool, explanation of the determining factors on the adoption decision process and mention of the factor's impact type. All the articles that meet the above criteria are considered potential articles for the realization of the literature review. The evaluation framework (see Table 1) is structured in terms of three types of concepts, which are described below.

1. Category: these are the main key points to be analysed in the articles.
2. Criterion: each category has a set of criteria that help us evaluate the articles.
3. Research question: each criterion is associated with a research question, which is used to analyse the contribution of the article to the defined criteria.

Table 1: Literature assessment framework.

Context category	
Size of the company(ies)	What is the size of the company(ies) studied in the article?
Type of study	Is it a qualitative or quantitative study?
Analytics category	
Type of EIS	On what type of EIS is the adoption analysis done in the article?
Component	Is the adoption of an internal or external analytics component being analysed?
Adoption category	
Method of study	What method is used to study adoption?
Factors	What are the main factors influencing adoption?
Impact	Do the identified factors positively or negatively impact adoption?
Significance	Do the identified factors have a significant effect or not?

The context category is to clearly understand the purpose of the research and the industrial context in which it was carried out. The following criteria are proposed: Size of the analysed company(ies), the industrial sector to which the companies studied belong and the type of study between qualitative and quantitative. The analytical category seeks to understand the type of tool studied in the article and its relationship with EIS, the purpose is to identify if the analytics tool is an internal module of the business system or it is a completely separate tool. Finally, the adoption category refers to the Study method, e.g. Technology-Organization-Environment (TOE) framework, the factors that according to the study have an impact on the adoption decision, the impact that each factor has on the decision to adopt the technology (positive or negative) and the significance that corresponds to the factors that are relevant to the adoption process. A significant factor is a determining factor in the decision to adopt a tool, while a non-significant factor is not very relevant to the process.

2.2 Realization

Having the selection criteria for the academic articles ready, a keyword search is started. Scopus, a database that indexes academic articles published in different scientific journals, conference proceedings and book chapters, among others, is used for this search.

As intelligent EIS can be implemented and adopted through embedded analytics modules or by implementing traditional EIS integrated with external analytics tools, we used keywords aimed at searching both possibilities. The query used for the search of academic articles using defined keywords is described as follows.

TITLE-ABS-KEY ((("intelligent enterprise information systems" OR "intelligent enterprise systems" OR "iEIS" OR "intelligent EIS" OR "I-ERP" OR "intelligent ERP" OR "I-CRM" OR "enterprise information systems" OR "enterprise systems" OR "enterprise systems" OR "EIS" OR "ERP" OR "CRM") AND ("business intelligence" OR "data analytics" OR "big data analytics" OR "BDA") AND ("technology adoption" OR "technological adoption" OR "IT adoption" OR "TOE" OR "DOI" OR "UTAUT2" OR "TRA" OR "TAM")) AND (LIMIT-TO (SUBHEARING , "COMP")) AND (LIMIT-TO (PUBYEAR , 2022) OR LIMIT-TO (PUBYEAR , 2021) OR LIMIT-TO (PUBYEAR , 2020) OR LIMIT-TO (PUBYEAR , 2019) OR LIMIT-TO (PUBYEAR , 2018) OR LIMIT-TO (PUBYEAR , 2017) OR LIMIT-TO (PUBYEAR , 2016)))

At the beginning there were more than 200 results, these results were downloaded to Excel with the information of the source, the title and the summary. Once in Excel, a first elimination was performed according to the titles, with this filter the number of articles went down to 46. Then another filter was performed, this time with the summary of the articles, which resulted in 24 articles. However, when the reading and application of the evaluation framework began, it was found that certain articles were not of great relevance to the study, so they were eliminated, thus ending up with 19 articles.

2.3 Synthesis and Analysis

Based on the application of the evaluation framework to the set of articles, an analysis is presented indicating the similarities and differences between the articles and the conclusions reached.

Regarding the criterion *Type of EIS* and *Components* (see Table 1), the conclusions are summarized in Table 2 and can be divided into 3 groups of papers. The first group of papers studies the adoption of intelligent EIS, where 4 of them focus on ERP adoption (Xu et al., 2017), (Nwankpa et al., 2016), (Mayeh et al., 2016), (Elkhani et al., 2014), 3 of them on CRM adoption (Cruz-Jesus et al., 2019), (Hasan Salah et al., 2019), (Ahani et al., 2017) and one on EIS in general, but hosted in the cloud (Şener et al., 2016). Although these papers refer to the adoption of intelligent EIS, they do not provide evidence of how they are integrated with internal or external analytics modules or components.

