NOVA IMS
Information Management School

MDSAA

Master's Degree Program in
Data Science and Advanced Analytics

Artificial Intelligence

Understanding the influence of intention to use the technology in BI&A maturity and firm performance

Tiago Manuel Tojal Figueiredo

Master Thesis

presented as partial requirement for obtaining a Master's Degree in Data Science and Advanced Analytics

NOVA Information Management School

Instituto Superior de Estatística e Gestão de Informação

Universidade Nova de Lisboa

NOVA Information Management School
Instituto Superior de Estatística e Gestão de Informação
Universidade Nova de Lisboa

Artificial Intelligence: Understanding the influence of intention to use the technology in BI&A maturity and firm performance.

by

Tiago Manuel Tojal Figueiredo

Master Thesis presented as partial requirement for obtaining the Master's degree in Data Science and Advanced Analytics, with a specialization in Data Science

Supervised by

Gonçalo Baptista, PhD, Universidade Nova de Lisboa

July, 2024

STATEMENT OF INTEGRITY

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism or any form of undue use of information or falsification of results along the process leading to its elaboration. I further declare that I have fully acknowledged the Rules of Conduct and Code of Honor from the NOVA Information Management School.

Lisbon,8th of July 2024

DEDICATION

Gostava de começar o agradecimento aos meus pais, este trabalho é mais vosso do que meu. É o fruto de uma vida inteira de esforços e sacrifícios, de lutas e vitórias que sempre tiveram um único propósito: proporcionar-me as melhores oportunidades de vida. Agradeço-vos por acreditarem em mim, mesmo quando duvidei, e por se manterem firmes e resilientes em cada desafio. Sem a vossa incansável luta e amor incondicional, eu não estaria aqui.

À minha irmã, quero deixar uma mensagem especial: custe o que custar, o caminho é sempre para a frente. Se eu consegui chegar até aqui, sei que tu irás conseguir muito mais. Continua a lutar pelos teus sonhos com determinação e coragem, porque o sucesso está ao teu alcance.

Aos meus avós, a vossa presença constante e o apoio inabalável foram o meu porto seguro nos momentos de dúvida e incerteza. As lições de vida que me passaram, as histórias que me contaram e os valores que me ensinaram são tesouros que carrego comigo e que se refletem em cada página desta tese. A educação não se faz apenas na escola, e vocês foram os meus primeiros grandes professores.

À NOVA Information Management School (NOVA IMS) e à Faculdade de Ciências de Lisboa (FCUL), agradeço a oportunidade de me terem acolhido e formado. As ferramentas e o conhecimento que agora possuo é algo que estas instituições ajudaram a cimentar. O rigor, a exigência e o incentivo ao pensamento crítico foram bases nesta minha jornada académica, que espero continuar a honrar na minha vida profissional.

Ao professor Gonçalo, a sua orientação foi uma luz que guiou este trabalho. A sua dedicação não conheceu limites e o seu apoio foi incansável. Agradeço por cada correção, por cada sugestão, por cada momento de aprendizagem. Este trabalho também é fruto da sua perseverança e comprometimento com a excelência académica e com o meu desenvolvimento enquanto estudante e profissional.

Por último agradecer a todos os restantes que não foram mencionados, que tornaram possível e contribuíram para concretização deste objetivo.

ABSTRACT

This work is motivated by the constant growth of Artificial Intelligence tools, within firms, and the performance impacts are currently being study. The research identifies some issues related to the synergy between the maturity of Business Intelligence and Analytics systems for enhancing performance, through AI adoption. The objective of this study is to examine how AI enhance BI&A maturity and improve firm performance. A conceptual model integrating the Unified Theory of Acceptance and Use of Technology (UTAUT) Venkatesh et al., (2003) with the firm performance model of Suša Vugec et al., (2020), BI&A from Dinter, (2012) Business Intelligence maturity model, and organizational culture construct. The study collected data from firm employees with roles related to BI&A and AI via an online questionnaire in south European country. The findings were analysed using Structural Equation Modelling (SEM) and Partial Least Squares (PLS). Performance expectancy, social influence, facilitating conditions and organizational culture significantly affect AI adoption intention. AI intentions to use was found to have a strong and positive direct effect on the maturity of BI&A systems and AI use, and the BI&A maturity systems positively influence firm performance. The findings of this research contribute firm level AI adoption in enhancing the maturity of BI&A systems to improve decision-making, efficiency, and competitive advantage.

KEYWORDS

Artificial intelligence; UTAUT; Business intelligence; Business analytics; Organizational culture; Firm performance; Maturity model

Sustainable Development Goals (SDG):

INDEX

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS AND ACRONYMS

AI	Artificial Intelligence	Technologies designed to perform tasks that normally require human intelligence
BI	Business Intelligence	Technologies and strategies to collect and convert raw data into meaningful information to support business decision-making and strategic planning.
BA	Business Analytics	Technologies to transform data into insights for better business decisions
BI&A	Business Intelligence and Analytics	The combination of business intelligence and analytics
UTAUT	Unified theory of acceptance and use of technology	Model to explain user intentions to use a technology and usage behaviour
ML	Machine Learning	A field of artificial intelligence that enable to perform tasks without explicit instructions
NLP	Natural Language Processing	A field of artificial intelligence that focuses on the interaction of computers and humans through natural language
ETL	Extract, Transform and Load	The process of extracting data from various sources, transforming it to fit operational needs, and loading it into a data storage system
OLAP	Online Analytical Processing	A category of software tools that provides analysis of data stored in a database and is used for complex calculations, trend analysis, and data modelling
DL	Deep Learning	A class of machine learning techniques based on artificial neural networks with representation learning, useful for tasks such as image and speech recognition

1. INTRODUCTION

The integration of artificial intelligence (AI) into Business Intelligence and Analytics (BI&A) systems is becoming crucial for firms to addresses challenges of analytical capabilities (Zohuri, 2020). The level of BI&A implementation as well as their adoption of artificial intelligence solutions, are expanding quickly within organizations, and requires some understanding (Brynjolfsson et al., 2011; Davenport et al., 2010). The enhance of decision-making, (Wamba-Taguimdje et al., 2020), the ability to extract meaningful insights from datasets (Zohuri, 2020), accuracy of predictive analytics and quick response to market changes (Chen et al., 2012), are just a few examples of what AI can achieve. Firms must leverage the AI´s capabilities to remain a competitive advantage (Agarwall et al., 2022), but focusing the investment and learning to effectively use these technologies can be challenging.

Previous research highlighted individual benefits of AI and BI&A systems on firm performance, just like enhancing firm performance by innovation and increasing firm growth (Babina et al., 2024; Mikalef & Gupta, 2021) and contributions of BI&A systems to provide insights, data-driven decisions and enhance business processes (Božič & Dimovski, 2019; Vidgen et al., 2017).

Our work extends current literature to better explore the impact of AI on BI&A system maturity and firm performance. Earlier literature, as far as we know, doesn't fully address these combined factors, leaving us an interesting area of research underexplored, a gap that we will try to fill by exploring the integration and impact of AI within BI&A systems, and their respective impact on firm performance. Consequently, the main objective of this research is to answer to three main questions: (1) How does the maturity of BI&A systems influence firm performance? (2) How does the intention to use AI technology influence the maturity of BI&A systems and firm performance, (3) How does organizational culture influence the adoption of AI technologies within firms?

The rest of the paper is structured as follows. We provide an overview of artificial intelligence (AI) and Business Intelligence and Analytics (BI&A) systems. Then we discuss the research model and hypotheses, followed by data collection methodology, results and discussion. Finally, we present the implications for research and practice, then we focus on the limitations and suggestions for future research.

2. LITERATURE REVIEW

Some researchers use the term business intelligence and business analytics cooperatively causing a combined overview (Rikhardsson & Yigitbasioglu, 2018). Consistent with the focus of this study, the objective is not to separate these concepts but to explore the synergistic value they offer when integrated with AI adoption.

2.1 ARTIFICIAL INTELLIGENCE OVERVIEW

Artificial Intelligence (AI) is not a new concept, but it has received significant attention in recent years and the evolution can be attributed to advances in big data (Burgess, 2018). Transitioning into the 21st century, artificial intelligence's effect grew, and uses a hierarchical approach to learn from previous experiences, changing firm performance around the world (Pencheva et al., 2020). AI, characterized by its capacity of machines to recreate intelligent human behaviour (Syam & Sharma, 2018), it will have a 50% chance of overtaking humans in 45 years for all tasks and automating all human processes in 120 years (Grace et al., 2017). This revolutionary potential has enabled firms to optimize processes and boost automation, reinventing information management and enhancing process performance (Wamba-Taguimdje et al., 2020). Previous researches highlights that AI has a positive impact on firm performance (Ma & Sun, 2020), and over 80% of organizations view AI as a strategic opportunity, who leads organizations to heavily invest in new technologies (chatbots, neural networks, virtual assistants, deep learning, and machine learning), to enhance business operations, support decision-making, leading to competitive advantage (Perifanis & Kitsios, 2023). According to Alsheibani et al., (2020), organizations deploying AI applications can enhance income, reduce costs, and improve productivity. Artificial Intelligence (AI) has become a pivotal force driving transformation across various sectors. In the transport sector, AI's most notable application is in autonomous vehicles, with sophisticated algorithms to navigate roads, interpret traffic signals, and make real-time decisions that bring safety (Garikapati & Shetiya, 2024). AI-powered programs can analyse medical images and identify patterns indicative of various conditions, including cancers and other diseases, at early stages (Savage, 2020). In marketing, AI's ability to analyse vast datasets offers businesses profound insights into customer behaviour and preferences, allowing firms to create personalized marketing strategies that significantly enhance customer loyalty and operational performance (Bag et al., 2021).

