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Factors Influencing the Adoption Intention of Artificial Intelligence in Small Businesses

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Abstract

A convergence of factors enabled unprecedented advances in Artificial Intelligence (AI). For example, new techniques known as Machine Learning (ML) allow an algorithm to learn from data without needing any prior programming. Thus, a new wave of automation has targeted activities performed by trained humans because they depend on elaborated cognitive processes. Therefore, a considerable magnitude of the impacts of AI is expected in society, organizations, and businesses. Among other impacts, it is estimated that changes will occur in business models, economic mechanisms, management, productivity, and the nature of the work that could put at risk 47% of jobs in the US and nearly 80% in developing countries. Such implications and opportunities have been little discussed in academia. Paradoxically, the shortage in research is even more pronounced in small businesses, which are vital for countries' economies. They accounted for around 99% of the business, 60% of jobs, and 27% of GDP in Brazil in 2017. Thus, to contribute to this debate, the present research's main goal was to identify the factors influencing the intention of adopting IA-based information systems in small companies in Brazil. Qualitative research was executed with 43 participants and identified 9 factors influencing the adoption intention (performance expectancy, business model, effort expectancy, self-efficacy, trust, business compatibility, social influence, trial ability, and technical support). Therefore, the present study helps reduce the gap in studies related to technology adoption in small businesses and AI-based technologies in companies, supporting academics and managers in future investigations and decision-making.

Keywords

Artificial Intelligence, Machine Learning, Technology Adoption, Adoption Intention, Small Business.

Introduction

In the 1950s, a new field inspired by the nature of human intelligence started to inquire about the new possibilities that could be explored by computer software to imitate (Benbya, Davenport, & Pachidi, 2020), emulate, enhance or complement the human intelligence (Simon, 1995). This new field was named Artificial Intelligence (AI) at Dartmouth College by Professor John McCarthy in 1956 (Benbya et al., 2020)

Recent technological, business, and social changes created momentum for the flourishment of new AI techniques (Benbya et al., 2020). The algorithms got the ability to learn by themselves, without needing previously programmed expert rules like was required in its previous generation (Expert Systems) (Asatiani et al., 2020). That made computers able to learn like humans by exploring alternatives with reinforcement feedback mechanisms. Thus, a new level of automation of cognitive processes has been reached. This new level of AI can drastically impact society and organizations (Gu, Santhanam, Berente, & Recker, 2019) because it could automate most of the current human activities.

Professor Andrew Ng, from Stanford University stated that artificial intelligence (AI) is the new electricity (Tani, 2016) because of its impact on all industries. On the one hand, an AI-based solution can potentially substitute a team of experts for specific tasks (Lacity & Willcocks, 2021). Some researchers claim this will result in a shift in the nature of work and unemployment (Frey et al., 2016; Susskind & Susskind, 2015). On the other hand, AI brings potential opportunities (Gu, Santhanam, Berente, & Recker, 2019) for small businesses.

With its advances in AI, the digital revolution has democratized access to many of these computational and machine learning resources (Dewhurst & Willmott, 2014; Müller & Bostrom, 2016). The phenomenon lowered the barriers to access technological tools (e.g., planning, decision making, automation, and optimization), previously only accessible to large firms (Dapp & Slomka, 2015). For example, the cost of the hardware and software needed to build a bank dropped drastically, making the blooming of a considerable number of fintech startups viable. Thus, small companies, even those without a history of innovation investments, can leverage those technologies to reduce their disadvantages compared to large companies and potentially create competitive advantages through their speed of adaptation and easiness of incorporating change (Christensen & Bower, 1996; Cohen & Klepper, 1996; Davenport & Bibby, 1999).

Moreover, small firms have many advantages when compared to large ones. Schumacher (1973) pointed out many advantages, such as their competitive structure, higher efficiency, ability to catch up to new demands and technologies much easier, less monotonous job roles, and higher resilience to the economic crisis. Şentürk & Keskin (2010) also pointed out their higher agility in decision-making.

