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Artificial Intelligence: Understanding the influence of BI&A systems and firm performance in technology adoption at firm level

MSc in Management – Specialization in Business Analytics

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Porto, April 2024

Abstract

Business Intelligence & Analytics (BI&A) systems have emerged as powerful tools for extracting insights from enormous data sets, giving businesses the ability to make wise decisions and obtain a competitive advantage. In a rapidly evolving Artificial Intelligence (AI) landscape, the world faces significant unknowns and potential disruptions, from the impact of automation and robotics on employment to security concerns regarding the use of autonomous AI systems. In today's quickly changing business environment, understanding the dynamics of BI&A and AI adoption is paramount for organizations seeking sustainable growth and competitive advantage. This work investigates the intricate relationships between BI&A maturity, firm performance and AI adoption within organizational contexts, shedding light on the factors shaping technology integration strategies, an area requesting further investigation. For these reasons, we designed an innovative and comprehensive theoretical framework that integrates the Unified Theory of Acceptance and Use of Technology (UTAUT) with Dinter's BI&A maturity model and the firm performance construct from Law and Ngai (2007). Structural Equation Modelling (SEM) was employed to analyse empirical data gathered from a sample of various organizations from a European country.

Our findings reveal compelling insights into the factors influencing AI adoption and firm performance. BI&A maturity perception emerges as a significant predictor of both AI adoption intention and firm performance, highlighting the pivotal role of mature BI&A systems in facilitating technology adoption and enhancing organizational performance. Additionally, the intention to adopt AI is found to positively influence AI actual use, underscoring the importance of fostering a culture of innovation and technology readiness within organizations. Overall, this work contributes to knowledge by providing a nuanced understanding of the interplay between the perception of BI&A maturity, firm performance and AI adoption, thereby providing new and useful insights about strategic decision-making processes and

guiding future research endeavours in the field of technology adoption and organizational performance.

Key words: Business Intelligence and Analytics, Artificial Intelligence, Firm Performance, Technology Adoption.

Resumo

Os sistemas de "Business Intelligence" e "Analytics" BI&A surgiram como ferramentas poderosas para extrair perspetivas de vastas quantidades de dados, permitindo às organizações tomar decisões informadas e obter acrescidas vantagens competitivas. Num cenário de Inteligência Artificial (IA) em rápida evolução, o mundo enfrenta incertezas significativas e possíveis perturbações, desde o impacto da automação e da robótica no emprego, até preocupações com segurança, relacionadas com o uso de sistemas de IA autónomos. No ambiente empresarial em constante mudança de hoje em dia, compreender a dinâmica da adoção de BI&A e IA é fundamental para as organizações que procuram crescimento sustentável e vantagens competitivas. Este trabalho investiga as relações entre a maturidade de BI&A, o desempenho da empresa e a adoção de IA dentro de contextos organizacionais, aprofundando fatores que impactam as estratégias de integração da tecnologia, uma área que requer investigação adicional. Por estes motivos, desenvolvemos um quadro teórico inovador e abrangente que integra a Teoria Unificada de Aceitação e Uso de Tecnologia (UTAUT) com o modelo de maturidade de BI&A de Dinter e o construto de desempenho empresarial de Law e Ngai (2007). O Modelo de Equações Estruturais (SEM) foi adotado para analisar dados empíricos obtidos através de uma amostra de várias organizações de um país europeu.

As nossas descobertas revelam perspetivas instigantes relativamente aos fatores que influenciam a adoção de IA e o desempenho das organizações. A perceção de maturidade de BI&A emerge como um indicador significativo da intenção de adoção de IA e do rendimento empresarial, destacando o papel crucial de sistemas de BI&A maduros na facilidade em adotar a tecnologia e na otimização do desempenho da organização. Além disso, a intenção de adotar IA mostrou influenciar positivamente a sua utilização, sublinhando a importância de fomentar uma cultura de inovação tecnológica dentro das empresas. Este trabalho contribui para o que é conhecido até à data, pois fornece uma compreensão detalhada da interação entre a perceção de

maturidade de BI&A, o desempenho empresarial e a adoção de IA, dando assim a conhecer novas visões sobre processos de tomada de decisão estratégica e orientando futuras pesquisas no campo da adoção de tecnologia e performance organizacional.

Palavras-chave: Business Intelligence e Analytics, Inteligência artificial, Performance da empresa, Adoção de tecnologia

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1. Introduction

Our study's main goal is to provide a comprehensive understanding of the impact of Business Intelligence and Analytics systems usage and firm performance in the adoption of Artificial Intelligence (AI) technology in firms.

The motivation to study this area stems from the increasing reliance on data-driven decision making in modern business environments. Data science is intricately intertwined with other important concepts, like big data and data-driven decision making, which are also growing in importance and attention (Provost & Fawcett, 2013) within firms. Understanding the usage, capabilities, and impact of BI&A systems on firm performance is crucial for organizations seeking to optimize their decision-making processes (Vugec et al., 2020). Artificial intelligence and its integration at the firm level is extremely important in today's world. AI has the potential to fundamentally alter conventional business models and operational paradigms. These technologies will eventually transform work (Davenport & Ronanki, 2018) as we know it.

It is imperative to comprehend the ways in which organizations can embrace and AI technologies for a multiplicity of reasons. First of all, it has a direct impact on a company's competitiveness, which determines its capacity to use creative solutions and maintain an advantage in a fast-moving market. Cognitive technology has the potential to usher in a golden age of prosperity, job satisfaction, and productivity with the correct development and planning (Davenport & Ronanki, 2018). Second, the adoption of AI has wider socioeconomic ramifications that affect workforce skills, employment structures, and even the general well-being of society. Prior to launching an AI initiative, businesses need to be aware of the kinds of tasks that different technologies can accomplish as well as the advantages and disadvantages of each (Davenport & Ronanki, 2018). Examining the relationship between AI and the adoption of this technology at the firm level is a critical strategy for managing the

challenges of the modern digital world (Bughin et al., 2017). Additional studies on this topic are fundamental to uncover valuable insights into how organizations can reach the maximum potential of BI&A systems in combination with AI to drive innovation, enhance decision-making capabilities, and ultimately achieve sustainable success in today's data-driven business world.

In more detail, the first objective of this study is to characterize the usage of BI&A systems in firms, focusing on their capabilities to support decision-making processes, complementing earlier literature. The second objective is to identify and describe the key areas, applications, services, and use cases of AI that are relevant to firms. By exploring the literature, this objective will uncover the range of AI capabilities that can be leveraged by firms to enhance decision-making processes and drive performance improvements. As third objective we have the design of an integrated and innovative theoretical model that considers the interplay between BI&A systems, AI adoption, and firm performance. This theoretical model will provide a foundation for understanding the relationships and interactions among these key factors. Lastly, we have the goal of investigate the direct and indirect effects of BI&A systems and firm performance on AI adoption at the firm level.