The relationship between a company's investments in AI and its growth, particularly within firm categorizations based on initial size, reveals these investments have a significantly greater positive impact on company expansion in larger firms (Babina et al., 2024). Studies indicate that these technologies positively influence business value by enhancing knowledge about customers, users, and markets (Bag et al., 2021). Researches by Mikalef & Gupta, (2021) and Mishra & Pani, (2021) explores how these capabilities allows for organizational innovation and improve overall performance. Additionally, findings from (Agarwall et al., 2022) emphasize the need to examine the link between operational performance and these technological tools, revealing that their strategic implementation in IT firms in India significantly boosts operating profits. This observation aligns with market trend data, which predicts that AI will generate nearly $90 billion in profits by 2025 (Tratica, 2018). The regions of North America, Europe, and Asia-Pacific are expected to be the main beneficiaries of AI's diverse technological advantages (Tratica, 2018). The precision and real-time data processing capabilities that AI brings to the financial sector are also critical in enhancing decision-making.

2.1.1 Key technologies of AI

2.1.1.1 Machine Learning

Organizations have invested heavily in AI and underlying machine learning (ML) algorithms to enhance business operations and support decision-making (Perifanis & Kitsios, 2023). Machine learning can be described as one of the pillars of AI (Joshi, 2020). According to Joshi, (2020) the learning can be based on three things: (1) Data consumption, where the algorithm learns from data to make predictions or decisions. The importance of data quality and diversity is significant since impact the learning outcomes (Joshi, 2020). Also, data preprocessing and feature selection are critical to prepare data for effective learning. (2) Loss function, an error metric to quantify the distance between the current behaviour and the desirable behaviour guiding to the optimization process. (3) Feedback Mechanism involves using error metric to adjust the model´s parameters.

Four categories exist for ML algorithms: supervised, semi-supervised, unsupervised, and reinforcement learning. Supervised learning is when an algorithm is trained on a labelled dataset (Schmidt et al., 2020). Establish relationship between the input variables and the desired result so that, in the face of new, unobserved data, the algorithm can generate accurate predictions or classifications. Unsupervised learning only has the input data to feed to the model but no corresponding output data (Raj, 2021). Both labelled and unlabelled data are used in semi-supervised learning (Harfouche et al., 2017). Algorithms that use reinforcement learning interpret results and determine the best course of action are used. The algorithm gets feedback after every action to help it decide if the decision is taken correctly.

A subset of machine learning called deep learning is built on neural networks, much like our brains, and consists of numerous connected units to build artificial nets that are capable of learning and making intelligent decisions on their own. Deep learning enables machine learning to identify patterns and draw conclusions from them that can be used to generate predictions for automation (Paschen et al., 2019). Without the need for human feature extraction, DL can automatically extract the representations required for feature detection or classification from raw data (Heaton, 2018). DL is better at tasks like image and speech recognition because it can learn complex patterns (LeCun et al., 2015). Machine learning is still very useful for situations involving small amounts of data or when more basic models will do. Therefore, the decision between ML and DL is based on the particular needs of the task at hand (Jordan & Mitchell, 2015).

2.1.1.2 Natural Language Programming

According to Liddy (2001), Natural Language Programming (NLP) is a set of computational methods that analyse and represent natural texts to achieve human-like language processing for various tasks and applications. Kreutzer & Sirrenberg, (2020), described different types of application of natural language processing: (1) Speech-to-Text – application converts the spoken words to digital text. (2) Speech-to-Speech – application converts the spoken words to another spoken language. (3) Text-to-Speech – Creates digital document text based on the spoken version. (4) Text-to-Text – Transform the written words to another language written words. Many firms consider NLP solutions are increasingly various business operations in order to reduce costs, money and human effort (Reznikov, 2023), reducing time spent on data collection tasks by 50% (Musto & Maguire, 2021). Automating routine tasks such as answering customer requests and processing transactions, accelerates response time and can also cut firm costs. Moreover, NLP applications helps in reducing human errors in data handling and responses, by delivering consistent and accurate information, minimizing the costly corrections ensuring that operations run more smoothly (Reznikov, 2023).

2.2 BI&A Systems

2.2.1 Overview of BI&A Systems

BI&A systems are more than just technological structures; they serve as the foundation for data-driven decision-making, driving organizations to new levels of operational efficiency and strategic skills (Davenport et al., 2010). From data collection tools that explore the huge digital expanse for valuable information to advanced analytical engines that produce through data, displaying previously unknown patterns, trends, and correlations (Chen et al., 2012). BI&A emerges as an essential tool for better decision-making, strategic planning, and performance improvement. It enables leaders and managers to use data to develop strategies that are simultaneously receptive to changing market dynamics and proactive in shaping future patterns (Turban, 2007). Research conducted by Blenko et al., (2010), revealed a correlation between decision effectiveness and financial performance, demonstrated the value of BI&A systems. Making decisions based on data leads to increased productivity, market value and profitability for businesses (Brynjolfsson et al., 2011).

Businesses use four types of BI&A Systems: reporting, analysis, monitoring, and prediction tools (Gauzelin & Bentz, 2017). Reporting creates documents that provide valuable information on past events. These reports provide businesses with information on their activities over a specific period. Intelligence business analysis systems provide insights into why an event happened (Gauzelin & Bentz, 2017). Business analysis helps improve business performance by collecting and analysing data for decision-makers and leaders to interpret (Gauzelin & Bentz, 2017). Monitoring is the process of constant collecting and analysing operational data to ensure that performance metrics are consistent with business objectives. Monitoring tools are intended to provide real-time insights into the operation of various aspects of a business, allowing managers and decision-makers to quickly detect any deviations from expected performance levels. Prediction tools help enabling organizations to not only visualize their current state but also to predict future trajectories with remarkable precision (Chen et al., 2012).

2.2.2 Key Technologies of BI&A

BI&A systems promotes intelligent exploration, integration, collection and multidimensional analysis of data from different resources (Yeoh & Koronios, 2010). A BI&A system must have at least four components. Data warehouses, ETL tools, OLAP techniques, and data mining (M. Olszak & Ziemba, 2007). (1) Data warehouses store organized and validated business data to support decision-making, populated from distributed and often heterogeneous databases. They are subject-oriented, time-relevant snapshots not updated to preserve historical integrity and are crucial for offline storage of business-critical data for analysis. These warehouses, central to business intelligence systems, facilitate managerial decisions through historical data analysis, improving productivity and competitive advantage (Cody et al., 2002; Hevner & March, 2003; M. Olszak & Ziemba, 2007; Negash & Gray, 2003). (2) ETL tools automate the extraction, transformation, and loading of data from various sources into a data warehouse. ETL tools are categorized based on their focus on extraction, transformation, or loading processes, facilitating data analysis and decision-making by organizing data into usable formats (Arnott & Pervan, 2015; Dayal et al., 2009; M. Olszak & Ziemba, 2007). (3) OLAP techniques enable real-time data analysis in constantly updated databases, optimizing data search through automatic SQL query generation. They allow multidimensional data analysis, enhancing managers' ability to discover hidden information across various perspectives for strategic decision-making. OLAP tools are pivotal for interactive report generation, forecasting, and exploring data from multiple angles (Hevner & March, 2003; M. Olszak & Ziemba, 2007). (4) Data mining identifies patterns, relationships, and rules within data warehouses, supporting predictive and descriptive analyses. It employs strategies like classification, prediction, and market basket analysis to align with organizational needs, aiding in decision-making. Data mining reveals insights into data, enabling organizations to predict outcomes or understand realities based on existing data patterns (Dejkam & Shahraki, 2017; Hevner & March, 2003; M. Olszak & Ziemba, 2007).

2.2.3 AI and BI&A systems integration

Supported by AI integration, BI&A is evolving from simply descriptive analytics to a robust system capable of providing prescriptive and predictive insights, promoting the increasing significance of AI and the necessity for organizations to adapt to this new era of analytical capabilities. However, this progression is accompanied by challenges, notably in data quality management. The expansion of BI&A to encompass unstructured and semi-structured data has necessitated a move from traditional data warehouses to more flexible data lakes (O'Leary, 2014). This transition emphasizes the need for effective AI implementation to manage data integration and enhance data analytics capabilities. The role of data-driven decision-making gains prominence importance of real-time data warehousing and fresh decision-support data. The direct correlation between data-driven decision-making and increased productivity, market value, establishing BI&A as an essential tool in organizational decision-making (Brynjolfsson et al., 2011). Data-driven organizations, where data serves as a forward-looking competitive advantage, demands not only effective data collection and analysis but also the strategic use of insights in decision-making processes. McAfee and Brynjolfsson highlight the management challenges in adopting a data-driven strategy and the need for leadership that embraces this change. Looking to the future, augmented analytics, as discussed by Howson, Idoine and Sallam, emerges as the next frontier in BI&A. The new domain promises to optimize data use through automation, leveraging machine learning and natural language processing to boost productivity and streamline the analytics process (Ukhalkar et al., 2021). The dynamic evolution of BI&A and AI, highlights the transformative power of technology in business, offering insights and guidance for the future of BI&A and AI in the rapidly changing landscape.