The second group of papers ((Maroufkhani et al., 2020), (Schüll & Maslan, 2018), (Park & Kim, 2021), (Maroufkhani et al., 2022), (Angwar, 2018), (Khan & Brock, 2017), (El-Haddadeh et al., 2021), (S. Sun et al., 2018)) discuss the adoption of data analytics as an external stand-alone tool that generates information by using, among others, the organisation's internal transactional data sources.

Finally, in the third group, we identified two subgroups. On the one hand papers dealing with the adoption of analytics as an external component, but mentioning explicitly that it is fed by data coming from one or more EIS (Alaskar et al., 2021), (Kyriakou et al., 2020) and on the other hand, articles analysing the adoption of analytics as an internal embedded module of an EIS (Junior et al., 2019).

Table 2: Tool adopted.

Tool	Type	Article
Intelligent EIS	ERP	(Xu et al., 2017), (Nwankpa et al., 2016), (Mayeh et al., 2016), (Elkhani et al., 2014)
	CRM	(Cruz-Jesus et al., 2019), (Hasan Salah et al., 2019), (Ahani et al., 2017)
	EIS on cloud	(Şener et al., 2016)
Stand-alone data analytics	External component	(Maroufkhani et al., 2020), (Schüll & Maslan, 2018), (Park & Kim, 2021), (Maroufkhani et al., 2022), (Angwar, 2018), (Khan & Brock, 2017), (El-Haddadeh et al., 2021), (S. Sun et al., 2018)
EIS with data analytics	EIS powered by an external analytics component	(Alaskar et al., 2021), (Kyriakou et al., 2020)
	Internal (embedded) analytics component in ERP	(Junior et al., 2019)

Regarding the question related to the criterion *size* of the company(ies), Table 3 shows the articles for which size is considered a relevant factor, the relationship between the type of tool studied in the article and the size of the companies, and the impact and significance it has on each one.

As it can be seen in Table 3, for all the articles that consider size as a factor to be taken into account, its impact is positive, which means that the larger the company, the more likely it is that the process of adopting the tool can be initiated. However, there is no unanimity regarding its significance, since one out of 5 articles considers it a non-significant factor (S. Sun et al., 2018).

When analysing the results by type of tool adopted, in the case of intelligent EIS, even though in (Şener et al., 2016) the company's size is argued to have a positive impact and be significant, making it a relevant factor, the size of the companies participating in this study is not presented. In the remaining cases, (i.e., standalone data analytics and EIS with data analytics) the articles study companies of all size categories, namely, small, medium and large.

Table 3: Company's size as relevant factor vs type of tool.

	Intelligent EIS	Stand-alone data analytics	EIS with data analytics
Size of the company is relevant	(Şener et al., 2016): positive and significant	(Angwar, 2018): positive and significant (Khan & Brock, 2017): positive and significant (S. Sun et al., 2018): positive and not significant	(Kyriakou et al., 2020): positive and significant

Regarding the criterion *type of study*, the vast majority of cases conducted quantitative studies (see Table 4) which usually began with an analysis of the academic literature on the subject in order to identify the significant factors for technology adoption. Subsequently, a survey was developed and distributed to the participating companies. Once the results were obtained, a process of elimination of incomplete surveys was carried out. Finally, different statistical techniques, such as linear regression, were used to determine the most significant factors.

In the case of qualitative studies, the first step was the same, the study of academic literature and identification of the most important factors. Then, a group of experts on the subject were surveyed to get their opinion on the information collected and, according to this, the factors were ordered from most to least significant by means of techniques such as the Analytic Hierarchy Process (AHP), which is a multi-criteria decision method (Şener et al., 2016). However, no statistical analysis was performed at any time.

Table 4: Type of study.