Contrary to some existing studies, like the one from Wamba-Taguimdje et al. (2020) that predominantly focus on examining the influence of artificial intelligence (AI) on firms and their business intelligence and analytics (BI&A) systems, our work provides a refreshing perspective exploring the impact of BI&A systems and firm performance on the adoption of AI within firms, filling an important gap in literature in this matter. By examining this relationship from a different angle, this research contributes to knowledge and to the existing literature by offering fresh insights into the dynamics between these key elements in the technological landscape of modern businesses. Additionally, by placing emphasis on the role of BI&A systems and firm performance as driving forces behind AI adoption, this study offers a new thorough

understanding of the factors influencing technological uptake within organizations, with valuable implications for academia and industry.

This document is composed of nine chapters. Starting with a detailed examination of the Theoretical Background and Literature Review, the journey explores the fundamentals of artificial intelligence (AI). The Research Model section establishes the foundation for the study combining AI, BI&A, and firm performance. The Methodology section follows with a smooth transition, giving a thorough explanation of the quantitative techniques used. The next section is the Data Analysis and Results. The Discussion section that follows analyses and explains work main results, as well as present the most significant theoretical and managerial implications. The work ends with the Conclusion section, which provides a brief summary of the entire work.

2. Theoretical Background/Literature Review

Artificial Intelligence (AI), often referred to as "machine intelligence," includes a variety of technological advancements that allow machines to simulate human cognitive abilities (Ruiz-Real et al., 2021). AI has emerged as a transformative technology that is reshaping various aspects of society and business. Over the past few years, advancements in AI have revolutionized industries, driving innovation and offering new possibilities for organizations. AI represents a ground-breaking field in computer science and related disciplines, enabling machines to engage in reasoning and perform cognitive functions (Meireles et al., 2021). AI is an interdisciplinary endeavour, intersecting fields like mathematics, statistics, philosophy, psychology, neuroscience, communication science, linguistics, and computational neuroscience (Davenport & Ronanki, 2018). Across these diverse disciplines, AI has demonstrated its capacity to accomplish highly specialized tasks. For those seeking to grasp the potential of AI in improving numerous fields, it is also crucial to explore both its capabilities and limitations. AI's footprint in various sectors is expanding in an extremely rapidly way (Meireles et al., 2021).

Evolution of AI:

Since the 1950s, conflicting feelings over the possible effects of a type of artificial yet non-human cognition have been present (Pedwell, 2022). However, because the conversation of today takes place concurrently with the real implementation of AI-based technology in daily life, the backdrop is fundamentally different. Artificial Intelligence is no longer limited to lab settings, niche uses in obscure scientific domains, or a supercomputer taking on a world champion chess player. Search engines, face recognition, chatbots for call centres, search engines, autonomous driving, medical diagnostics, and more are just a few of the many AI-enabled goods and services currently available on the market. (Jacobides et al., 2021)

As a result, the topic of conversation has moved from an intellectual discussion about the nature of intelligence and humanity to one that is more applicable to business models, ethics, regulations, data property rights, reskilling, and the effects on employment practices. But there's still debate in academia about the nature of intelligence, and for good cause. AI is a top priority right now. (Jacobides et al., 2021)

In its 2018 report, The Future of Jobs, the World Economic Forum named artificial intelligence (AI) as the central component of a group of related technologies that are set to dominate the 2018–2022 period as drivers positively affecting business growth (World economic forum, 2018). These technologies include big data analytics, cloud computing, and high-speed mobile internet. According to the report, adoption will happen quickly, with significant implications for employment trends and business development strategies (World Economic Forum, 2018). A new type of firm, one in which AI runs the show, is reshaping markets, according to Iansiti & Lakhani (2020). They explain this new type of firm's distinct underlying economics and organizing principles. Artificial intelligence has also generated a great deal of practical excitement for businesses. Additionally, whole nations are prioritizing AI. (Jacobides et al., 2021).

The evolution of AI has been shaped by technological advancements, increased computational power, and the availability of big data. Early AI systems focused on rule-based approaches, but with the advent of machine learning, AI systems became capable of learning from data and improving over time (Kibria et al., 2018). Recent advancements in deep learning have enabled AI to process complex patterns, leading to breakthroughs in areas such as computer vision and natural language processing (Ruiz-Real et al., 2021). As AI continues to evolve, researchers and practitioners are exploring explainable AI and human-AI collaboration to address concerns related to bias and transparency.

The Importance of AI in Organizations:

AI's importance lies in its potential to create significant value for organizations by augmenting human capabilities, automating processes, and enabling insights-driven decision-making (Enholm et al., 2022). At the process level, AI-driven automation improves efficiency, productivity and quality, reducing repetitive tasks and freeing up employees to focus on more strategic and creative endeavours (Davenport & Ronanki, 2018). As said by Sundar Pichai, CEO of Google, said at Davos, in the World Economic Forum conference in January 2018, AI is arguably the most significant invention in human history, even more significant than electricity or fire; and when using technology, one must learn to maximize its advantages while minimizing its drawbacks (Pichai, 2018). The ability of AI to generate insights from large datasets enables organizations to make data-driven decisions, optimize operations, and respond swiftly to market Dynamics (Kibria et al., 2018). Additionally, AI plays a pivotal role in introducing new products and services, enhancing customer experiences, and driving business model innovation (Enholm et al., 2022).

The workforce landscape is undergoing notable transformations driven by a confluence of technological advancements and amplified by economic, geopolitical, social, and environmental factors (Abulibdeh et al., 2024). Particularly, the maturation of generative artificial intelligence is emerging as a pivotal catalyst for change (Zahidi, 2023). Within the realm of technology adoption, big data, cloud computing, and AI stand out as prominent drivers of change. Over 75% of companies are actively exploring the integration of these technologies into their operations within the next five years (Zahidi, 2023).

The fastest-growing employment roles are inextricably tied to technology, digitalization (McGowan & Shipley, 2020). AI and Machine Learning Specialists headline the list of rapidly emerging professions, closely followed by Sustainability Specialists, Business Intelligence Analysts, and Information Security Analysts (Zahidi, 2023).

Implications of AI Adoption:

The adoption of AI brings both opportunities and challenges for organizations and also, in general, to the world as a whole.