The integration of AI with BI&A Systems has become a crucial component in enhancing employee satisfaction within organizations. Professionals with new skills who can handle big data sets are in great demand (Brynjolfsson et al., 2011). Many studies have suggested that decision-making authority is distributed across different levels of organizations, instead of being focused on the top, has a positive impact on how satisfied and motivated the employees feel (Aminbeidokhti et al., 2016; Freeman et al., 1969; Schminke et al., 2002). This integration empowers employees by providing them with advanced tools and insights, enabling them to make informed decisions quickly and on their own, easy access and the ability to analyse and share the information with others (Arefin et al., 2015). Investing in BI&A and AI-powered systems can automate repetitive processes, freeing up talent to focus on strategic issues, in innovative ways, leveraging their skills, adding more value to the organization (Vidgen et al., 2017; Zohuri, 2020). Improves organizational dynamics by allowing for real-time problem solving and personalized employee support. This specific approach enhances job satisfaction by matching work to individual strengths and interests, making each employee's role more significant. It additionally promotes a culture of innovation in which contributions are valued and personal development is related to organizational goals. This strategic alignment not only streamlines processes, but it also gives the workplace a sense of purpose and achievement. In addition, a higher AI focus is positively correlated with the number of employees in a firm. AI generates jobs and boosts employee numbers (Huang & Rust, 2018; Tschang & Almirall, 2021).

Managers should prioritize customer satisfaction as a strategic goal to improve their companies' financial performance (Pancić et al., 2023). Leveraging BI&A's customer-centric capabilities improves its effectiveness and helps organizations meet market demands and identify new business opportunities. Organizations should have two BI&A processes in place: (1) Learn from mistakes and gain customer knowledge. (2) Integrate data and information from interactions to solve customer issues, improve loyalty, and meet future demands (Prairie View A&M University et al., 2019). Managers can use BI&A's customer process capability to analyse this data and effectively improve organizational performance. AI's introduction makes it even simpler to offer clients faster, more efficient services. Analysing customer behaviours and preferences, supports more effective marketing strategies. Strategies like customer segmentation, which is supported by BI&A systems, enables organizations to reduce marketing costs by targeting customers more precisely (Cooil et al., 2008; Prairie View A&M University et al., 2019). The findings predominantly reveal that the data utilized for Business Intelligence & Analytics (BI&A) is sourced internally, largely originating from established organizational systems like CRM. While explaining AI to customers can be difficult, often due to a lack of awareness that their automation needs are a request for AI solutions. Integrating AI into BI&A systems not only simplifies operations, but also significantly improves firm performance by increasing customer satisfaction. This integration enables businesses to leverage their existing data in more sophisticated ways, ensuring that customer needs are met more efficiently and effectively, resulting in significant improvements to the overall customer experience (Enehage and Khurana, 2020).

2.3 Maturity Models

Maturity implies an evolutionary progress in the demonstration of a specific ability or in the accomplishment of a target, moving from an initial, basic state to a more developed, or normally occurring end stage, often through a series of intermediate phases (Fraser et al., 2002; Paulk et al., 1993). Maturity can be defined as a combination of the presence of a process and the organization's attitude toward it (Fraser et al., 2002), and firms must always evaluate and improve their capabilities if they want to remain competitive. Maturity models are a conceptually useful tool for evaluating how effectively processes and activities are established, managed, and executed, resulting in accurate results (De Bruin, 2005; Fraser et al., 2002). According to Boughzala & De Vreede (2015), the key strengths of maturity models are (1) Simple to use and requires simple quantitative analysis; (2) They can be applied from both functional and cross-functional perspectives; (3) They provide opportunities for consensus and team building around a common language and a shared understanding and perception; (4) Can be performed by external auditors or through self-assessment. A foundational characteristic of maturity models is their ability to define multiple dimensions at varying stages of maturity while detailing performance characteristics at different levels of detail. These models typically consist of several basic components: (1) a range of maturity levels, usually between three and six, (2) specific descriptors for each level, (3) a comprehensive summary that encapsulates the attributes of each level, (4) multiple dimensions, (5) diverse elements or activities within each dimension, and (6) an explicit description of how each element or activity is executed at every maturity level. There are several uses for the maturity model across multiple technologies. The original models are based on Humphrey, (1988) Capability Maturity Model (CMM) from the Software Engineering Institute. These models provide as a method for assessing the software competencies present in businesses. The Capability Maturity Model (CMM), is one of the best-known maturity models, specifically designed to assess and enhance software capabilities in organizations. CMM has demonstrating a significant link between maturity levels and improved software quality encouraging the development of numerous other maturity models across different technologies, helping organizations to understand and improve their software process development (Boughzala & De Vreede, 2015; Harter et al., 2000). The core idea of maturity models is that performance, effectiveness, control, and predictability will improve with increasing levels of maturity (Boughzala & De Vreede, 2015).

2.3.1 Impact of BI&A Maturity Models in firm performance

Numerous studies highlight the benefits of BA and BI systems maturity, with different characteristics: dimensions, constructs, elements, indicators and process areas. Selecting a maturity model for the appropriate organization can be challenging, and the size of the organization and the areas of improvement are two important considerations when selecting the appropriate model (Keppels, 2018). The level of an organization’s BI&A implementation can be determined by considering BI&A maturity. Davenport & Harris (2007) findings, emphasis that a higher level of maturity correlates favourably with better BA outcomes for firms, shown that analytic maturity has a positive effect in decision-making (Popovič et al., 2012). Firms with greater maturity in either dimension outperform competitors in unique ways. The 25% of organizations that are more mature in both aspects, known as Digirati, outperform other firms in terms of digital innovation and enterprise-wide transformation. Digirati is 26% more profitable than their industry competitors. They produce 9% more money from employees and physical assets and they increase market valuations by 12% (Westerman, G., Tannou,M., Bonnet, D., Ferraris, P., &McAfee, A, 2012). Some research has already examined the impact of BI maturity on firm performance, showing that this adoption is positively related to in financial and non-financial perspective (Ping Teoh et al., 2014). Furthermore, BI&A maturity has a favourable impact on total BI&A success and according to Chen & Nath (2018) study's findings, larger firms have better levels of BI maturity and success than small and medium-sized organizations. Constant investment in artificial intelligence (AI) and other information technology (IT) by an organization can greatly enhance business operations by providing staff with ongoing training and expertise and will have a direct effect on the enhancement of organizational performance. The maturity of Business Intelligence and Analytics (BI&A) is not just about having sophisticated technologies but also about how these technologies are implemented and used to drive business strategies. The continuous investments in AI and analytics technologies are crucial as they provide the necessary tools that enhance employees with decision-making capabilities. Thus, BI&A is not only important to support decision-making within business processes but also for improving business processes (Wanda & Stian, 2015). Wamba-Taguimdje (2020) used 500 case studies from various international IT organizations to examine how artificial intelligence affects firm performance. They have emphasized how artificial intelligence enhances process and organizational effectiveness. Consequently, it is impossible to overestimate the moderating role that AI ambitions play in converting BI&A maturity into firm performance. As organizations become more mature in their BI&A practices, their readiness to adopt and integrate AI significantly improves, making the moderation by AI intentions to use a critical factor in achieving superior organizational performance.

Dinter (2012) developed one of the most accurate and organized BI maturity model (biMM), essential for analysing and evaluating the effectiveness and success of research initiatives, that was structured in 3 levels: (1) functionality, include aspects of the use and impact of BI in organizations, (2) technology, the system, data architecture, BI tools along with their related functionality, (3) organizational dimension, describing distinct organizational structures, procedures, profitability, and company´s BI strategies. The original research conducted in 2004 by Steria Mummert Consulting in collaboration with universities served as the foundation for this model, with five stages of BI maturity: (1) individual information, isolated and uncoordinated data queries with high manual effort and no systematic BI methodologies or structures; (2) information islands, beginning data consolidation and department-wide coordination with dedicated but heterogeneous BI tools that improve availability and automation to some extent; (3) information integration, enterprise-wide BI solutions with standardized data and a central data warehouse supported by organizational structures; (4) information intelligence, widespread analytical information availability and advanced analytics with mature BI processes and structures; and (5) enterprise information management, fully integrated analytical and operational systems, establishing BI as essential for corporate management (Dinter, 2012). Bach et al., (2022) proposed a reduced Dinter (2012) biMM with only ten questions, assuming the measurement tool has all the necessary maturity components included. The questions address the following topics: (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 technical architecture maturity, (5) the level of data management maturity, (6) type of BI tools used within the organization, (7) organizational structure related to BI, (8) the level of BI processes maturity, (9) the level of BI profitability assessment and (10) BI strategy. The results of Bach´s research, clearly shows that, comparing to lower performers, firms classified as high performers tend to have more mature BI, demonstrating the positive relationship between organizational success and BI maturity (Bach et al., 2022).