Type of study	Article
Quantitative study	(Xu et al., 2017), (Cruz-Jesus et al., 2019), (Kyriakou et al., 2020), (Junior et al., 2019), (Alaskar et al., 2021), (Nwankpa et al., 2016), (Maroufkhani et al., 2020), (Ahani et al., 2017), (Schüll & Maslan, 2018), (Mayeh et al., 2016), (Park & Kim, 2021), (Maroufkhani et al., 2022), (Angwar, 2018), (Khan & Brock, 2017), (El-Haddadeh et al., 2021), (Elkhani et al., 2014)
Qualitative study	(Hasan Salah et al., 2019), (Şener et al., 2016), (S. Sun et al., 2018)

With respect to the criterion *method*, as expected, the Technology-Organization-Environment (TOE) framework is the most commonly used adoption model, being used in 13 out of 19 articles (see Table 5). In addition, there are two more articles that made use of variations of the TOE, namely, TOEP (Ahani et al., 2017) and TOES (Angwar, 2018). Both study the same three categories of the TOE, which are Technology, Organization and Environment, however, they add a new one. TOEP adds the processes category because of its focus on the company's business processes. TOES add the security category which considers factors such as information security and privacy. Regarding other methods, some works use different adoption models simultaneously. For instance, (Junior et al., 2019) uses TOE, Diffusion of Innovations (DOI) and Inter-organizational Relations (IOR) theory, (Hasan Salah et al., 2019) uses TOE, DOI and Resource-based View (RBV) and (S. Sun et al., 2018) uses TOE, DOI and Institutional theory. The combination of methods allowed researchers to have a broader view of significant factors of adoption.

Table 5: Adoption models.

Adoption model	Article
TOE	(Xu et al., 2017), (Cruz-Jesus et al., 2019), (Kyriakou et al., 2020), (Junior et al., 2019), (Alaskar et al., 2021), (Hasan Salah et al., 2019), (Maroufkhani et al., 2020), (Schüll & Maslan, 2018), (Park & Kim, 2021), (Maroufkhani et al., 2022), (El-Haddadeh et al., 2021), (Şener et al., 2016), (S. Sun et al., 2018)
DOI	(Junior et al., 2019), (Hasan Salah et al., 2019), (S. Sun et al., 2018)
Technology Acceptance Model (TAM)	(Mayeh et al., 2016), (Khan & Brock, 2017), (Elkhani et al., 2014)
TOEP	(Ahani et al., 2017)
TOES	(Angwar, 2018)
IOR	(Junior et al., 2019)
Real Options Theory	(Nwankpa et al., 2016)
RBV	(Hasan Salah et al., 2019)
Institutional theory	(S. Sun et al., 2018)

Concerning the factor *criterion*, this analysis is characterized according to the adopted tools within 3 groups, namely, intelligent EIS, stand-alone data analytics and EIS with data analytics. For this analysis the information is gathered in Table 6 which describes for each tool the factors influencing adoption, as well as the impact (positive or negative) and the significance level of each factor where S stands for significant (i.e., it is a determining factor in the decision to adopt a tool) and NS means non-significant (i.e., it is not very relevant to the process).

According to Table 6 the most currently found determining factor in the intelligent EIS group is management support, which implies that the management is involved in the EIS adoption process (Xu et al., 2017), i.e., that it knows the competitive advantages that can be provided by the technological tool and is willing to accept its cost. This factor is mentioned in 7 out of 8 articles and in all cases, it has a positive impact that is significant.

Other important factors are described as follows. Relative advantage relates to the increasing of benefits that the new intelligent EIS can bring (Xu et al., 2017). It has a positive impact that is considered significant in all the articles. Competitive market pressure concerns the pressure level a company feels to implement a certain EIS due to market competition (Xu et al., 2017). It is determined to have a positive impact that is significant. Compatibility refers to the degree of consistency between the EIS to be adopted and the values, needs, experiences and practices of the company (Xu et al., 2017). It also has a positive impact which is significant. In the case of the factors complexity and government policies, even though all research works consider the former has a negative influence and the later a positive one, there is no consensus regarding their significance, as in both cases, the same research work (Şener et al., 2016) determines that these two factors are not significant. This may be due to 2 reasons, the context and the type of study: regarding the context, this work is the only one that focuses on EIS in the cloud, which may imply a change in the determinants, since the complexity of deployment in this type of model does not make its adoption easier or more difficult, and possibly in the environment in which the analysis was made, it is possible that government policies are neutral regarding the adoption of cloud technologies. Now, regarding the type of study, this article conducts a qualitative study unlike articles (Xu et al., 2017), (Hasan Salah et al., 2019) and (Ahani et al., 2017).