On one hand, it can lead to improved financial and market-based performance, increased customer satisfaction, and environmental sustainability (Enholm et al., 2022). AI's potential for innovation and operational efficiency can propel organizations ahead of their competitors (Soni et al., 2019). On the other hand, challenges such as biased outcomes, lack of transparency, and security concerns must be addressed to prevent negative consequences (Abulibdeh et al., 2024). The ethical implications of AI and its impact on organizational culture, decision-making structures, and employee roles require careful consideration (Enholm et al., 2022).

AI has become increasingly intertwined with our daily lives, underpinning a vast array of solutions, applications and services (Dobrescu & Dobrescu, 2018). This technology presents both advantages and disadvantages, as previously said. AI has introduced several positive developments across society, prompting research in multiple fields, including economics, law, and technical domains like verification, security, and control (Abulibdeh et al., 2024). However, concerns regarding the evolution of AI are growing, with notable figures such as Stephen Hawking, Elon Musk, Steve Wozniak, and Bill Gates questioning the implications of creating super intelligent AI systems that could potentially surpass human cognitive capabilities (Dobrescu & Dobrescu, 2018). The prospect of AI systems continually self-improving has raised the possibility of a superintelligence emerging, transforming global dynamics and potentially addressing long-standing issues such as war, disease, and poverty. Conversely, this newfound power could pose existential risks if the objectives of AI systems are not aligned with human values (Dobrescu & Dobrescu, 2018).

It's critical to understand that AI's influence extends far beyond any one industry, with the potential to fundamentally alter how we approach and resolve

complicated problems. Whether in the fields of healthcare, banking, or other industries, AI is becoming a more significant component of contemporary life, spurring innovation and expanding the capabilities of machines (Meireles et al., 2021).

AI has emerged with a powerful set of tools with transformative potential for the organizations. Its importance lies in the ability to augment human capabilities, automate processes, and generate valuable insights. However, AI adoption also comes with implications that need to be carefully managed. As AI continues to evolve, organizations must strike a balance between leveraging its benefits and addressing the ethical and cultural challenges it presents. By understanding the evolution and implications of AI, organizations can use its potential to create value and gain a competitive edge.

BI&A and Firm Performance

In the 50s, firm performance was considered as the equivalent of organizational efficiency, which represents the degree to which an organization, as a social system with some limited resources and means, achieves its goals without an excessive effort from its members. The criteria used for assessing performance are productivity, flexibility, and interorganizational tensions (Georgopoulos & Tannenbaum, 1957). Later, according to Bartoli & Blatrix (2015), factors like efficiency, effectiveness, quality, effectiveness, piloting, and evaluation should all be considered in defining performance.

According to Chen et al. (2012), business intelligence and analytics (BI&A) encompasses a range of methods, tools, platforms, and software designed to assist a particular organization in analysing various business and market data and information to improve its capacity for making decisions. Additionally, it permits a meaningfully extensive search information, internal and external to the firm, offering

fresh, viable solutions to business requests, opportunities, and issues (Katila & Ahuja, 2002; Kowalczyk & Buxmann, 2015). Earlier research also characterizes BI&A as a strategic endeavour that increases the potential for innovation and the efficacy of businesses (Lavalle et al., 2011; Watson & Wixom, 2007).

Business Intelligence (BI) and Business Analytics (BA) have emerged as crucial elements in modern-day business strategies, successfully balancing between explorative and exploitative innovation practices, which in turn enhances firm performance (Božič & Dimovski, 2019). Data-driven approaches have the potential to significantly impact firm performance, through offering insightful information, strengthening decision-making procedures and raising general effectiveness, speeding up decision-making and boosting economic value as a result of the ever-increasing volume of data available to firms (Awan et al., 2021).

BI refers to the technologies, applications, and practices that analyse and transform raw data into meaningful and actionable information for business decision-making (Olszak, 2014). It entails gathering, combining, and analysing data from multiple sources, enabling organizations to gain insights into past performance and current trends. BI tools facilitate data visualization and reporting, empowering stakeholders to make informed decisions to optimize operational efficiency and identify growth opportunities. In the mid-1950s, decision-makers primarily used business intelligence to enhance the calibre of their decision-making process (Negash & Gray, 2008). However, one of the largest technological disruptions in the field of BI was caused by the massive streams of data in various formats generated through high-velocity communication technologies, also known as "big data" (Agarwal & Dhar, 2014); massive data sets with large, more varied and complex structures. The process of research into massive amounts of data to reveal hidden patterns and secret correlations was named as big data analytics (Sagiroglu & Sinanc, 2013).

BA goes beyond BI by leveraging advanced statistical and predictive models to analyse data and forecast future trends, involving the application of techniques (such

as data mining, machine learning, and predictive modelling) to explore data patterns, discover valuable insights, and support strategic decision-making (Holsapple et al., 2014). These two in turn prompted the development of BI&A, whose ultimate goal was to make it easier to generate and acquire knowledge to support decision-making (Holsapple et al., 2014).

By being integrated into goods and services, enhancing decision-making, and streamlining business procedures, BI&A assets can be turned into value and produce value for the company (Ravichandran & Lertwongsatien, 2005). Several studies, such as the one from Božič & Dimovski (2019) in Slovenia, have explored the relationship between BI, BA, and firm performance, and they consistently highlight their positive impact. BI and BA are associated with improved decision-making processes, leading to better strategic planning and resource allocation. Organizations that effectively use these data-driven approaches are more agile and responsive to market changes, gaining a competitive edge over their peers.

Through the establishment of knowledge-creation routines as crucial dynamic capabilities and the processing of large volumes of information through the information-processing capability, BI&A enables organizations to create knowledge more easily (Chen et al., 2015; Olszak, 2014; Shollo & Galliers, 2016). This, pairing with the facilitated data-driven insights their systems allow, result in giving the possibilities to firms to identify operational inefficiencies and optimize business processes. By analysing historical data and predicting future trends, companies can align their operations with market demands, reducing costs and maximizing productivity. The integration of data from multiple sources also fosters a more comprehensive understanding of customer behaviour and preferences, resulting in improved customer relationship management and increased client satisfaction (Lim et al., 2013). Moreover, BI&A enable organizations to identify new revenue streams and business opportunities. The data-driven insights can highlight unexplored markets, niche customer segments, and emerging trends, helping businesses to diversify their

offerings and expand into new areas. This adaptability and proactiveness contribute to long-term sustainability and growth.