Therefore, small business owners will potentially have access to a newer level of production and cognitive capacity with the new AI tools, much beyond what they could afford to hire if they relied on a team of experts. Also, small companies will access labor-intensive business opportunities and markets that were only a privilege of large economic groups. AI can provide small firms with new possibilities to create innovative and intelligent products and services, inventing new business models and organizational forms (Gu et al., 2019). For example, AI can increase the accuracy of planning and operational optimization on several fronts, even with the scarcity of resources intrinsic to the size of the business (Nascimento, Melo, Queiroz, Brashear-Alejandro, & de Souza Meirelles, 2021). Another important aspect of AI is its potential positive impact on productivity (Alexopoulos & Cohen, 2019; Mayer, Strich, & Fiedler, 2020)

This challenging but intriguing transformational scenario is causing significant changes in our society. Consequently, AI will impact businesses and management (Asatiani et al., 2020; Lacity & Willcocks, 2021; Mayer et al., 2020; Nascimento, Cunha, Meirelles, Scornavacca, & Melo, 2018; Nascimento & Bellini, 2018; Reis, Maier, Mattke, Creutzenberg, & Weitzel, 2020; Zhang, Nandhakumar, Hummel, & Waardenburg, 2020). Therefore, understanding the adoption of AI in businesses became an essential topic in which more research is required (Lacity & Willcocks, 2021).

In this context, it seems small businesses are not the focus of the already insipient research (Lacity & Willcocks, 2021) about this topic since modern AI is still in the early stage in large enterprises and mostly absent from smaller ones, except startups (Benbya et al., 2020). Paradoxically, over 90% of the businesses are done by small firms in Brazil, Europe, and the US. However, small businesses have an essential role worldwide in the economy and society (Şentürk & Keskin, 2010). According to Şentürk & Keskin (2010), they play a significant role in driving family savings to investments. Small companies represent an important source of national income in the countries and play an essential role in increasing the employment rate worldwide. Empirical studies show that small and medium enterprises (SMEs) are responsible for over 55% of GDP and over 65% of total employment in high-income countries (Şentürk & Keskin, 2010). Low-income countries are responsible for over 60% of GDP and over 70% of total employment (Şentürk & Keskin, 2010). Middle-income countries contribute over 95% of total employment and about 70% of GDP (Şentürk & Keskin, 2010). For example, in European Union countries, 25 million small businesses, constituting 99% of all businesses, employ almost 95 million people, representing 55% of total jobs in the private sector (Şentürk & Keskin, 2010). In the US, the 30.2 million small businesses represent 99.9% of the country's businesses, and they account for 58.9 Employees, representing 47.5% of United States employees (The US small business administration, 2019). Therefore, the impact on small firms can affect not only their local economies but also their countries and, ultimately, the economy and the society worldwide.

In Brazil, the importance of small companies is also considerable. Research commissioned by SEBRAE in 2018 (SEBRAE, 2018) indicated that during the recent crisis, the rate of job termination in small businesses was proportionally lower than in medium and large businesses. In fact, from 2006-2016, they generated over 5 million new job positions, and the average salary was raised by 25.3% (compared to only a 14.3% average rise in the medium and large businesses). The small companies represent 99% of the total business, which generates 27% of the GDP in Brazil. In those 10 years, their output went from R$144bi to R$599bi. Regarding each sector's representativeness, the small businesses of commerce, industry, and services accounted for 53.4%, 22.5%, and 36.3% of their sectors' GDP. They generated the income of 70% of the private sector's employees. According to the IBGE (Silveira, 2017), small businesses account for 60% of the around 100 million formal job positions in Brazil.

Understanding the factors influencing technology adoption in small businesses is essential. Identifying those factors helps to understand the technology diffusion process to support sales and product managers with the correct information to enhance the product introduction into the new markets. Usually, small companies have scarce financial resources to invest in new technologies. Therefore, they will be more cautious in adopting since a mistake could risk their survival. Also, they often suffer from forced technology adoption by the imposition of their more significant business partners. That could create user resistance. Therefore, managers in those large companies would benefit from understanding the factors that could create user resistance, which could lead projects to failure (Reis et al., 2020). Finally, it could help managers to avoid the unintended consequences of introducing new technology to a business (Mayer et al., 2020).