2.4 UTAUT ACCEPTANCE MODEL

Regarding generic technology acceptance models, one of the most widely used frameworks is the Unified Theory of Acceptance and Use of Technology (UTAUT) by Venkatesh et al., (2003). It seeks to advance usage behaviour and explain user intentions to utilize an information system, much as previous acceptance models, giving a complete picture of the acceptance process than was possible with any previous individual models. A unified model was created based on the conceptual and empirical similarities across eight models: Theory of Reasoned Action (Fishbein & Ajzen, 1975) Technology Acceptance Model (Davis, 1989), Motivational Model (Davis et al., 1992), Theory of Planned Behaviour (Ajzen, 1991), Combined TAM and TPB (Taylor & Todd, 1995), Model of PC Utilization (MPCU) (Thompson et al., 1991), Innovation Diffusion Theory (Moore & Benbasat, 1991), and Social Cognitive Theory (Compeau et al., 1999). Technology acceptance theories and models have examined how people behave and how accepting they are of new technology based on certain components and variables. These theories have been placed on the psychological and behavioural perspectives of technology users. According to the theory, usage intention and behaviour are directly influenced by four major constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003). In addition, UTAUT also posits the role of four key moderator variables: gender, age, experience and voluntariness of use (Venkatesh et al., 2003).

2.4.1 Previous UTAUT in Artificial Intelligence

The application of the UTAUT model has been investigated in a variety of modern technological situations involving AI. Gursoy (2019) used the UTAUT model to assess consumers' capacity to interact with AI-powered devices. Their research identified that factors such as social influence, hedonic motivation, and anthropomorphism significantly contribute to shaping performance expectancy and effort expectancy. These factors influence emotional responses and, as a result, the willingness to accept AI technologies. Grover et al., (2020) argues that numerous factors, including societal components and supportive environments, have influenced AI integration in operations management. Furthermore, Chatterjee et al., (2023) investigated the use of AI in customer relationship management systems in Indian organizations, supporting the model's core concepts as well as other external variables linked to customer management. Also, Chatterjee & Bhattacharjee, (2020) explored AI adoption in higher education, discovering that perceived dangers, facilitating environments, and effort expectancy all play important roles in determining attitudes and intentions toward AI use in this sector. Cao et al., (2021) built on this concept, creating a comprehensive AI acceptance-avoidance model that identifies both positive and negative elements impacting management attitudes and behaviours toward AI adoption. The research also acknowledges the adverse effects of technology on user acceptability and behaviour, as highlighted by Agogo & Hess, (2018) and Vimalkumar et al., (2021).

2.5 ORGANIZATIONAL CULTURE

Organizational culture is described by many authors using a range of criteria, including observed behavioural regularities, social norms, values, philosophy, environment, shared meanings, formal rituals, and celebrations (Schein, 2004). According to Xu et al., (2012), organizational culture refers to the common values and assumptions that drive an organization's actions and priorities. Organizational Culture is pivotal in determining the organization's readiness for technological changes and can have a positive influence on performance (Warrick, 2017). Previous studies indicate that organizational culture is more successful than organizational strategy and structure and has a substantial impact on financial performance (Hogan & Coote, 2014). Denison & Mishra (1995) highlights that firms may significantly impact their overall stability and performance by keeping a clear and simple objective. This theory is based on observations that the most significant problems in organizations frequently occur when their core objectives are questioned or changed, leading to a loss of focus and eventually has a negative impact on effectiveness. While some researches has often focused on the technical aspects of AI or its adoption (Collins et al., 2021), where organizational culture is merely mentioned as one of several factors for successful AI implementation. Bley et al., (2022) findings show that organizational culture positively influences AI capabilities and consequently, enhances firm performance, revealing an indirect positive effect of organizational culture on firm performance.

Sashkin & Rosenbach (1996) created the human resource Organizational Culture Assessment Questionnaire (OCAQ) based on the work of Talcott Parsons. Parsons (1960) created a theory of action and a framework for social systems. He believed that for any firm to remain successful for a significant period, it must perform four essentials' tasks: (1) Managing change, the rate to which participants perceive the organization's ability to effectively adapt to and manage change; (2) Achieving goals, describe how effective the organization is in achieving goals (Kriemadis et al., 2012); (3) Coordinating teamwork, how well people's work is connected, organized, and sequenced inside the business to ensure that their individual and group efforts complement one another (Sashkin & Rosenbach, 1996); (4) Build a strong culture, the pattern of values and beliefs shared by some, most, or all of the organization's members (Sashkin & Rosenbach, 1996). Based on these organizational cultural dimensions, firms can effectively evaluate and enhance their internal dynamics offering a comprehensive approach to assessing how well an organization enhance a productive and cohesive work environment, ensuring long-term success.

3. RESEARCH MODEL AND HYPOTHESES

The research model of the current study was developed based on three main models, by merging the relevant aspects of both and applying them in the context of understanding the influence of intention to use AI in BI&A maturity and firm performance. A combination of the unified theory of acceptance and use of technology (UTAUT) constructs with Suša Vugec et al., (2020) model was used. Age, gender, experience and voluntariness of use are part of UTAUT model (Venkatesh et al., 2003), but, they will not be used in this work, assuming that these are moderations already well studied in literature (Fetaji, 2023). For the BI&A maturity measurement we used Dinter, (2012) Business Intelligence maturity model (biMM). Initially, we integrate Business Intelligence (BI) with Business Analytics (BA) systems, merging these traditionally areas into a unified framework, then we focus our analysis on identifying and evaluating six dimensions of Dinter´s model: (1) The scope of BI&A systems use, (2) The level of data architecture maturity, (3) The impact of BI&A systems, (4) The organization structure related to BI&A systems, (5) The level of maturity of BI&A systems processes, (6) The level of BI&A systems strategy. To develop the organizational culture construct, we combine the research of Sashkin & Rosenbach (1996) and Denison & Mishra (1995). Based on Sashkin & Rosenbach (1996) the two dimensions approached were: (1) Achieving goals, (2) Managing Change. The aspects of defining a meaningful long-term direction for the organization were also addressed, drawing on the contributions of Denison & Mishra (1995). The five of the ten characteristics of firm performance dimensions described by Mikalef et al., (2019) were used to measure firm performance. These dimensions address many non-financial dimensions in addition to the financial ones. It included five statements that evaluated the following items: (1) Profitability of the company, (2) Response to Market Demand, (3) Customer Satisfaction, (4) Service Quality, (5) Reducing Operating Costs.

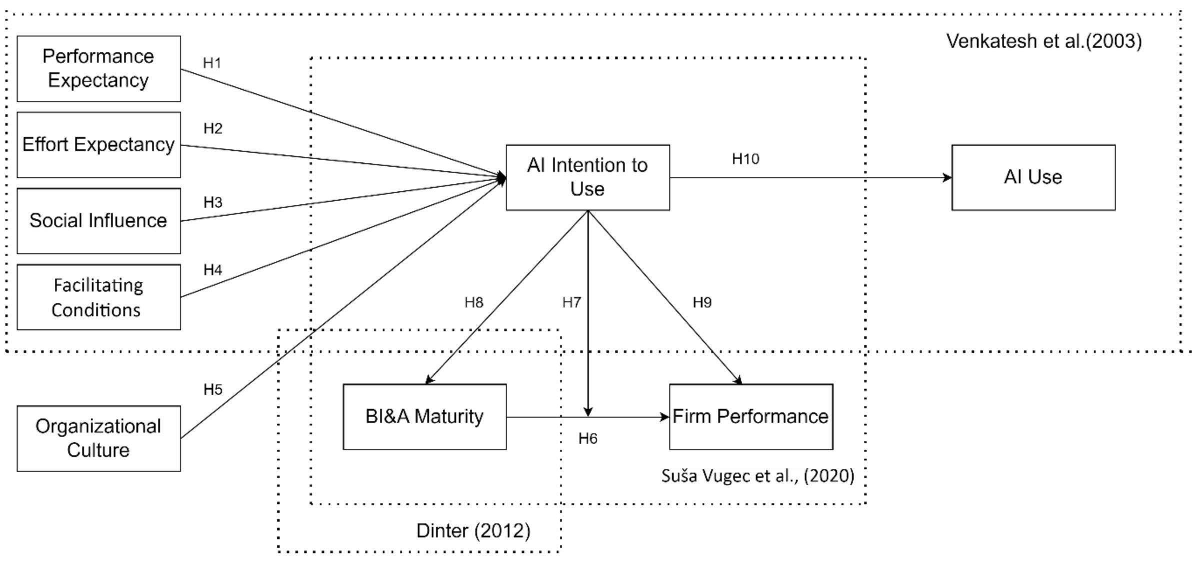

Figure 1 – Research model

Performance expectancy is defined as the degree to which an individual believes that using the system will help to attain gains in job performance (Venkatesh et al., 2003). Shin (2009) identified three primary elements that significantly influence performance expectancy: (1) including perceived usefulness, which refers to the degree to which an individual believes that using a system will enhance their job performance; (2) extrinsic incentives, the rewards or benefits received from using the system; (3) job fit, referring to how effectively the system aligns with requirements of specific roles. Performance expectancy was found to be the most significant predictor of intention to adopt the target technology in all studied models, emphasizing the need of corresponding technology with user needs, with AI adoption rates (Fridin & Belokopytov, 2014). Therefore, we hypothesize:

Hypothesis 1: *Performance expectancy positively influences AI intention to use.*

Users usually evaluate the effort required to operate an information system before using it. Effort expectancy is defined as the degree of ease associated with the use of the system (Venkatesh et al., 2003), and users are more likely to adopt technology that is easily accessible (Davis, 1989). The constructs focusing on effort are crucial for adopting new behaviours and new initiatives (Davis, 1989). By simplifying the initial interaction with AI technologies, is possible that user will be the positively attracted to adopt the technology (Mensah & Khan, 2024). As a result, we hypothesize:

Hypothesis 2*: Effort expectancy positively influences AI intention to use.*

In UTAUT, social influence is defined as the degree to which an individual feels that it is important for others to believe he or she should use the new system (Venkatesh et al., 2003). Peers, supervisors, and management made up the social influence environment, and its impact on the adoption of AI-enabled solutions in firms (Jain et al., 2022). In addition, Raza et al., (2021) research highlights the positive influence in social influence on Learning Management System among students and Im et al., (2011) also demonstrated the positive significance in Business Intelligence. Therefore, we hypothesize:

Hypothesis 3*: Social influence has significant influence on AI intention to use.*

Facilitating condition is defined as the degree to which an individual believes that organizational and technical infrastructure exists to support use of the system (Venkatesh et al., 2003). The facilitating condition construct aligns with the compatibility construct from perceived characteristics of innovation, which includes items that assess the fit between an individual's work style and the system used in the organization (Riemenschneider et al., 2002). There are some other studies that found facilitating conditions a good construct to predict the usage of AI integrated customer relationship management (CRM) systems (Chatterjee et al., 2021) and the research of Dwivedi et al., (2019) in demonstrating the adoption and use of advancements in information technology (IT) and information systems (IS). Therefore, we hypothesize:

Hypothesis 4: *Facilitating conditions has a positive impact on AI intention to use.*

Based on previous studies that incorporate as an item construct of the UTAUT model to framework, organizational culture proves to be a good predictor of technology adoption. Dasgupta & Gupta, (2013) demonstrated how organizational culture influences the adoption of Internet technology, increasing the capacity for innovation for successful technology adoption. The use of such technologies frequently necessitates major changes to workflows, procedures and sometimes even organizational structure. Mahara et al., (2021) found that during the COVID-19 pandemic, organizational culture played an important factor in showing the intentions of faculties to adopt a virtual classroom. Given that, this study aims to investigate assess the ambition of organizational goals, evaluates if the organization has a clear strategic vision and how supports and values employee input and how this affects their adoption of new technologies, we hypothesize:

Hypothesis 5: *Organizational culture positively influences AI intention to use.*

Some researchers found a positive relationship between BI&A and firm performance (Ahmad & Akbar, 2021; Božič & Dimovski, 2019). Firms with higher maturity of BI&A systems have more facilitating usage of the technology and can be used with more effectiveness across various sectors (Divatia et al., 2021). To achieve that the continuous investments on training can lead to a higher level of BI&A systems usage (Antoniou et al., 2015). The maturity of BI&A systems, is influenced by AI in enhancing the decision-making capabilities and accuracy (Emmanuel Osamuyimen Eboigbe et al., 2023). Enehage and Khurana, (2020) highlights the AI crucial work in adding value to BI&A, with data management and quality improvement, the potential to streamline processes and accelerate insights within BI&A. In addition, AI use can lead to a performance improvement in financial, administrative and marketing sectors (Wamba-Taguimdje et al., 2020), and the possibility to adjust rapidly to market changes (Sullivan & Fosso Wamba, 2024). Building on literature review insights, we hypothesize:

Hypothesis 6: *BI&A maturity positively influences firm performance.*
Hypothesis 7: *The impact of BI&A maturity on firm performance is positive and moderated by the AI intention to use.*
Hypothesis 8: *AI intention to use positively influences BI&A maturity.*
Hypothesis 9*: AI intention to use positively influences firm performance.*

The current research that intention to use AI technology have an important impact in actual usage within organizational settings. Previous research has underscored the importance of user intention in determining the adoption and integration of new technologies (Isaac et al., 2019; Venkatesh, 2021). It has been observer that when employees intend to use AI-enabled tools, there is an increase in the frequency and effectiveness of their actual utilization in daily operations (Chatterjee et al., 2021; Makarius et al., 2020). Moreover, the intent to engage with AI technologies is often shaped by the perceived benefits these tools bring to task management and organizational communication, suggesting a direct link between the intention to use AI and its practical application (Montesdioca & Maçada, 2015; Raza et al., 2021). Therefore, we hypothesize:

Hypothesis 10: *AI intention to use positively influence AI use.*

4. DATA COLLECTION

A questionnaire remains one of the most popular approach in business research (Bryman, 2012; Slevitch, 2011; Yin, 2009). For the data collection purpose, an English language questionnaire was created. The questionnaire (**Appendix B - Survey**) contains six phases: (1) UTAUT data constructs, adapted from (Venkatesh et al., 2003); (2) Organizational Culture questions, from the Sashkin & Rosenbach (1996) Organizational Culture Assessment Questionnaire (OCAQ); (3) Firm performance questions, based on Mikalef & Gupta (2021) dimensions; (4) BI&A Maturity measurements based in Dinter, (2012), (5) AI Use from Im et al., (2011), and (6) Demographic characteristics. For measuring each item, a seven-point Likert scale was used, which is intended to quantify different levels of agreement or disagreement, with ranges from "Strongly Disagree" (1) to "Strongly Agree" (7). The BI&A maturity is measured with two opposing statements (A and B) for each stated item, where (1) means strong agreement with statement A, and 7 strong agreement with statement B, according to what is presented in **Appendix A - BI&A maturity measures.** For AI use construct, Im et al., (2011) measures with a 9-point Linkert scale was used, from "Have not used" (1) to "Almost every day" (9). For demographic data such as age, it was measured qualitatively, using age intervals. The level of education was also measured qualitatively, and gender was coded using "0" for women and "1" for men. The questionnaire was translated to Portuguese, submitted to a local academic to review it and correct whenever necessary according to local speech characteristics, and translated back again to English, by others, to validate the translation and ensure consistency. The survey request, with the Portuguese and English versions, was sent to through the LinkedIn network, targeting adults that professionally work with and are in daily contact with Business Intelligence & Analytics (BI&A) systems, that may have a potential also for contacting with Artificial Intelligence technologies within firms.

The relevant target population of the research includes various levels of the organization, such a Data Analysts, Data Scientists, Business Analysts, BI Developers, Project Managers, Data Engineers, Machine Learning Engineers, IT Managers and Chief Technology Officers. Participants participated voluntarily and anonymously. A total of 1057 messages invitations to participate in the survey were sent, obtaining a final response rate of 18.92%. After checking the responses, 54 questionnaires were found with missing information and, thus, were discarded from the survey, leaving us a total of 146 valid responses at the end. In quantitative research, where surveys are used as the primary data collection tool and lead to a smaller total number of participants, missing data is a regular occurrence (Allison, 2002). Respondents may choose not to answer survey questions that they believe to be sensitive or may fail to notice questions because of human error (Allison, 2002).

The profile of the responders is represented in **Appendix E - Respondents characteristics**. The gender distribution of the participants was predominantly male, accounting for approximately 60.3%. In terms of age, the largest age group among respondents was the 18-25 category, representing 54.1% of the sample. Educationally, the respondents were highly qualified, with those holding a master's degree constituting the largest educational group at 50%. Bachelor's degree holders were also well represented, making up 40.4% of the participants.

The common method bias (CMB) was also evaluated. CMB is caused by the fact that the constructs are measured by the same methods (e.g., multiple item scales in the same questionnaire), which might result in spurious effect because of measurement instruments (Kamakura, 2010). To address this, the Harman's Single Factor Test was applied using SPSS, with the total variance explained at 27.86%, which is below the threshold of 50% as required (Podsakoff et al., 2003). Additionally, the random dependent variable approach was tested and passed, with a VIF less than 5 (Hair et al., 2017; Kock et al., 2012).