The shift towards evidence-based decision-making in various domains, such as medicine and management, has highlighted the significance of relying on data and empirical evidence to support choices (Silva, 2019). Evidence-based practice is particularly relevant in the context of BI and BA, as organizations increasingly embrace data-driven cultures. Evidence-based decision-making involves using the best available evidence, whether from BI reports, BA predictions, or other data-driven sources, to inform decisions. This approach reduces reliance on intuition and gut feelings, minimizing the potential for biased decisions. By employing evidence-based practices, organizations can improve their accuracy and precision in decision-making, directly impacting firm performance.

Despite all of the advantages that BI and BA bring, there are challenges to overcome. Organizations may face difficulties in effectively integrating and managing data from diverse sources (Hartmann et al., 2014). Data quality issues, data silos, and privacy concerns can obstruct the accurate analysis and interpretation of data, allowing the proximity to an optimal decision-making process.

Furthermore, the successful implementation of BI and BA requires a cultural shift within organizations (Hartmann et al., 2014). This includes fostering a data-driven mindset, promoting data literacy among employees, and encouraging data-driven decision-making at all levels. Resistance to change and lack of awareness about the potential benefits of BI and BA can impede progress.

In conclusion, BI&A play a pivotal role in shaping firm performance in today's data-driven business environment. These data-driven approaches empower organizations with valuable insights, enhanced decision-making capabilities, and improved operational efficiency.

Technology adoption models

Information technology (IT) is a vital instrument for a nation's economic competitiveness. IT significantly affects businesses' productivity. Only if and when IT is widely adopted and used will these benefits become apparent; it is necessary to comprehend what elements impact the adoption of IT. As a result, familiarity with theoretical adoption models is essential (Oliveira & Martins, 2011). Some of the most well-known and widely used theories for firm-level adoption models found in the literature are: the technology, organization, and environment (TOE) framework; the diffusion on innovation (DOI) theory and the Technology Acceptance Model (TAM), according to Bryan & Zuva (2021).

In more detail, according to the DOI model, there are three key factors that precede organizational innovativeness: individual traits (attitude toward change), organizational structure's internal traits (centralization, complexity, formalization, interconnectedness, organizational slack and size), and the organization's external traits (system openness) (Rogers, 1995). The technological, organizational, and environmental contexts are the three elements of an enterprise's context that the TOE framework identifies as having an impact on how it adopts and applies a technological innovation (Tornatzky et al., 1990). The TOE framework and DOI theory serve as the foundation for much empirical research. The TOE framework seems more comprehensive since it incorporates the environmental context, which the DOI theory does not; as a result, it is more suitable to describe how internal innovation adoption occurs (Oliveira & Martins, 2011).

The technology acceptance model (TAM) was introduced by Fred Davis (1985) and became a dominant model in investigating factors influencing users' acceptance of new technology (Bryan & Zuva, 2021). Perceived usefulness and ease of use are two variables that the TAM assumes have a mediating role in the complex relationship between potential system usage and external variables that describe the characteristics of the system. Derived from the psychology-based theory of reasonable action (TRA)

(Fishbein & Ajzen, 1975) and theory of planned behaviour (TPB) (Ajzen, 1991), TAM has taken a leading role in explaining users' behaviour toward technology (Marangunić & Granić, 2014). Venkatesh et al. (2003) combined TAM with e the innovation diffusion theory (IDT) (Rogers, 1995) and the theory of perceived risk (TPR) (Featherman & Pavlou, 2003) to introduce the unified theory of acceptance and use of technology (UTAUT).

3. Research Model and Hypotheses

Our study uses an innovative and comprehensive theoretical framework that integrates the Unified Theory of Acceptance and Use of Technology (UTAUT) from Venkatesh et al. (2003) with Dinter's (2012) BI&A maturity model, and the firm performance construct from Law and Ngai (2007).

UTAUT was considered the most complete model to predict information technology acceptance at firm level (Martins, Oliveira, & Popovič, 2014) and therefore was used in this work to study two stages of AI technology adoption by firms: intention to use and the actual use, testing the two remaining variables. Our theoretical model is presented in Figure 1.

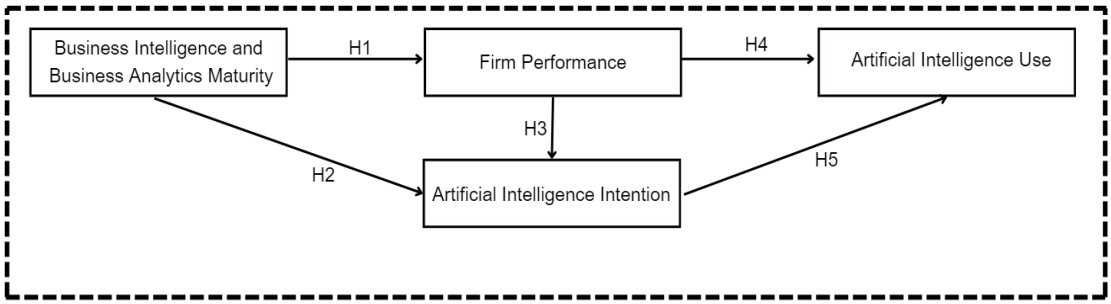

Figure 1 - Theoretical research model

Earlier results support the fact that BI&A use is positively associated with successful balancing between explorative and exploitative innovation activities, which in turn enhances firm performance (Božič & Dimovski, 2019).

Generally, a maturity level represents an organization's capabilities as regards a specific class of objects and application domain (Röglinger et al., 2012). Raber et al. (2013) believe that the benefits achieved from BI are significantly correlated with the BI maturity of an organization. For effects of this work we consider this relates to BA

as well since the same principle applies to Business Analytics maturity, as both BI and BA share similar goals and processes in leveraging data for decision-making. Therefore we hypothesize that:

H1 BI&A maturity will positively influence firm performance.