In this context, understanding the current factors affecting the intention of adopting AI-based tools in those businesses in Brazil is essential. However, although many studies about technology adoption intention for a wide range of technologies for large companies, only a few focus on the small ones. Also, no study on adopting AI tools for small companies has been found. Moreover, no such studies focused on companies in Brazil were identified. Thus, it is not yet clear how entrepreneurs perceive adopting AI-based solutions in small businesses. Understanding their perception is essential to comprehend how hard it will be to adapt their business models to new economic mechanisms, which businesses often struggle to do (Loebbecke & Picot, 2015). Therefore, the research problem tackled by the present research is to identify the factors influencing the small company owners' adoption intention of AI-based solutions in their businesses to answer the research question, "Which main factors influence the entrepreneur's intention to adopt AI in small companies?". The main contribution of the present study is the proposition of a theoretical model considering the factors influencing AI adoption intention in small firms.

Methodology

The present study has the main research question: "Which main factors influence the entrepreneur's intention to adopt AI in small companies?". Therefore, this research targeted small companies. The adopted definition of small companies is the same adopted by the "Lei Geral das Microempresas e Empresas de Pequeno Porte de 2006"[1]. That definition is based on the number of employees for each one of the distinct sectors where a firm can be classified: manufacturing, construction, commerce, and services. A manufacturing or construction firm can be considered a small business if its employees range from 20 to 99. Furthermore, a commerce or services firm can be considered a small business if its employees range from 10 to 49.

There is a tradition in IS field of qualitative studies to identify factors influencing an IS acceptance or intention of using an IS in the literature (Alia, 2017; Courduff, Szapkiw, & Wendt, 2016; Kim, Gajos, Muller, & Grosz, 2016; Mallat, 2007; Ng, Shroff, & Lim, 2013; Tobbin, 2012). Like Moraes (2013), qualitative research was executed to elicit the factors influencing the intention of adopting AI-related systems in small businesses. In the same way, the research here aimed to elicit the factors influencing the adoption intention and propose a model to explain the adoption intention based on those factors.

The unit of analysis was the entrepreneur, who owns a small company in Brazil. The number of subjects was not defined in advance because it depended on the quality of the information obtained in each semi-structured interview and the depth and degree of recurrence and divergence of this information (Duarte, 2002). Moreover, it also depended on the availability of participants, which became critical during the COVID-19 pandemic period. Thus, as Duarte (2002) pointed out, while new information or clues were

[1] Reference: http://www.sebrae.com.br/sites/PortalSebrae/artigos/entenda-as-diferencas-entre-microempresa-pequena-empresa-e-mei,03f5438af1c92410VgnVCM100000b272010aRCRD

emerging and participants were available, that might indicate new perspectives, which indicated the interviews needed to continue.

The analysis was performed using content (Bardin, 2006), comparative, and interpretational analysis (Vergara & Caldas, 2005). The content analysis and the pertinent links to the existing literature were investigated. The excerpts from the interviews were coded into concepts and grouped into categories. A code consolidation effort was performed based on the literature and theoretical references, aiming to achieve a proposed model which could provide a reasonable generalization. Finally, the discovered factors were identified.

Validity is an important concept (Dellinger & Leech, 2007). Thus, the first validation criteria were done thru a comparative analysis between the raw data and the model to verify if the model could explain most of the cases (Strauss & Corbin, 1998). This validation was used to guide the code consolidation efforts toward enhancing the model's generalization. Another validation effort was performed to check the credibility, transferability, dependability, and confirmability of the findings as proposed by Pozzebon, Rodriguez, and Petrini (2014)

Data collection procedures

The 43 respondents (E1, E2, ..., E43) who participated in this study were identified by *ids* assigned uniquely to each participant. The interviews were executed from January 1st, 2020, to April 7th, 2020. The respondents were selected based on their accessibility and availability using the researcher's professional network and with the support of the researcher's colleagues. Each interview corresponds to a distinct company, where the interviewee was a partner with an executive role in the company.

The interviews were conducted over WhatsApp call or Skype call. The business size, accessibility, and intentionality (Vergara, 2006) were used as selection criteria. Thus, the research subjects were business owners who agreed to be interviewed.

A small semi-structured interview script was used to remind the main topics to be covered during the interviews to help uncover the factors the entrepreneurs perceived as influencers on their intention of adopting AI-based IS. The questions mainly explored the participants' knowledge about artificial intelligence, their perceptions about the topic and its impacts on businesses, and the factors influencing each participant's adoption intention.