5. RESULTS

Structural equation modelling (SEM) technique was used to test our theoretical model (Ringle et al., 2005). This is a statistical technique that focuses on confirmatory analysis, used to test hypotheses about the structural relationships to explain particular events, crucial for validating theoretical models (Kline, 2005). SEM approach supports the interrelationships among all constructs at the same time, it is possible to derive the direct, indirect, and total effects of the independent variables on the dependent variables as well as test a variety of complex variable relationships in the model. In detail, Partial least square (PLS), a variance-based technique was used, with Smart PLS v4 to test the research model (Ringle et al., 2005). PLS was considered appropriated for our study, because: (1) Handling complex models efficiently even with small sample sizes (Hair et al., 2017) ; (2) The dimension of our sample is ten times more than the greatest number of arrows pointing to a construct (Gefen & Straub, 2005); (3) allows estimations in complex models, with many constructs and indicator variables (Hair et al., 2017); (4) Does not require data to meet the distributional assumptions needed for factor-based SEM, making it suitable for data that do not meet normality requirements (Chou et al., 1991). Is also important to mention that for the initial UTAUT model, Venkatesh et al., (2003) used the PLS approach. Our analysis was done in two different steps following Anderson & Gerbing (1988). First, we assess the reliability and validity of the measures, then we assess the structural relationships of the model.

5.1 MEASUREMENT MODEL

The results of the construct reliability, internal consistency, convergence validity, and discriminant validity assessment are presented in **Table 1**. For the items reliability assessment, the factor loadings a good level of reliability, above the threshold value of 0.7 (Hair et al., 2017), identified as best practice. To ensure reliability, FC3, FC4, OC1, PE4, SI3, and SI4 items were removed from the measurement model due to low factor loadings. To ensure internal consistency, FC1 and AU2 were removed because they didn't achieve the minimum acceptable value does of 0.7 for the composite reliability and Cronbach's Alpha (Hair et al., 2017). After that, the average variance extracted (AVE) test was used to assess the convergent validity. All the remaining constructs compared favourably to the minimum acceptable value of 0.50 (Fornell & Larcker, 1981), that is, each construct covers over half of the variation in its indicators (Hair et al., 2019).

Table 1 - Quality criteria and factor loadings

Construct	AVE	Composite Reliability	Cronbach´s Alpha	Item	Loadings	t-value
Performance expectancy (PE)	0.764	0.907	0.847	PE1	0.851	34.063
				PE2	0.893	23.947
				PE3	0.878	23.622
Effort expectancy (EE)	0.735	0.917	0.879	EE1	0.790	19.591
				EE2	0.873	33.285
				EE3	0.872	21.492
				EE4	0.889	39.133
Social influence (SI)	0.903	0.949	0.893	SI1	0.956	102.528
				SI2	0.945	61.315
Organizational culture (OC)	0.803	0.891	0.755	OC2	0.893	18.034
				OC3	0.899	16.360
AI intention to use (AI)	0.906	0.951	0.896	AI1	0.953	58.836
				AI2	0.951	56.405
BI&A maturity (BIA)	0.736	0.944	0.928	BIA1	0.822	22.281
				BIA2	0.818	21.562
				BIA3	0.877	28.126
				BIA4	0.919	47.626
				BIA5	0.855	24.454
				BIA6	0.853	30.722
Firm performance (FP)	0.706	0.923	0.895	FP1	0.821	21.271
				FP2	0.803	12.477
				FP3	0.864	35.988
				FP4	0.922	64.926
				FP5	0.784	15.459

To assess the discriminant validity, three measure were used. First, we analysed the Fornell-Larcker criterion, whether the square root of AVE is greater than the correlations between the constructs (Fornell & Larcker, 1981), as presented in **Table 2**. Second, we examined if the loading of each indicator is higher than all cross-loadings (Götz et al., 2009) represented in (**Appendix C - Cross-Loadings**).Third, the heterotrait-monotrait ratio of correlations (HTMT) was assessed, (**Appendix D - Heterotrait-monotrait ratio of correlations**) getting lower than 0.9 (Henseler et al., 2015). All these tests were conducted and successfully passed, the discriminant validity confirmed, ensuring that the constructs can be used to test the structural model.

Table 2 - Correlation matrix

	AI	AU	BIA	EE	FC	FP	OC	PE	SI
AI intention to use (AI)	**0.959**								
AI use (AU)	0,742	**NA**							
BI&A Maturity (BIA)	0,295	0,313	**0,858**						
Effort expectancy (EE)	0,417	0,376	0,118	**0,857**					
Facilitating conditions (FC)	0,509	0,409	0,099	0,552	**NA**				
Firm Performance (FP)	0,210	0,181	0,491	0,145	0,147	**0,840**			
Organizational culture (OC)	0,278	0,222	0,512	0,121	0,119	0,459	**0.896**		
Performance expectancy (PE)	0,549	0,430	0,147	0,512	0,294	0,108	0,305	**0,874**	
Social influence (SI)	0,435	0,328	0,059	0,455	0,261	0,086	0,102	0,506	**0,950**

5.2 STRUCTURAL MODEL AND HYPOTHESES TESTING

Since the constructs' reliability, indicator reliability, convergent validity, and discriminant validity were all acceptable, the variance inflation factor (VIF) was used to evaluate the structural model's collinearity between the constructs (**Appendix F - Collinearity statistics (VIF)**). All values, except for AI3 item were below 5 and met the criterion for avoiding collinearity (Hair et al., 2017). Collinearity exists whenever an independent variable is highly correlated with one or more of the other independent variables in a multiple regression equation (Allen, 1997). Consequently, AI3 was removed from the analysis.

The hypotheses were tested by estimating the path coefficients, using the bootstrapping method with 5,000 subsamples. **Figure 2** presents and highlights the findings.

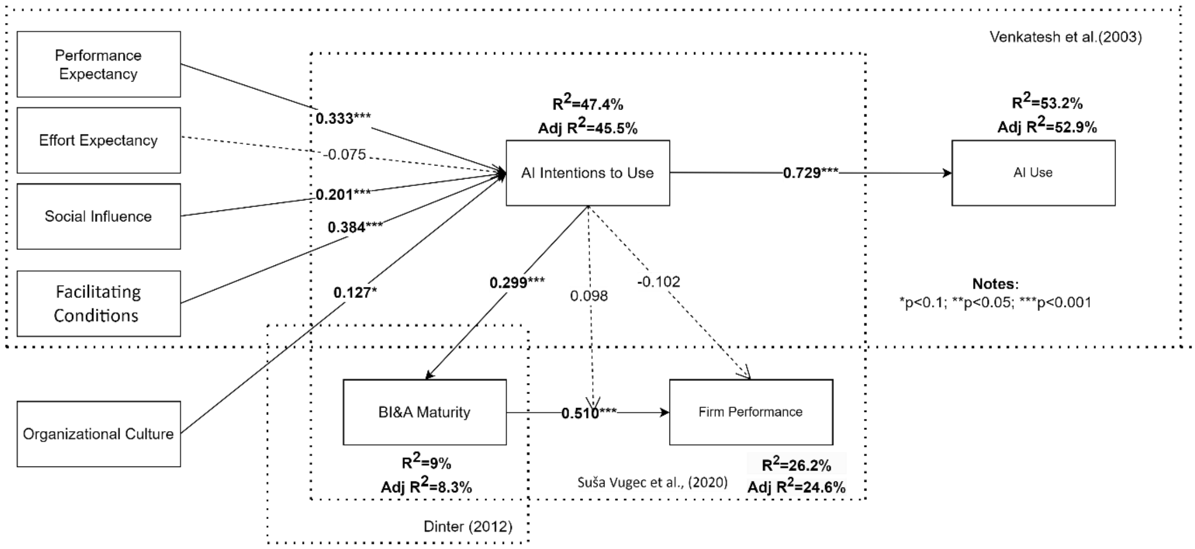

Figure 2 – Structural model results

(*p<0.10; **p<0.05; ***p<0.01)

Based on model´s results, the adjusted coefficient of determination (R^2) was used to assess the model's predictive power. Adjusted R^2 is a more accurate measure of the model's true explanatory power, especially when many predictors exist (Leach & Henson, 2007). The model explains 45.5% of the adjusted variation in AI intention to use and 52.9% in the adjusted AI Use. The items performance expectancy ($\hat{\beta}$ = 0.333; p < 0.01), social influence ($\hat{\beta}$ = 0.201; p < 0.05), organizational culture ($\hat{\beta}$ = 0.127; p < 0.1) and facilitating conditions ($\hat{\beta}$ =0.384; p<0.01) were found to be statistically significant in explaining AI intention to use, thus confirming hypotheses H1,H3,H4 and H5 respectively. Effort expectancy was not found statistically significant. In terms of AI use, AI intention to Use ($\hat{\beta}$ = 0.729; p < 0.01) was found to be significant predictor, confirming the hypothesis H10. For firm performance, BI&A maturity ($\hat{\beta}$ = 0.510; p < 0. 01) shows a substantial and significant impact, and the direct effect of AI intention to use on BI&A maturity ($\hat{\beta}$ = 0.299; p < 0.05) is also significant. The moderation effect of AI intention to use over the relationship between BI&A maturity and firm performance, was also not found statistically significant. The model also explains 9% of the adjusted variance in BI&A maturity and 26.2% in firm performance.