BI&A has changed over the years, moving from creating static reports to offering information in real time and is often divided into three maturity stages (Chen, Chiang & Storey, 2012). BI&A 1.0 was the time of descriptive analytics, where data was structured and gathered from within the organization (Chen, Chiang & Storey, 2012). Big data introduced BI&A 2.0, and all of a sudden it was a treasure trove for understanding consumer demands (Chen, Chiang & Storey, 2012; Davenport, 2018). With the increasing development of IT, BI&A 3.0 was further developed with the increase of web and mobile devices, also introducing the challenge of working with unstructured data (Chen, Chiang & Storey, 2012; Olszak, 2016). Even though BI&A is now an essential part of many businesses, using data effectively is getting harder for enterprises as the volume of data increases (Olszak, 2016). Simultaneously, artificial intelligence is becoming more widely known. Although the term is not new, the abundance of data available has recently drawn increased attention to it (Burgess, 2017). AI has the power to improve predictive analytics in a number of ways, including intelligence, speed, and actionability. It can also produce results that are more accurate due to its capacity to handle vast volumes of real-time data (Akerkar, 2018). As AI can improve BI&A's value, Davenport (2018) contended that AI ought to be viewed as an expansion of an organization's analytical capacity. It goes on to say that it paves the way for a new maturity level, marking the BI&A 4.0, which puts more emphasis on prescriptive and predictive analytics than on descriptive analytics. Additionally, AI makes possible for businesses to automate data analytics, which transforms the way BI&A is applied (Prat, 2019). Furthermore, earlier research by Davenport and Harris

(2017) demonstrates that a company gains a greater competitive advantage with a more intelligent BI&A. Therefore we hypothesize that:

H2 BI&A maturity will positively influence the intention of firms to adopt AI.

Decisions made using data are demonstrated to be more accurate and effective, which has an impact on the performance of the organization and is a valuable tool for decision-support systems (Feng, Richards & Raheemi, 2009; Brynjolfsson, Hitt & Kim, 2011; Russom, 2011; Watson, 2014; Wieder & Ossimitz, 2015).

Given AI's propensity for working more effectively with data, it is clear that integrating AI into decision-support systems can result in more effective decision-making (Akerkar, 2018). The influence of firm performance on the intention to adopt AI technology can be understood through the lens of data-driven decision-making.

Moreover, we believe companies that aim to sustain or improve their performance levels are more likely to adopt cutting-edge technologies like artificial intelligence (AI) in order to stay ahead of the curve and stay competitive in the increasingly data-driven business environment (Enholm et al., 2022). Therefore we hypothesize that:

H3 Firm performance will positively influence the intention of firms to adopt AI.

A data-driven organization employs data as a strategy (Anderson, 2015; Morrison, 2015). When a firm uses BI&A as a strategy, decisions are made using data rather than gut feelings, which has been demonstrated in earlier research to result in more effective decisions and, consequently, higher performance (McAfee & Brynjolfsson, 2012). A management team that embraces a data-driven strategy is a necessary factor for an organization to become data-driven (McAfee & Brynjolfsson, 2012). Additionally, the collection of the right data and its use predictively in order to gain a competitive edge is also required (Anderson, 2015; Morrison, 2015). Davenport &

Bean (2018) further emphasize the need for companies to become data-driven, which is more easily achieved by what is considered to be good performance nowadays, as it is a requirement to succeed with AI. Therefore we hypothesize that:

H4: Firm performance will positively influence the use of AI in organizations.

The role of intention as a predictor of use behaviour is critical and has been well-established in the IS field and their reference disciplines (Ajzen, 1991; Sheppard et al. 1988; Taylor and Todd, 1995b).

Behavioural intention is one of the most prominent factors that lead toward use, is an inner force that drives to act (Wang et al., 2023). UTAUT model supports the belief that behavioural intention has a significant impact on technology use (Venkatesh et al., 2003). Therefore we hypothesize that:

H5 Intention of firms to adopt AI will positively influence its actual use.

4. Methodology and Data

In this work, we followed a natural science methodology approach, including a literature review, theoretical model design/ identification, and a survey for data collection to test the theoretical model, results discussion, theoretical and practical implications identification, and conclusions.

Based on the research model, an English-language questionnaire (appendix A) based in earlier literature was designed and reviewed for content validity by information systems academics. The questionnaire contained two sections with: (i) data constructs and (ii) demographic characteristics. The items and scales for BI&A maturity perception were based in Dinter (2012), comprising nine items: (1) the scope of BI systems use; (2) the level of data architecture maturity; (3) the relevance of BI for the organization; (4) the level of data management maturity; (5) the type of BI tools used by the organization; (6) the organizational structure related to BI; (7) the level of BI processes maturity; (8) the level of BI profitability assessment; and (9) the BI strategy.

Organizational performance items were adopted from Law and Ngai (2007), whose work provides the basis for designing this part of the questionnaire, collecting the respondents' perception on this construct. With the goal of capturing both the financial and non-financial dimensions, they defined the pertinent aspects based on earlier research. It included five statements that assessed the subsequent: (1) level of customer satisfaction with products/services ('value for money'); (2) customer retention rate; (3) sales growth rate; (4) profitability of the organization; and (5) competitive position of the organization.

The items and scales for the UTAUT constructs were adapted from Venkatesh et al. (2003).

For each stated item respondents were asked to state the level of their opinion about it, following a 7-point Likert scale, meaning 1- strongly disagreement and 7- strongly agreement. The last question ("What is your actual frequency of use of systems with AI?") followed a 12-point scale, from "have never used" (AI) to "several times a day" (use of AI), according to Martins et al. (2014).

By adopting a quantitative method approach, this research aims to provide a better understanding of the complex dynamics that are present in the integration of BI&A systems and AI technologies within firms, offering practical and valuable insights for both academics and practitioners in the field of technology adoption and AI implementation at the firm level.

An on-line survey instrument was designed based on the English questionnaire, hosted on a well-known service provider for collecting data, based on the fact that adoption studies have traditionally been conducted using survey instruments (Venkatesh et al., 2003). It was deliberately disseminated via social media, email, and within specific firm teams with links only could be used once per respondent. Since the questions were created to dive into the specifics of BI&A systems, firm performance, AI intention, and use, each one has a unique significance that is in line with the goals of the research. All the questions used have been already tested in literature.

4.1 **Data Collection**

The work sample size required was defined before launching the survey instrument, according to the theoretical model and a statistical power of 80%, a significance level of 5% and a minimum coefficient of determination (R^2) of 0.10, while having a maximum of 2 arrows pointing at a construct. The target population comprised individual adults (18 years old or older) who work in a business that use BI&A systems and might have, or not, contact with AI technology adapted to their

work. This deliberate focus made sure that the responses gathered were directly related to the objectives of our study. On January 26th, 2024, the data collection process started. An initial pilot test involved 30 respondents. Preliminary evidence showed that scales were reliable and valid, allowing us to proceed to the main data collection period phase, where total 128 individuals' responses were gathered over a span of about a month and a half.

The responses common method bias was examined using the Harman's single factor test (Podsakoff et al. 2003) and the random dependent variable method. No significant common method bias was found in the data.