At the beginning of each interview, the Windows Voice Recorder app was opened, and the recording was started. A USB microphone was positioned near the mobile phone and placed in Speakerphone mode. Therefore, the conversation audio could be captured by the microphone. All audio files were imported into a transcription management software called Express Scribe Transcription Pro. Each audio was completely transcripted. Then, a complete review of each interview transcription was performed. During this step, the transcription of each file has been validated and corrected according to the corresponding audio. All validated interview transcriptions totaled 370 pages of text (using Microsoft Word and 11-point Times New Roman font). Soon after, the transcriptions were saved in text format and were imported into the RQDA tool to aid content analysis and categorization. The RQDA tool is an open-source library for the statistical software R Studio.

Analysis and Results

A total of 38 hours, 2 minutes, and 12 seconds of the interview was executed, ranging from a 13 min interview to 2 hours, 2 minutes, and 18 seconds interview. The average time of the interviews was 53 min and 4 seconds. The standard deviation of the interview duration was 22 minutes and 31 seconds. Regarding the interviewees' distribution, most of the interviewees' companies are service provider firms (79%; 34). Only 9 companies (21%) are commerce firms.

The interviews covered many industries. Most businesses offer consulting services (23%,10), followed by retail (16%,7) and tourism & entertainment (12%,5). The other businesses are dispersed among many segments: tourism (7%,3), food (7%,3), education (7%,3), finance (5%,2), entertainment (5%,2), building & construction (5%,2), real estate (5%,2), communication (5%,2), healthcare & hygiene (5%,2). The industries with only an interview were grouped into the "others" category (12%,5).

The interviewees' reports were analyzed, and the information, differences, and similarities that emerged were summarized in categories. Initially, the categories emerged naturally in the interviews, where often the participants even validated whether the understanding was correct. A different code was assigned to each category. The primary codes created in the first step were initially used for classification during the analysis step, resulting in 54 codes. The codes were attached to the text portions identified as necessary for interpretation (Cassell & Symon, 2004) to help to categorize the text. The texts' portions not found to be related to any specific category were ignored for the analysis. During the first step of the analysis, it was refrained from categorizing the information according to the existing literature to avoid confirmation bias and missing new potential categories not covered by the existing literature.

Then, an effort to merge the codes towards categories at higher levels of abstraction was performed. This step was essential to enable model simplification and better generalization. Because of the large number of codes found initially, this step was performed in 3 iterations of successive approximation, aiming for a model that could better explain the findings in the interview and provide good coverage of the interviews and industries.

In the first iteration, the codes were compared to the ones in the literature. Then, they were grouped and renamed accordingly to the findings in the literature. By mapping the current research's findings to previous findings from the literature, this iteration provided a reduction from 54 to 18 codes. This step was instrumental to the analysis and validation of the findings. Then, because some codes achieved low rates of interview coverage, another iteration was performed to group the codes according to a higher abstraction order factor. Those higher abstraction order factors were influenced by those already been reported in the literature. As the result of a new code merging iteration, 9 codes remained, as presented in Table 1.

Factor	**#(%) Interviews**	**Reference**	Food	Retail	**Coverage (%)**	Civil Construction	Communication	Consulting	Education	Tourism & Entertainment	Finance	Healthcare & Higiene	Realstate	Others	**Coverage (%)**
			Commerce			**Service**									
Performance Expectancy	42 (98%)	Venkatesh et al. (2003)	x	x	**100%**	x	x	x	x	x	x	x	x	x	**100%**
Business Model	35 (81%)	Yew Wong (2005)	x	x	**100%**	x	x	x	x	x	x	x	x	x	**100%**
Effort Expectancy	22 (51%)	Venkatesh et al. (2003)	x	x	**100%**	x	x	x	x	x	x	x	x		**89%**
Self Efficacy	20 (47%)	Bandura (1986)	x	x	**100%**	x	x	x	x	x				x	**67%**
Trust	19 (44%)	Eneizan et al. (2018); Assegaff et al. (2011); Kerr (2004); Jaafreh and Al-Abedallat (2011)	x	x	**100%**	x		x	x	x	x	x	x		**78%**
Business Compatibility	18 (42%)	Kerr (2004)	x	x	**100%**	x	x	x	x	x	x		x	x	**89%**
Social Influence	17 (31%)	Venkatesh et al. (2003); Ajzen (1991)	x	x	**100%**	x			x	x	x	x	x	x	**78%**
Trial ability	9 (21%)	Kerr (2004)	x	x	**100%**	x		x	x	x	x	x			**67%**
Technical Support	7 (16%)	Buchanan et al. (2013); Eneizan et al. (2018); Khlaif (2018); Lee and Coughlin (2015); Ngai et al. (2007); Sumner and Hostetler (1999)		x	**50%**		x	x	x					x	**44%**
Coverage (%)			**91%**	**100%**		**64%**	**91%**	**100%**	**91%**	**82%**	**55%**	**64%**	**55%**	**91%**	