In the second's group case, it is to say, the articles dealing with stand-alone data analytics, the determinants for the adoption of data analytics tools are practically the same as for intelligent EIS, i.e., all the EIS factors also appear in the data analytics list, but 2 more factors are added: cost and organizational readiness (see Table 6).

Table 6: Factors for the three groups of tools.

Tool	Factors	Imp	Signific	Article
Intelligent EIS	Management support	+	S	(Xu et al., 2017), (Cruz-Jesus et al., 2019), (Nwankpa et al., 2016), (Hasan Salah et al., 2019), (Ahani et al., 2017), (Elkhani et al., 2014), (Şener et al., 2016)
	Relative advantage	+	S	(Xu et al., 2017), (Nwankpa et al., 2016), (Hasan Salah et al., 2019), (Ahani et al., 2017), (Şener et al., 2016)
	Competitive market pressure	+	S	(Xu et al., 2017), (Cruz-Jesus et al., 2019), (Hasan Salah et al., 2019), (Ahani et al., 2017), (Şener et al., 2016)
	Compatibility	+	S	(Xu et al., 2017), (Hasan Salah et al., 2019), (Ahani et al., 2017)
	Government policies	+	S	(Hasan Salah et al., 2019), (Ahani et al., 2017)
			NS	(Şener et al., 2016)
	Complexity	-	S	(Xu et al., 2017), (Hasan Salah et al., 2019)
			NS	(Şener et al., 2016)
	Expected benefits	+	S	(Nwankpa et al., 2016), (Mayeh et al., 2016), (Elkhani et al., 2014)
	IT capabilities	+	S	(Cruz-Jesus et al., 2019), (Ahani et al., 2017)
	IT infrastructure /resources	+	S	(Hasan Salah et al., 2019), (Şener et al., 2016)
	Security	+	S	(Hasan Salah et al., 2019), (Şener et al., 2016)
	Size	+	S	(Şener et al., 2016)
Stand-alone data analytics	Management support	+	S	(Maroufkhani et al., 2020), (Schüll & Maslan, 2018), (Park & Kim, 2021), (Maroufkhani et al., 2022), (Angwar, 2018), (S. Sun et al., 2018)
	Competitive market pressure	+	S	(Maroufkhani et al., 2020), (Schüll & Maslan, 2018), (Angwar, 2018), (El-Haddadeh et al., 2021)
			NS	(S. Sun et al., 2018)
	Compatibility	+	S	(Maroufkhani et al., 2020), (Maroufkhani et al., 2022), (Angwar, 2018)
			NS	(Park & Kim, 2021), (S. Sun et al., 2018)
	Complexity	-	S	(Maroufkhani et al., 2020), (Maroufkhani et al., 2022), (Angwar, 2018), (El-Haddadeh et al., 2021), (S. Sun et al., 2018)
	Organizational readiness	+	S	(Maroufkhani et al., 2020), (Maroufkhani et al., 2022), (El-Haddadeh et al., 2021)
			NS	(Angwar, 2018)
	Expected benefits	+	S	(Park & Kim, 2021), (Khan & Brock, 2017), (El-Haddadeh et al., 2021)
	Relative advantage	+	S	(Maroufkhani et al., 2020), (Angwar, 2018), (S. Sun et al., 2018)
	Government policies	+	S	(Park & Kim, 2021), (El-Haddadeh et al., 2021), (S. Sun et al., 2018)
		-		(Maroufkhani et al., 2020)
	Size	+	S	(Angwar, 2018), (Khan & Brock, 2017)
			NS	(S. Sun et al., 2018)
	IT infrastructure / resources	+	S	(Khan & Brock, 2017), (El-Haddadeh et al., 2021), (S. Sun et al., 2018)
	IT capabilities	+	S	(Schüll & Maslan, 2018), (Park & Kim, 2021)
	Security and privacy	+	S	(Angwar, 2018)
		-		(Park & Kim, 2021), (S. Sun et al., 2018)
	Cost	-	S	(Park & Kim, 2021), (S. Sun et al., 2018)
EIS with data analytics	Management support	+	S	(Junior et al., 2019), (Alaskar et al., 2021)
	Competitive market pressure	+	S	(Junior et al., 2019), (Alaskar et al., 2021)
	Compatibility	+	S	(Junior et al., 2019), (Alaskar et al., 2021)
	IT capabilities	+	S	(Kyriakou et al., 2020)
			NS	(Junior et al., 2019)
	Expected benefits	+	S	(Alaskar et al., 2021)
	Relative advantage	+	S	(Junior et al., 2019)
	Size	+	S	(Kyriakou et al., 2020)