The analysis of demographic information from the respondents of the questionnaire offers valuable insights into the sample composition and characteristics of the study population. As we can see below, in table 1, among the 128 respondents, gender distribution indicates a relatively balanced representation, with slightly more male respondents (50.8%) compared to female respondents (49.2%). When it comes to age, the majority of responders are between the ages of 18 and 35, with 37.5% being between the ages of 18 and 25 and 38.3% being between the ages of 26 and 35. However, notable diversity exists across different age groups, with 23 respondents (18%) being over the age of 46. Geographically, the majority of respondents (65.6%) are from the Oporto region, while smaller percentages represent Lisbon (12.5%) and other cities, both with more than 500,000 inhabitants (10.2%), and less than 500,000 inhabitants (11.7%). With regard to education, the majority of respondents (60.9%) have a Master's degree, while those with a Bachelor's degree (29.7%) and a Doctorate (3.1%) are less common than those with other educational qualifications (4.7%). The thorough examination of demographic data offers a fundamental comprehension of the characteristics of the respondents, enabling deeper interpretation of the study findings and implications.

Table 1 – Descriptive statistics of respondents' characteristics

Measure	Value	Frequency	%
Gender	Female	63	49.2%
	Male	65	50.8%
Age	Between 18 and 25	48	37.5%
	Between 26 and 35	49	38.3%
	Between 36 and 45	8	6.3%
	Over 46	23	18%
Region	Oporto	84	65.6%
	Lisbon	16	12.5%
	Other city with more than 500.000 habitants	13	10.2%
	Other city with less than 500.000 habitants	15	11.7%
Education Level	High School	2	1.6%
	Bachelor	38	29.7%
	Master	78	60.9%
	Doctorate	4	3.1%
	Other/Prefer not to say	6	4.7%

5. Data Analysis and Results

Structural Equation Modelling (SEM), which is a general term that has been applied to many statistical models that assess the applicability of substantive theories supported by empirical data, was used in this work. Two SEM techniques prevail: covariance-based and variance-based. A variance-based techniques was used, more specifically, the Partial Least Squares (PLS), to comprehensively analyse the intricate relationships within the proposed research model (Ringle, Wende, & Becker, 2022). This is a practical and effective statistical method that is thought to be suitable for numerous research scenarios (Henseler, Ringle, & Sinkovics, 2009), appropriate for studying complex models with multiple constructs (Chin, 1998). Following J. C. Anderson & Gerbing's (1988) guidelines, the methodology involved a two-fold process. Initially, the measurement model was analysed to rigorously evaluate the reliability and validity of the selected measures. This crucial step allowed for a robust foundation, ensuring that the variables of interest—BI&A Maturity, Firm Performance, AI Intention, and AI Use—were accurately captured and represented in the subsequent analyses. Subsequently, as next step, the structural model analysed to delve into the intricate web of relationships embedded in the model, to assess the structural dynamics and interplay between the variables. This two-tiered SEM-PLS approach is presented in detail, as follow.

5.1 Measurement model

The measurement model was assessed for (i) item's reliability, (ii) internal consistency/composite reliability, (iii) convergent validity, and (iv) discriminant validity.

Table 2 lists the average variance extracted (AVE), composite reliability (CR), Cronbach's alpha values, loading and t-values. The indicator reliability was evaluated based on the criteria that loading should be higher than 0.7 (Hair et al., 2017). As also shown in the table, all the constructs have composite reliability and Cronbach's alpha is greater than 0.7, suggesting the constructs' reliability and validity (Hair et al., 2017). The convergence validity was tested with AVE, and all constructs compared positively against the minimum acceptable value of 0.5 (Fornell & Larcker, 1981), as seen in Table 2. At the end all criteria were satisfied.

Table 2 - Quality criteria and factor loadings

Construct	**AVE**	**Composite reliability**	**Cronbach's Alpha**	**Item**	**Loadings**	**t-value**
BI&A Maturity	0.750	0.964	0.958	BIA1	0.867	29.722
				BIA2	0.846	27.231
				BIA3	0.878	36.188
				BIA4	0.877	37.218
				BIA5	0.877	39.293
				BIA6	0.850	27.038
				BIA7	0.876	40.316
				BIA8	0.860	29.368
				BIA9	0.866	26.464
Firm Performance	0.757	0.940	0.919	FP1	0.828	22.018
				FP2	0.855	28.185
				FP3	0.881	46.013

Construct	AVE	Composite reliability	Cronbach's Alpha	Item	Loadings	t-value
				FP4	0.884	33.923
				FP5	0.900	45.620
AI Intention	0.926	0.961	0.920	AII2	0.958	92.840
				AII3	0.966	123.967
AI Use	0.936	0.967	0.932	AIU1	0.968	136.953
				AIU3	0.967	124.069

Discriminant validity was analysed using three measures: (i) cross-loadings, (ii) Fornell-Larcker criterion and (iii) HTMT – heterotrait-monotrait ratio of correlations.

As shown in table 3, each item presents a higher loading on its corresponding factor than the cross-loading on other factors (Götz, Liehr-Gobbers, & Krafft, 2009).

Table 3 Cross-loadings

Construct	Item	BIA	FP	AII	AIU
BIA	BIA1	**0.867**	0.524	0.565	0.557
	BIA2	**0.846**	0.643	0.440	0.448
	BIA3	**0.878**	0.591	0.496	0.523
	BIA4	**0.877**	0.618	0.556	0.568
	BIA5	**0.877**	0.623	0.452	0.456
	BIA6	**0.850**	0.543	0.520	0.545
	BIA7	**0.876**	0.540	0.532	0.583
	BIA8	**0.860**	0.586	0.554	0.488

Construct	Item	BIA	FP	AII	AIU
	BIA9	**0.866**	0.619	0.516	0.465
FP	FP 1	0.581	**0.828**	0.513	0.431
	FP 2	0.569	**0.855**	0.384	0.334
	FP 3	0.575	**0.881**	0.478	0.398
	FP 4	0.638	**0.884**	0.429	0.381
	FP 5	0.586	**0.900**	0.449	0.347
AII	AII2	0.549	0.484	**0.958**	0.735
	AII3	0.593	0.517	**0.966**	0.834
AIU	AIU1	0.571	0.415	0.800	**0.968**
	AIU3	0.579	0.430	0.782	**0.967**

Table 4 contains the square root of the AVE in bold along the diagonal and the factor correlation coefficients, verifying the condition that they are greater than the correlation between constructs (Fornell & Larcker, 1981). This way, we can say that the Fornell-Larcker criterion is met.