Table 3 - Hypotheses outcomes

Hypothesis	Independent variable	→	Dependent variable	Findings	Conclusions
H1	Performance expectancy	→	AI intention to use	Positive and statistically significant ($\hat{\beta}$ =0.333; p<0.01).	**Supported**
H2	Effort expectancy	→	AI intention to use	Non-significant effect.	**Not supported**
H3	Social influence	→	AI intention to use	Positive and statistically significant ($\hat{\beta}$ =0.201; p<0.01).	**Supported**
H4	Facilitating conditions	→	AI intention to use	Positive and statistically significant ($\hat{\beta}$ =0.384; p<0.01).	**Supported**
H5	Organizational culture	→	AI intention to use	Positive and statistically significant ($\hat{\beta}$ =0.127; p<0.1).	**Supported**
H6	BI&A maturity	→	Firm performance	Positive and statistically significant ($\hat{\beta}$ =0.510; p<0.01).	**Supported**
H7	AI intention to use x BI&A maturity	→	Firm performance	Non-significant effect.	**Not supported**
H8	AI intention to use	→	BI&A maturity to use	Positive and statistically significant ($\hat{\beta}$ =0.299; p<0.01).	**Supported**
H9	AI intention to use	→	Firm performance	Non-significant effect.	**Not supported**
H10	AI intention to use	→	AI use	Positive and statistically significant ($\hat{\beta}$ =0.729; p<0.01).	**Supported**

6. DISCUSSION

The results of our study contribute to the understanding of the influence of AI intention to use on BI&A maturity and firm performance. The research model explains 45.5% of the variation of AI intention to use, less than the 57.1 % of Norzelan et al., (2024) research, and according to our findings, we suggest that performance expectancy, social influence, and organizational culture are the most important factors. The model also explains 52.9% in AI Use., a higher than the 39% of Elkhatibi et al., (2024).

This study includes ten hypotheses, of which seven (H1,H3,H4,H5,H6,H9,H10) were supported, while the remaining were rejected, confirming our model strong explanatory capacity. The following discussion provides an explanation of the results based on empirical observations. Our findings suggest that performance expectancy, social influence, facilitating conditions and organizational culture significantly affect AI intention to use. In line with our hypotheses, facilitating conditions emerged as a strong predictor of AI intention to use (Venkatesh et al., 2003). Consistent with Fridin & Belokopytov, (2014) and Venkatesh et al., (2003) findings, performance expectancy is a critical determinant of new technology acceptance. Even in some research, this is the only UTAUT dimension that has a substantial effect on behavioural intention (BI) (Oliveira et al., 2014). Similar results were reported by Chatterjee et al., (2023) and Chatterjee & Bhattacharjee, 2020), reinforcing that an higher performance expectancy enhances the intention to use AI technologies. Contrary to the hypothesized association, effort expectancy did not show a significant impact on AI intention to use. This contradicts the claims of (Davis, 1989; Dwivedi et al., 2019; Venkatesh et al., 2003), suggesting effort expectancy as a key factor on technology acceptance behaviour. Previous research conducted by Fitrianie et al., (2021), explored the acceptance of a mobile cognitive behavioural therapy app and demonstrated that effort expectancy did not give any significant impact on intentions to adopt the app. Similarly, research by Wang et al., (2024) examining e-learning systems found that effort expectancy was also not associated with pre-service teachers' behavioural intention of using GenAI-Assisted teaching, contrasting with the general technology adoption models. In our study, effort expectancy was found to have a negative and non-significant path coefficient concerning AI usage intention. This suggests that users perceive AI technologies as difficult to understand or use, which can create a barrier to adoption. As a result, users may prefer simpler and more familiar technologies. According to social influence (SI), affects positively AI intention to use, contradicting studies such as Andrews et al., (2021) and Cao et al., (2021). However, in our study, social influences appear as the second strongest factor. This might be because of the contextual nature of the study that we conducted for this research. In our case, social influence may be even higher since these technologies are relatively new in organizational context. Therefore, ideas supported in firms by superiors and colleagues could be very helpful in the process of encouraging the adoption. The significance of social influence in the acceptance and use of new technology is highlighted by other research that have been presented (Baptista & Oliveira, 2016; Jain et al., 2022). Organizational culture positively and significantly influences AI intention to use, confirming the crucial role that a supportive and innovative organizational environment can have on the adoption and utilization of AI technologies (Bley et al., 2022). In line with Dasgupta & Gupta, (2013) findings, a culture that promote adaptability and clear objectives, enhances the intention of using new technologies. A firm with long-term purpose and direction, are better able to integrate and leverage AI.

The results also support the claims of Venkatesh et al., (2003), that users are more likely to use AI if they have the intention to use it. Consist with the conclusions of Enehage and Khurana, (2020), that organizations with a strong intention to adopt AI are more likely to develop mature BI&A practices. The potential of AI in managing large volumes of both unstructured and structured data, can lead to more efficient use of BI&A. This efficiency can be AI adoption are better positioned explained from the AI´s ability of data processing and automate complex tasks. Thus, organizations that prioritize AI adoption, are better placed to achieve higher levels of BI&A maturity. As expected, the impact of BI&A maturity on firm performance was found to be significant, in accordance with numerous studies (Chen & Nath, 2018; Wamba-Taguimdje et al., 2020). The significant impact of BI&A maturity on firm performance can be explained by several factors. Firstly, mature BI&A systems enhance decision-making capabilities by providing accurate and actionable insights (Davenport & Harris, 2007; Popovič et al., 2012). Then the organizational maturity of using BI&A systems, immediate financial gains, customer satisfaction, operational efficiency and innovation capacity (Ping Teoh et al., 2014). Contrary to our expectations and previous studies, AI intention to use do not directly contribute to firm performance, and even found to be a negative association. The negative coefficient might introduce several factors that might explain this outcome. The intention to use AI is not always related to effective implementation and utilization, and firms may have face such as high costs who might not to be seen an immediate return on investment, less skilful employees that need time to understand and effectively utilize AI technologies, and some integration issues with the current firm systems (Agarwall et al., 2022). Consequently, the moderate effect of AI intention to use in BI&A maturity to impact the firm performance was not found significant.

7. IMPLICATIONS FOR RESEARCH AND PRACTICE

The findings from this study provides a comprehensive framework for understanding the influence of Artificial Intelligence (AI) usage on the maturity of Business Intelligence and Analytics systems (BI&A) and their impact on organizational performance. By applying the Venkatesh et al., (2003) famous UTAUT model alongside Suša Vugec et al., (2020) model, and an organizational culture construct this research delivers valuable insights that can serve as a basis for further refinement of combining technology adoption and maturity models. Instead, it highlights the role of organizational culture, performance expectancy, facilitating conditions and social influence, supporting previous theories by confirming the valuable importance of performance expectancy in explaining the adoption of the technologies (Oliveira et al., 2014). Although the UTAUT model has been used for many researchers to study the behaviour intention of using different technologies, it may need to be adapted or extended to address specific and relevant factors in various contexts (Fetaji, 2023). Factors such as organizational culture enhance the importance of predicting and study technology acceptance in diverse firm sectors (Silic & Back, 2013). Additionally, the potential for combining AI with the maturity of different technologies used in different firm contexts, provide a deeper understanding of how a technology adoption impacts firm performance and how these effects are moderated by the intention to use AI. Into future research, a comprehensive interaction insight between technology adoption, maturity and firm outcomes can be achieved.

For the practitioners, this research provides support and direction for organizations to integrate AI technologies effectively within their BI&A systems to enhance firm performance. The importance of a supportive organizational culture should not be minimized, since plays a crucial role in shaping the perspectives towards AI adoption. The focus goes to promote an innovation environment, with continuous learning of new technologies, and a long-term direction defined for the future. This will lead to a successful implementation of AI technologies, but also will reduce the employee's barriers for acceptance and utilization of that technology. It is also important to underline that the benefits of AI be proven to employees, creating an improving environment, communicating and motivating them to use it. Moreover, businesses should engage in AI projects to improve the maturity of BI&A systems and prioritize strong intention to utilize AI among employees through training programs and effective AI implementations. Mature BI&A systems improve decision-making capabilities, and an investment in maintaining high levels of BI&A maturity should be for better performance (Popovič et al., 2012).