Organizational readiness is the ability to make available the technological, financial and human resources necessary for the adoption of the analytics technology (Angwar, 2018). Cost refers to the amount of money that needs to be invested to be able to adopt an analytics technological tool which includes acquisition cost, modifications to the company's infrastructure, employee training and hiring new personnel. The most mentioned factors for this group are management support, competitive market pressure and compatibility. When there is more consensus in in the management support factor, which is addressed in 6 out of 8 articles

Regarding negative impact factors, complexity that is the degree of difficulty perceived by the company when faced with a technological tool (Angwar, 2018) is looked as significant and mentioned in this way in 5 articles. It is worth to note that, in this case, the size of the company can be considered a determining factor, since it is mentioned in 3 articles and is significant in 2 of them. In addition, the impact is always positive, which means that the larger the company, the easier the adoption.

Finally, for the third group, i.e., EIS with data analytics, two papers study the adoption of an external analytics component fed by EIS (Kyriakou et al., 2020)(Alaskar et al., 2021), while one research work studies the adoption of an internal embedded analytics component in an ERP (Junior et al., 2019). For this group the analysis shows that the most determining factor is again management support, followed by competitive market pressure, compatibility and IT capabilities (see Table 6). However, there is a discrepancy regarding the significance of the latter, since in (Kyriakou et al., 2020) it is considered a significant factor and in article (Junior et al., 2019) it is not. It is worth to note that here complexity is not considered by any of the articles and size is only mentioned in article (Kyriakou et al., 2020), so it is not possible to reach a conclusion of their importance in the process of adopting enterprise systems with embedded data analytics modules. On the other hand, management support, competitive market pressure and compatibility are once again determining factors, as in the case of adoption of enterprise systems and stand-alone data analytics.

3 ADOPTION OF INTELLIGENT EIS IN COLOMBIA

This section is intended to carry out a first approach to the identification of the determining factors for the adoption of intelligent EIS in the context of the Colombian industry. To collect information, a focus group is conducted. The results of the literature review will be used as a basis to guide this activity.

3.1 Focus Group

The objective of the focus group is to determine if the determinants identified in the literature review are also determinants in the context of the Colombian industry or if discrepancies are found.

For the focus group, 5 professionals were selected to participate in this activity considering their work experience in the field of data analytics and enterprise information systems. They have knowledge in the different EIS and data analytics tools available in the market. The group is composed of men and women between 35- and 65-years old working in private sector companies, in the IT department or as IT consultants. The information on the participants' current position, their companies' size and the industry sector to which they belong is presented as follows:

Table 7: General information of the participants.

Participant	Current position	Company size	Industrial sector
P1: Participant 1	IT Manager	Medium	Consulting
P2: Participant 2	BI Architect	Large	Technology
P3: Participant 3	Product Manager	Large	Technology
P4: Participant 4	Expert Engineer	Large	Technology
P5: Participant 5	Independent BI Consultant	Large	Financial

This activity lasts approximately one hour, during which the participants discussed among themselves and answered the researcher's questions. The focus group questions are semi-structured, that is, there are some basic questions, and the researcher can add questions according to the evolution of the discussion. The used questions are presented below:

- Does your company currently use an EIS?
- Does your company currently use a data analytics tool?
- Is the analytics tool external or is it a module embedded in the EIS? Who is your supplier?
- During the literature review phase, we identified factors influencing the adoption of intelligent EIS. How would you prioritise these factors, from the least to the most significant?
- Why do you rank them this way? Would you add any other factors?