Table 4 - Fornell-Larcker

	BIA	FP	AII	AIU
BIA	**0.866**			
FP	0.679	**0.870**		
AII	0.595	0.521	**0.962**	
AIU	0.594	0.437	0.818	**0.967**

To satisfy best practices principles, the heterotrait-monotrait ratio of correlations (HTMT) need to be inferior to 0.9 and every ratio above that value should be

eliminated (Henseler, Ringle, & Sarstedt, 2015). Two items had to be dropped from the model at this stage, namely AII1 and AIU4, in order to comply with HTMT. Final HTMT' results can be seen in the table 5, as follow.

Table 5 - HTMT – heterotrait-monotrait ratio of correlations

	BIA	FP	AII
FP	0,722		
AII	0,631	0,563	
AIU	0,629	0,470	0,881

5.2 Structural model and hypotheses testing

To avoid collinearity and ensure the stability of the estimates, the Variance Inflation Factor (VIF) cannot be higher that 5 (Hair et al., 2017). To follow this rule, the item AIU2 was eliminated from our model to guarantee there is no multicollinearity among the predictor variables. The analysis of hypotheses and constructs' relationships were based on the examination of standardized paths. The path significance levels were estimated using bootstrapping resampling method (Henseler et al., 2009), with 5000 iterations of resampling for a minimum significance level of 0.05 (5%). The results obtained are presented in Figure 2.

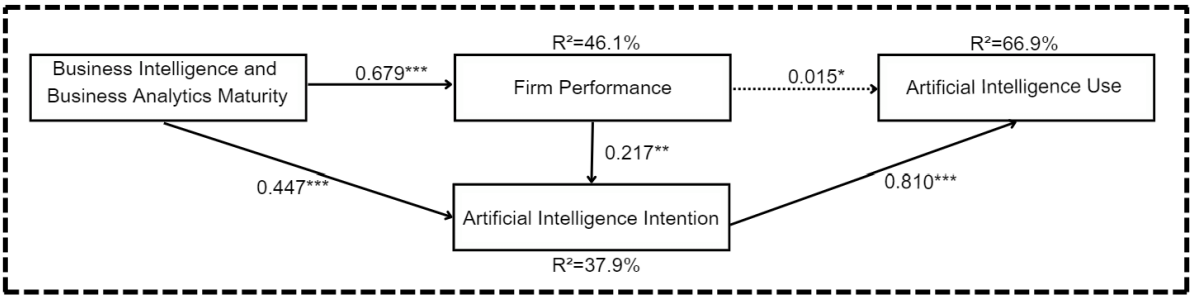

Figure 2 - Structural model results

According to the R^2 obtained, that measure the goodness of fit of the model to the observed data, our model explains a 46.1% of variation in firm performance, 37.9% in intention of adopting AI and 66.9% in AI use.

BI&A maturity and firm performance were found to be statistically significant in explaining AI intention, respectively with $\hat{\beta}$ =0.447 ($p<0.01$) and $\hat{\beta}$ =0.217 ($p<0.05$). In the same manner BIA maturity relationship over firm performance and AI intention over AI use were also found statistically significant, respectively with $\hat{\beta}$ =0.679 ($p<0.01$) and $\hat{\beta}$ =0.810 ($p<0.01$). Thus, supporting hypotheses H1, H2, H3 and H5. In the opposite situation is firm performance relationship with AI use, which was found not to be statistically significant due to its high p-value ($p=0.098$, $p>0.05$), not supporting hypotheses H4.

Overall, of the five hypotheses formulated, four were supported by the collected data.

6. Discussion

Our innovative theoretical combine the Unified Theory of Acceptance and Use of Technology (UTAUT), of Venkatesh et al. (2003), with Dinter's BI maturity model (Dinter, 2012) and the firm performance construct from Law and Ngai (2007).

6.1 Main Findings

The research model explains 66.9% of variation in Artificial Intelligence use in firms. The factors that positively influence this technology acceptance are BI&A maturity, and the intention to adopt, this last one confirming earlier research (Venkatesh et al., 2003). The effect of firm performance on AI use was found to be not significant.

The model's ability to explain a substantial portion of the variance in AI use (66.9%) underscores its effectiveness in capturing the complex dynamics of technology integration. This research model also explains 46.1% of variation in firm performance.

Our findings indicate a significant positive relationship between BI&A maturity and firm performance. This result is aligned with many earlier literature presents in the literature review chapter, that demonstrates how important mature BI&A systems are to the success of an organization (Katila & Ahuja, 2002; Kowalczyk & Buxmann, 2015; Lavalle et al., 2011; Watson & Wixom, 2007). Nevertheless, it contradicts others works that were not able to support this connection (Suša Vugec et al., 2020). Our result suggests that companies with well-established BI&A departments are better able to use data-driven insights, streamline decision-making procedures, and eventually improve performance results (Ravichandran & Lertwongsatien, 2005) and increases the likelihood of implementing cutting-edge technologies like artificial intelligence (Akerkar, 2018). The results also highlight how crucial it is to invest BI&A capabilities before implementing successful technology adoption strategies (Soni et al., 2019).

Our study confirms that BI&A maturity has a significant impact on the intention to use AI, supporting the idea that sophisticated BI&A skills lay the foundation for embracing new technologies (Akerkar, 2018). Furthermore, the positive correlation between firm performance and AI adoption intention highlights how strategically important it is for businesses to use technology as a means of sustaining their competitive edge and driving innovation (Božič & Dimovski, 2019).

Contrary to expectations, our findings show that firm performance has no statistically significant direct influence on the use of AI. Although prior research has indicated a favourable correlation between company performance and technology adoption (Davenport & Bean, 2018), our findings do not show it. It suggests that while high-performing firms may prioritize technology adoption, other factors such as organizational culture, resource availability, and implementation challenges may moderate the translation of performance outcomes into actual technology utilization (Hartmann et al., 2014).

The significant positive influence of the intention to adopt AI on actual AI use reaffirms the importance of psychological factors in shaping technology adoption behaviour (Ajzen, 1991; Wang et al., 2023). Strong AI adoption intentions increase the likelihood that an organization will get past implementation barriers and actively incorporate AI into daily operations (Wang et al., 2023). This finding emphasizes how crucial it is for businesses to promote an innovative and technological culture, in order to facilitate successful AI adoption initiatives and programs.

6.2 Practical Implications

The findings of this study offer several practical implications for organizations seeking to enhance their BI&A capabilities, firm performance and facilitate AI adoption.

Firstly, organizations should prioritize investments in BI&A capabilities to enhance data-driven decision-making and encourage a culture of innovation. Firms can create

a strong basis for the effective adoption and integration of cutting-edge technologies like artificial intelligence (AI) by utilizing mature BI&A systems.