Table 1 *Factors and interview coverage*

Performance Expectancy is the degree to which people believe that using a system will help them to obtain gains in their job performance (Venkatesh, Morris, Davis, & Davis, 2003). This factor was the most mentioned by the interviewees (98%) and had very high coverage of industries (100%) and business types (90% of commerces and 100% of services). That is a well-known factor in the literature because of the Unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003). Before UTAUT, Davis (1986) named this factor as **perceived usefulness**. Interviewees pointed out many aspects related to the performance expectancy which would impact their intention of adopting an AI-based IS, such as Assertivity, ROI, Value Creation, Human Replacement Ability, Operational Impact, Productivity, Efficacy, Efficiency, Cost-benefit, Business Results, Customer Experience, Timing for Results, User Experience, Financial Results [*" (...) the number one factor that would make me to seek this type of solution would be an increase in revenue" (E02)*], Automation Capability, Solution's Amplitude of Scope, Scalability, Cost Reduction [*"So I'm not talking about increasing revenue but I'm talking about eliminating costs and that would also make me look for this type of solution" (*E02)], Value Perception, Quality, Alternatives, Usefulness, Obsolescence (Solution Life Time) [*"a certainty that the solution will in fact adapt to not become obsolete over time." (E06); "it would have to be something that is always updating, (...)" (E08)*].

Business Model (Yew Wong, 2005) for acquiring the AI-based IS was mentioned as an essential factor influencing the adoption intention by 81% of the interviewees, with very high coverage of industries (100%) and business types (80% of commerces and 82% of services). Interviewees stated it was essential to understand the acquisition cost and type of contract. Most expected a software as a service (SaaS) business model. A participant (E10) stated that the primary value of SaaS is that he does not need to take care of the maintenance. A participant (E41) preferred a flexible model, such as pay-per-use with no lock-ins. Therefore, payments would be made only when the solution was used, and the company would be free to move on anytime. However, four participants (E08, E12, E23, E38) said they preferred to own the solution. Two (E08 and E12) demonstrated that they prefer to purchase and own the solution. Beyond the solution ownership, the other two participants (E23, E38) described concerns about how strategic the solution could be to their core businesses. In this way, participant E23 described some additional needs such as source code, exclusivity, and redistribution rights could be necessary. Meanwhile, participant E38 pointed out to develop the solution by themselves or outsourcing the development could be necessary depending on how strategic the solution could be for the business. Finally, another participant (E21) believes the best business model would be thru a partnership for higher commitment.

Effort Expectancy (Venkatesh et al., 2003) is the degree of effort people believe is needed to use a system. This factor is also well-known because of the UTAUT (Venkatesh et al., 2003), and it was the third most mentioned factor by the interviewees (51%). Before UTAUT, this factor was known as perceived usability, the Technology Acceptance Model (TAM) (Davis, 1986). This factor achieved high coverage of industries. Here, the concept of effort expectancy was broader than usability since it encompasses all the efforts needed to keep the system ready and available. Interviewees pointed out many aspects related to the effort expectancy which would impact their intention of adopting an AI-based IS, such as Deployment Timing *["it would need to be something quick (deployment) since I don't have time"* (E06)], Learning Curve, Integrability, Configurability [the lack of configurability creates a "fear of making initial choices and not being able to change them later" (E13)], Setup Easiness, Deployment Efforts [*"(...) And second, the easiness of implementation, you know (...) Our experience is that when you buy something very cheap in terms of monthly fees, you have an implementation problem"* (E24)], Maintenability [*"Because I am not a super technological person, so it would have to be something easy for us to maintain, something easy, other rocket science, and, it would not give me more work than I already have, that would really help me." (E14)*], and Usability.