The first questions were asked with the objective of gathering general information about the type of EIS and analytics tool that has been implemented in the participants' companies, while the subsequent questions aimed at generating a discussion about the determining factors for the adoption of data analytics in companies of the Colombian industry.

The focus group was conducted virtually and recorded considering confidentiality criteria. During the session, participants had the right to ask to be identified by their name or a pseudonym. All transcribed fragments were anonymized. The recording of the session is securely stored in a private folder in the cloud to which only the researchers have access. All these norms were presented to the participants in a written informed consent, which was signed by them prior to the session.

3.2 Synthesis

We present the synthesis of the answers for each of the questions as follows.

Does your company currently use an EIS?

In most cases, the participants' companies do not use a single EIS, but a combination of several tools within which the transactions associated with their business processes are registered. It means that in most of the cases they do not have an integrated EIS for all areas of the business.

In the case of participant 1, his company manages the different business processes separately and with different tools, for example, it uses one of the leading ERP systems in the market for financial processes, however, the main system in which they run most of their processes was custom developed. On the other hand, the organisation of participant 2 works with multiple internal systems, from which information is collected. The information is also collected from different sources such as JSON or CSV files and applications, and then a data warehouse is assembled.

Does your company currently use a data analytics tool?

All participants' companies have one or more analytics tools and different analytics strategies. In general, companies use third parties' analytics tools and data science techniques implemented in-house. The only exception to this is participant 4's company, which works exclusively with one of the leading cloud computing services companies in the market.

Regarding techniques implemented in-house, 3 of the 5 participants (Participant 2, Participant 3 and Participant 5) mention that in their companies data science is performed internally, with which they can obtain a better knowledge of their clients. Specifically, it is mentioned that in the company of Participant 2 an information analysis system was created based on a data warehouse in which the collected data is stored and, once all the data is there, a commercial BI tool is used to create reports on the processes. On the other hand, participant 3's company has developed its own algorithms for demand forecasting. Finally, participant 5 indicates that they develop "in situ" algorithms in Python for predictive analytics through linear regression models, classification, decision trees and correlation between variables. These algorithms are invoked then by a commercial BI tool for performing business intelligence processes.

How would you prioritise adoption influencing factors, from the least significant to the most significant?

Regarding the relevance of factors identified in the literature review, it was not possible to reach a final/total consensus in the group, since viewpoints were divided between organisational and technological factors. However, cost is a common factor among all, being always placed among the first places. Likewise, management support, complexity, competitive market pressure and IT capabilities are important for the participants. The reasoning for such results is presented below:

- Cost: companies can contract cloud services specifically for what they need and thus reduce costs, however, if a company wants accurate analytics process it must develop robust tools, which comes with a high cost. Additionally, the cost of hiring expert personnel must also be taken into account.
- Management support: it is important for the management to know exactly the objective of analytics tools and be aware of the benefits that can be gained from them. In this way, they will be willing to assume the cost of adoption and staff training.
- Complexity: many of the tools available in the market may be difficult to handle at the beginning, which would imply a great expense in staff training. For this reason, it is important to maintain the level of complexity not too high.
- Competitive pressure from the market: if a company starts to offer a better service to customers, other companies must start to innovate in order not to be left behind, in the words of one of the participants "those who do not move, die".
- IT capabilities: it is important for a company to have expert staff in data analysis and with the

necessary knowledge on the use of the tool adopted, otherwise data analytics processes will not be performed correctly and faithful.

For certain participants, the fact that there are analytics tools available in the cloud makes some factors not so decisive when looking for their adoption. These factors are:

- Security and privacy: cloud service providers guarantee the confidentiality, integrity and availability of customer information, so security and privacy take a back seat.
- IT infrastructure: it is not necessary to have a large number of on-premise servers and facilities because the data can be stored on cloud servers.

One of the most debated factors by the participants is the size of the company, as for some the size is related to the available resources of the organization, which means that a small company, for example, could not have the necessary resources to acquire an analytics tool. On the other hand, other participants argue that for smaller companies, analytics may be the only differentiator that allows them to increase their competitiveness and thus grow.

4 DISCUSSION

From the analysis of the literature review and the focus group, it is possible to determine that there are both coincidences and discrepancies regarding the adoption of data analytics tools and strategies. At this point it is important to note that the literature review is a study of international literature, while the focus group is based on the Colombian context, so it is reasonable to find certain differences.