Secondly, the integration of technology adoption strategies such as fostering a culture of innovation and technology readiness can promote greater intention and willingness to adopt AI among employees and decision-makers, so to maintain coherence and optimize value realization, organizations must match their technology adoption initiatives with more general strategic goals.

Thirdly, addressing organizational readiness and change management processes is crucial for facilitating smooth technology adoption. Organizations should concentrate on proactively handle change resistance, offer sufficient training and support, and cultivate a culture of experimentation and learning.

6.3 Theoretical Implications

The theoretical framework employed in this study, combining UTAUT constructs, Dinter's BI maturity model, and Law and Ngai (2007) firm performance construct offers a comprehensive approach to understanding BI&A maturity, technology adoption and firm performance.

By integrating diverse theoretical perspectives, this study contributes to a deeper understanding of the intricate dynamics underlying technology adoption decisions within organizations, being able to make significant contributions to the field. It provides a solid basis on which further research projects can be built, serving as a foundational framework for refining adoption models at the enterprise level.

Moreover, its methodology incorporates diverse theoretical viewpoints, consequently opening doors for more profound investigations into the complex dynamics of technology adoption procedures. This study has the potential to guide decision-making processes, inform organizational strategies, and enable the successful

integration of technologies into a variety of business contexts, in addition to its applications. Because of its adaptability and versatility, it is a useful tool for scholars, practitioners, and policymakers to use when navigating the constantly changing field of technology adoption and implementation.

7. Limitations and further research

Even though this study offers valuable insights about the connections between BI&A maturity, firm performance, and AI adoption, several limitations warrant consideration**.** Firstly, the study relied on self-reported data, which may be subject to response bias and social desirability effects. For example, the focus on specific geographic regions may limit the generalizability of the findings. Future research could adopt a larger and more diverse sample to enhance the external validity of the results. Moreover, the study focused primarily on the influence of internal factors on technology adoption, overlooking external factors such as market dynamics and regulatory environments. Future research could explore the interplay between internal and external factors in shaping technology adoption decisions. Finally, unexpectedly our research findings reveal that firm performance does not exert a statistically significant influence on the use of AI in organizations, despite previous studies suggesting a positive correlation between company performance and technology adoption (Davenport & Bean, 2018). This discrepancy suggests that although high-performing firms may prioritize technology adoption, various other factors such as organizational culture, resource availability, and implementation challenges may influence the translation of performance outcomes into actual technology utilization (Hartmann et al., 2014). Therefore, further research is imperative to fully comprehend these factors and their impact on technology adoption strategy.

8. Conclusions

The integration of Business Intelligence and Analytics (BI&A) with the adoption of Artificial Intelligence (AI) represents a pivotal paradigm shift in modern organizational strategies, heralding a new era of data-driven decision-making and technological innovation.

As a result of the thorough examination of the research model, empirical data, and practical implications discussed in the earlier chapters, this study's conclusion provides insightful information about the intricate connection between Business Intelligence and Analytics (BI&A) maturity, firm performance and Artificial Intelligence (AI) adoption in organizations.

The integration of the Unified Theory of Acceptance and Use of Technology (UTAUT) intention and use constructs with Dinter's BI maturity model and the performance measurement from Law and Ngai (2007), provided a robust theoretical framework for understanding the complex dynamics of AI technology adoption at firm level.

The main findings of this study underscore the critical role of BI&A maturity and intention to adopt AI in driving technology acceptance within organizations. Specifically, BI&A maturity emerges as a key determinant of both firm performance and the intention to adopt AI. This highlights the importance of investing in BI&A capabilities as a precursor to successful technology adoption initiatives. Furthermore, the positive correlation between firm performance and AI adoption intention highlights the strategic imperative for organizations to leverage technology for competitive advantage and innovation.

For practitioners this study offers actionable insights for organizations seeking to enhance their BI&A capabilities, firm performance, and to reinforce AI adoption. Also, this study gives researchers a foundation for future improvement of firm models of acceptance for future research.

In terms of work's objectives, they were fully accomplished, contributing to knowledge advancement and to the growing body of literature on technology adoption and organizational performance with new and significant insights. By leveraging these, organizations can formulate more informed technology adoption strategies and drive sustainable competitive advantage in an increasingly competitive digital landscape.

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Appendix A. Survey

Construct	Item	Adapted Questions	Author
BI&A Maturity (BIA)	BIA1	BI&A is used in all organizational units, hierarchical levels, and application areas (wherever needed).	(Dinter, 2012)
	BIA2	Both internal (structured and unstructured) and external data are fully integrated, meeting requirements such as data quality.	
	BIA3	Decision-making relies on BI&A, and it is perceived as having a critical impact on organizational performance.	
	BIA4	Data integration is automated, dedicated tools for data management and integration are used.	
	BIA5	A broad range of BI&A tools and techniques is used, including reporting tools, ad hoc analytics (OLAP), in-memory analytics, planning, alerts, forecasts, scorecards, mobile BI, data mining, predictive analytics, and other advanced analysis and visualization techniques	
	BIA6	A BI&A (business Intelligence and analytics or similar) competence center with a comprehensive spectrum of tasks and competencies exists.	
	BIA7	BI&A specifc processes are defined and actively managed.	
	BIA8	A benefit-oriented and cross-project profitability assessment of BI&A is conducted.	
	BIA9	A dedicated BI&A strategy exists and clearly reflects the business/IT alignment.	
Firm Performance (FP)	FP1	Our customers perceive our products and services as the best in our industry.	(Law & Ngai, 2007)
	FP2	Our customer retention rate is high above the average of the industry.	
	FP3	Our sales are growing at a rate high above the industry average.	
	FP4	The profitability of our company is high above the industry average	
	FP5	Our overall competitive position is high above the average of the industry.	
AI Intention (AII)	AII1	I intend to use systems with AI at work in the future.	(Venkatesh et al., 2003)
	AII2	I will always try to use systems with AI in my daily work life.	

Construct	Item	Adapted Questions	Author
	AII3	I plan to continue to use systems with AI at work frequently.	
AI Use (AIU)	AIU1	I find systems with AI useful in my daily work life.	(Venkatesh et al., 2003)
	AIU2	Using systems with AI increases my work productivity.	
	AIU3	Using systems with AI helps me accomplish work things more quickly.	
	AIU4	What is your actual frequency of use of systems with AI? i) Have not use; ii) Once a year; iii) Once in six months; iv) Once in three months; v) Once a month; vi) Once a week; vii) Once in 4–5 days; viii) Once in 2–3 days; ix) Almost every day; x) Every day; xi)Several times a day.	(Martins et al., 2014)