Self Efficacy was defined in the Social Cognitive Theory by Bandura (1986) as people's judgment on their ability to organize and execute courses of action needed to achieve a specific outcome. Bandura (1986) states that self-efficacy is distinguished from outcome expectations. That is, self-efficacy is related to the people's belief about their own ability to perform the behavior required to achieve the outcomes, which in the context of the interview is related to the interviewees' belief about their own ability to master the use of an AI-based IS, regardless of their belief about the potential results that could be achieved by using the AI-based IS. Interviewees (47%) demonstrated concerns about if they would be able to master the use of an AI-based system and how it would influence their adoption intention. For example, E30 pointed out the idea of being unsure on being able to overcome the barrier of mastering the system use in "... you can't overcome that first barrier ... but the main question is how much I could use ...".

Trust is an adoption factor found in many studies related to IS adoption (Assegaff, Hussin, & Dahlan, 2011; Eneizan, Mostafa, & Alabboodi, 2018; Jaafreh & Al-Abedallat, 2011; Kerr, 2004). Trust is the degree someone beliefs in IS' trustworthiness to perform a task (McKnight, 2005). Interviewees (44%) demonstrated many aspects related to trust which would impact their intention of adopting an AI-based

IS, such as Risk to Business [*"... after it learned, it doesn't need me anymore, so I need to be careful with that too." (E24)*], Trust, Explicability, Control ["I must keep the control..." (E01).], Colaborativeness. Trust has been pointed out as a relevant topic in the AI field because most of the recent achievements were achieved by black-box techniques, which fails to demonstrate how a result was achieved, which raises concerns depending on the field of application. Managers want to understand why and how an AI model achieved a particular conclusion so that they can evaluate and decide. A participant (E16) even mentioned the concerns to a black-box solution: *"The first criterion that I would not give up, Alexandre, is the possibility of having feedback. I need it, I cannot give up the process safety, so if, for example, it is a type of black-box technology, I mean 'trust here that it will spit on the other side there, then I think the answer is no... because I cannot take the risk that my client in the initial phase is receiving messages or is distorted or that it is not really interesting due to some technical problem. So if it would be something that I can use, I can follow, right, to the point that I can do checks about if, in fact, we are meeting the expectations in the interaction. (...) This is an important factor".*

Business Compatibility was found by Kerr (2004) as a factor influencing the adoption intention of IS by small businesses. In the present research, this factor encompasses the factors pointed out by interviewees (42%) related to the compatibility to the business size, compatibility to the business core values [*"(...) and what we would really need, the critical factor in the case of software, would be to make it happen without hurting our values, the things that we believe in, the way we conduct the work, are other factors but that is different for each case and another (...)" (E21)*], and compliance with data security and privacy regulations. Among the compatibility to the business size factors, interviewees stated concerns related to the required business technological maturity [*"I think so, it is not for any corner store that will be able to put Artificial Intelligence. I think you need to reach a certain stage of technology and automation within your business so that you can come up with these solutions and add them (...)" (E02); "As much as I find it interesting, maybe I am not at the level of being eligible for the technology, do you understand?" (E25)*], specialized labor and other business size-related requirements, which could prevent them from extracting the best value from the AI-based IS.

Social Influence has been known as a factor of influence in IS adoption (Ajzen, 1991; Venkatesh et al., 2003). In the UTAUT (Venkatesh et al., 2003), it is the degree users believe others believe they should use an IS. In the present study, this factor encompassed a broader concept since it also considered customer and employees' perceptions of the AI-based system, which were also pointed out by almost a third of interviewees (31%) as factors that would influence their adoption intention. E03, for example, even mentioned how hard it is for employees to accept changes in "... the first point would be the collaborators, they are hardheaded ...". Indeed, AI has been associated with progress and some threats such as human replacement and customer deception, which explain why small business owners consider their employees' and customers' perceptions an essential factor.