First, concerning the integration of EIS and analytics tools and the parallelism in their adoption we discuss as follows both perspectives. Regarding the literature review perspective, the search and selection process of articles on EIS integrated with data analytics, only 2 articles were obtained in which the data analytics components were fed by the company EIS (Alaskar et al., 2021), (Kyriakou et al., 2020) and one in which the data analytics component was embedded in the EIS (Junior et al., 2019) (see Table 2). In the case of the 8 articles that talk about the adoption of intelligent EIS, the relationship that these could have with other systems or analytics components was not clearly mentioned, and authors addressed the capabilities of such systems to generate specific reports using analytics technics.

Concerning Colombian context perspective, all participants mentioned their companies have multiple EIS that are not integrated and register data generated independently for each process. As a consequence, they do not have centralized information for all the areas of the business, but only have access to isolated data for each process. However, once the data has been successfully stored, the business intelligence process begins, in which analytical tools are used to generate knowledge from this data, so that the current situation of the company as a whole can be understood, and informed decisions can be made.

According to these conclusions from the literature and the focus group, we can say that the adoption of a centralized EIS and the adoption of a data analytics tool are not necessarily linked. Companies can adopt an EIS with data analytics modules embedded if this system is the only one to be used across the entire enterprise, otherwise the reports generated by the analytics process would not be completely accurate, as the enterprise system would not have access to all enterprise data, but only to some areas of the business. Otherwise, in most of the cases the process of adoption of EIS and data analytics tools are independent so that links between both adoption processes and integration between both types of tools are not strictly mentioned nor addressed.

Second, between the literature review and the focus group, the determinants for the adoption of independent data analytics tools vary. Table 8 shows the most frequently identified factors in both the literature review and the focus group. From this, it can be seen that 3 of the 5 factors are determinants in both cases (management support, competitive market pressure and complexity), however, the other 2 are in each case completely different.

Table 8: Literature review vs focus group factors.

Factor	Literature review	Focus group
Management support	X	X
Compatibility	X	
Complexity	X	X
Competitive market pressure	X	X
Expected benefits	X	
IT Capabilities		X
Cost		X

From the analysis of the literature review, it is found that the factor with the least relevance when adopting a data analytics tool is cost, which is only mentioned in 2 articles, (Park & Kim, 2021) and (S. Sun et al., 2018). However, it was the most determining factor in the focus group because the participants agreed that the cost of a robust analytics tool can be quite high. Regarding IT capabilities and skills of employees, in the case of the Colombian context it is a relevant factor because of the shortage of professional profiles in the country with experience in this field, even though in the literature review it was not identified as an influencing factor.

5 CONCLUSIONS

In this document an extensive analysis of the main factors that can affect the process of adoption of intelligent EIS in companies is made, as well as a first approach to this topic focused on the Colombian industry. In order to carry out this analysis, techniques such as a literature review and a focus group are used. Regarding the literature review, an evaluation framework is created to analyse the selected set of academic articles. Each article is evaluated according to 3 categories: research context, type of data analytics studied and adoption process. Through the analysis of the academic articles, it is possible to identify the determining factors for the adoption of intelligent EIS.

To get a first approach on the subject to the Colombian context, a focus group is conducted with 5 experts on the subject of EIS and data analytics. The focus group is intended to identify the main characteristics of intelligent EIS in Colombian companies as well as the main factors influencing their adoption.

Based on the analysis of both the literature review and the focus group, a comparison is made to determine the similarities and differences that exist between them. Through this comparison, it was found that there are three factors that are determinant in both cases and two that are different. On the one hand the common factors are: management support, competitive market pressure and complexity. On the other hand, specific factors for the literature review are compatibility and expected benefits, while specific factor for the Colombian companies from the focus group are cost and the company's IT capabilities and skills.

Concerning the limitation of our study, it is worth bearing in mind that the results of the focus group is a first approach to the topic, since the participation of 5 experts is not enough to determine the process of adoption of intelligent EIS to the whole Colombian context. As future work, the information collected through this study can be used to design additional collection tools such a surveys' questionnaires in order to carry out a representative analysis of quantitative nature.

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