Trial ability is the ability and possibility to try the IS before deciding to adopt it (Kerr, 2004). Kerr (2004) found this factor to influence the IS adoption intention for small firms, which was confirmed by the present study in the context of the AI-based system adoption in small companies. Interviewees (21%) mentioned that a trial period would influence their intention of adopting an AI-based IS. A participant (E28) demonstrated concerns about the trial policies usually available since they provide only 30 days, which is not enough for a good evaluation. Finally, another interviewee (E35) described that the trial would be necessary, but he would also require some real customer referral and testimony.

Technical Support availability has been in the IS adoption literature for decades (Buchanan, Sainter, & Saunders, 2013; Eneizan et al., 2018; Khlaif, 2018; Lee & Coughlin, 2015; Ngai, Poon, & Chan, 2007; Sumner & Hostetler, 1999). Interviewees (16%) stated this factor would influence their AI-based IS adoption intention; for example, in*"(...) there is some kind of assistance, help, right, from those who developed it, from those who conceived it, I think that having an after-sales service there, assistance is something that often impacts the decision to purchase one thing or another." (E22); and "I think I would take the support to do the deployment, it is the, the support that was needed (...)" (E36).*

The proposed 9-factors model that emerged from the present qualitative research is shown in Figure 1. It indicates that the behavioral intention of adopting an AI-based system in small firms is influenced by performance expectancy, business model, effort expectancy, self-efficacy, trust, business compatibility, social influence, trial ability, and technical support.

Although the present research is qualitative, adherence analysis (coverage) was performed to provide a sense of the proposed model's potential generalization across industries and types of activity (commerce and service). Table 1 shows the adherence of each factor per number of interviews and activity type. Performance expectancy and business model achieved 100% coverage in industry and activity types. There is a lack of balance when considering the factors coverage for commerce and service. Only the technical support factor did not achieve 100% coverage for the commerce activity. However, only performance expectancy and business model achieved 100% for the service activity. Those may be related to specific needs of each type of activity, which requires further investigation.

Moreover, the coverage analysis shows a reasonable potential for generalization for both commerce and service firms. Indeed, the minimum coverage of factors is 55% (real estate and finance), and the highest coverage is 100% (retail and consulting).

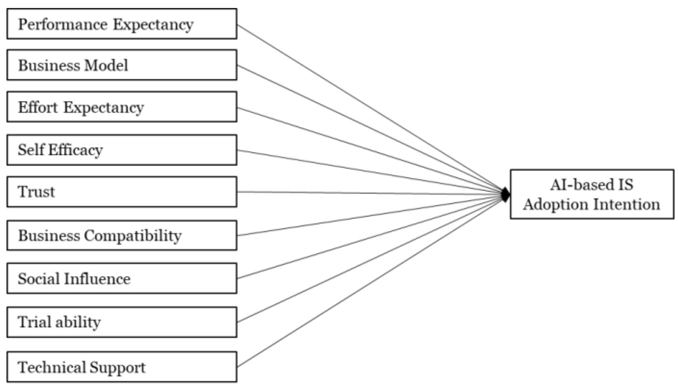

Figure 1 *Proposed model for the adoption intention* of *AI-based IS in small firms*

Conclusions

This study's main goal was to elicit the factors influencing the entrepreneur's intention to adopt AI in small companies, whose results can bring meaningful contributions to the management field. A qualitative study with 43 entrepreneurs was executed and resulted in a model proposing that the adoption intention was influenced by nine factors: performance expectancy, business model, effort expectancy, self-efficacy, trust, business compatibility, social influence, trial ability, and technical support.

This research highlights that it is possible to propose ways to enhance the behavior intention of adopting those AI-based systems, such as offering easy-to-use solutions under a SAAS business model. Also, those system vendors must provide a reasonable trial period and good technical support to increase the adoption intention.

Future work will include quantitative research to test the proposed model. Moreover, more research is needed to confirm the proposed model in other countries and to discover other factors. Understanding those topics and new factors will be helpful for small companies to make informed decisions when implementing AI and for AI suppliers to design more efficient implementation processes, considering the human factors involved in AI adoption. Finally, the outcomes of this research have an impact and applicability in the management field for both researchers and practitioners.

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