8. LIMITATIONS AND FUTURE RESEARCH

There are some limitations in the study. First, the generalizability of the results is limited by the relatively small sample size. A larger data sample could eventually provide stronger results. Our research also focuses on firm employees, mostly from Portugal, from a various spectrum of companies with varying levels of technological maturity, and a vast range of job roles. In a future study it may be recommended to focus on a certain job role, take into account a more diverse range of industries, the size of each firm, previous study to the firm resources and possibilities to invest in AI tools (Mikalef & Gupta, 2021), and even try to reach different countries and cultures (Jain et al., 2022). The quantitative research method used is a good approach, but if could have used mixed-methods like qualitative interviews to access the BI&A maturity levels, different results could have been obtained (Agarwall et al., 2022). For understanding and exploring BI&A maturity and AI effect in firm performance in future studies, we suggest using key performance indicators, instead of dimensions to measure the performance, to allow a more precise understanding of organizational outcomes. Indicators like profitability performance, market value performance, growth performance, employee satisfaction, customer satisfaction, environmental performance and social performance could also provide additional insights. Due to the lack of longitudinal data, we cannot confirm the long-term effect of AI adoption on BI&A maturity and firm performance, so we suggest long-term research to evaluate these relationships and potential benefits. Our methodological framework, which combines the Unified Theory of Acceptance and Use of Technology (UTAUT) with Suša Vugec model and Dinter's maturity model, may not capture all the factors influencing AI adoption and BI&A maturity. Specifically, choosing the right maturity model can be difficult, due to the lack of documentation and the validation of these models (Dahlgren & Nilsson, 2019). For future work we suggest testing and developing a BI&A maturity model combining both the characteristics of Business Intelligence (BI) and Business Analytics (BA), without the need to generalize the qualities of both. If we had used a model that inherently addressed these two technologies, we probably would have achieved different results. Additionally, we recommend expanding the UTAUT model part, since it, in the current format, may not capture all the specific factors that may influence AI intention to use. According to some authors, the original UTAUT model needs to be a renovated to better address modern technologies like AI, since some constructs like social influence, may differ significantly in environments mediated by AI compared to traditional technology interactions (Fetaji, 2023). We identify user trust, adaptability, ethical considerations and reliability an interesting construct to be also tested, in future studies. Finally, the influence of organizational culture on these variables may have more importance than our models capture, and a direct effect on BI&A maturity should also be examined.

.

9. CONCLUSION

The accumulation and accessibility of data in recent years, requires an effective data management and a utilization of new strategies for gain meaning to improving firm performance. The emergence of Artificial Intelligence (AI) and the expansion of Business Intelligence and Analytics (BI&A) systems, represent a new era in organizational strategy and performance. Also, the rapid growth of AI in the last decade, promises a revolution in both living and working environments. This study provides an empirically validated integrated model for understanding the influence of Artificial Intelligence (AI) usage on the maturity of Business Intelligence and Analytics (BI&A) systems and their impact on organizational performance. Our findings reveal insights into how AI influences BI&A maturity and firm performance, namely they indicate that the performance expectancy, social influence, facilitating conditions and organizational culture are strong predictors of the intention to use AI. The study also highlights the importance of organizational culture role in adoption of AI technologies and tools. BI&A maturity has a direct impact on firm performance, underscoring the importance of investing in mature BI&A systems at firm level, to achieve faster decision-making, efficiency and effectiveness. For researchers, this study combines technology adoption model and maturity frameworks, offering a basis for future investigations between AI, maturity and firm performance. For practitioners, a strategic approach to AI integration underscores the importance of investments in AI and BI&A systems, enhance a supportive cultural environment, and ensure that these technologies are aligned with firm strategic plans.

BIBLIOGRAPHICAL REFERENCES

Agarwall, H., Das, C. P., & Swain, R. K. (2022). *Does Artificial Intelligence Influence the Operational Performance of Companies? A Study:* 2nd International Conference on Sustainability and Equity (ICSE-2021), Bhubaneswar, India. https://doi.org/10.2991/ahsseh.k.220105.008

Agogo, D., & Hess, T. J. (2018). "How does tech make you feel?" a review and examination of negative affective responses to technology use. *European Journal of Information Systems*, *27*(5), 570–599. https://doi.org/10.1080/0960085X.2018.1435230

Ahmad, T., & Akbar, A. (2021). Role of Information System Strategies, Business Intelligence and Analytics used to Enhance Firm Performance: Mediating role of Innovation Ambidexterity. *Journal of Digitovation and Information System*, *1*(2), 13–24. https://doi.org/10.54433/JDIIS.2021100006

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Allen, M. P. (1997). The problem of multicollinearity. Em *Understanding Regression Analysis* (pp. 176–180). Springer US. https://doi.org/10.1007/978-0-585-25657-3_37

Allison, P. (2002). *Missing Data*. SAGE Publications, Inc. https://doi.org/10.4135/9781412985079

Alsheibani, S., Messom, C., & Cheung, Y. (2020). *Re-thinking the Competitive Landscape of Artificial Intelligence*. Hawaii International Conference on System Sciences. https://doi.org/10.24251/HICSS.2020.718

Aminbeidokhti, A., Nikabadi, M. S., & Hoseini, A. M. (2016). The role of transformational leadership and knowledge management processes on the rate of organisational innovation. *International Journal of Knowledge Management Studies*, *7*(3/4), 270. https://doi.org/10.1504/IJKMS.2016.082345

Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. *Psychological Bulletin*, *103*(3), 411–423. https://doi.org/10.1037/0033-2909.103.3.411

Andrews, J. E., Ward, H., & Yoon, J. (2021). UTAUT as a Model for Understanding Intention to Adopt AI and Related Technologies among Librarians. *The Journal of Academic Librarianship*, *47*(6), 102437. https://doi.org/10.1016/j.acalib.2021.102437

Antoniou, G., Papoglou, N., & Pierce, P. (2015). *Business Intelligence & Analytics (BI&A) Systems*.

Arefin, Md. S., Hoque, M. R., & Bao, Y. (2015). The impact of business intelligence on organization’s effectiveness: An empirical study. *Journal of Systems and Information Technology*, *17*(3), 263–285. https://doi.org/10.1108/JSIT-09-2014-0067

Arnott, D., & Pervan, G. (2015). A critical analysis of decision support systems research. Em L. P. Willcocks, C. Sauer, & M. C. Lacity (Eds.), *Formulating Research Methods for Information Systems* (pp. 127–168). Palgrave Macmillan UK. https://doi.org/10.1057/9781137509888_5

Babina, T., Fedyk, A., He, A., & Hodson, J. (2024). Artificial intelligence, firm growth, and product innovation. *Journal of Financial Economics*, *151*, 103745. https://doi.org/10.1016/j.jfineco.2023.103745

Bach, M. P., Jaklič, J., & Vugec, D. S. (2022). Understanding impact of business intelligence to organizational performance using cluster analysis: Does culture matter? *International Journal of Information Systems and Project Management*, *6*(3), 63–86. https://doi.org/10.12821/ijispm060304

Bag, S., Gupta, S., Kumar, A., & Sivarajah, U. (2021). An integrated artificial intelligence framework for knowledge creation and B2B marketing rational decision making for improving firm performance. *Industrial Marketing Management*, *92*, 178–189. https://doi.org/10.1016/j.indmarman.2020.12.001

Baptista, G., & Oliveira, T. (2016). A weight and a meta-analysis on mobile banking acceptance research. *Computers in Human Behavior*, *63*, 480–489. https://doi.org/10.1016/j.chb.2016.05.074

Blenko, M. W., Mankins, M., & Rogers, P. (2010, junho 1). The Decision-Driven Organization. *Harvard Business Review*. https://hbr.org/2010/06/the-decision-driven-organization

Bley, K., Fredriksen, S. F. B., Skjærvik, M. E., & Pappas, I. O. (2022). The Role of Organizational Culture on Artificial Intelligence Capabilities and Organizational Performance. Em S. Papagiannidis, E. Alamanos, S. Gupta, Y. K. Dwivedi, M. Mäntymäki, & I. O. Pappas (Eds.), *The Role of Digital Technologies in Shaping the Post-Pandemic World* (Vol. 13454, pp. 13–24). Springer International Publishing. https://doi.org/10.1007/978-3-031-15342-6_2

Boughzala, I., & De Vreede, G.-J. (2015). Evaluating Team Collaboration Quality: The Development and Field Application of a Collaboration Maturity Model. *Journal of Management Information Systems*, *32*(3), 129–157. https://doi.org/10.1080/07421222.2015.1095042

Božič, K., & Dimovski, V. (2019). Business intelligence and analytics use, innovation ambidexterity, and firm performance: A dynamic capabilities perspective. *The Journal of Strategic Information Systems*, *28*(4), 101578. https://doi.org/10.1016/j.jsis.2019.101578

Bryman, A. (2012). *Social research methods* (4. ed). Oxford Univ. Press.

Brynjolfsson, E., Hitt, L. M., & Kim, H. H. (2011). Strength in Numbers: How Does Data-Driven Decisionmaking Affect Firm Performance? *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1819486

Burgess, A. (2018). *The Executive Guide to Artificial Intelligence*. Springer International Publishing. https://doi.org/10.1007/978-3-319-63820-1

Cao, G., Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2021). Understanding managers' attitudes and behavioral intentions towards using artificial intelligence for organizational decision-making. *Technovation*, *106*, 102312. https://doi.org/10.1016/j.technovation.2021.102312

Chatterjee, S., & Bhattacharjee, K. K. (2020). Adoption of artificial intelligence in higher education: A quantitative analysis using structural equation modelling. *Education and Information Technologies*, *25*(5), 3443–3463. https://doi.org/10.1007/s10639-020-10159-7

Chatterjee, S., Rana, N. P., Khorana, S., Mikalef, P., & Sharma, A. (2021). Assessing Organizational Users' Intentions and Behavior to AI Integrated CRM Systems: A Meta-UTAUT Approach. *Information Systems Frontiers*, *25*(4), 1299–1313. https://doi.org/10.1007/s10796-021-10181-1

Chatterjee, S., Rana, N. P., Khorana, S., Mikalef, P., & Sharma, A. (2023). Assessing Organizational Users' Intentions and Behavior to AI Integrated CRM Systems: A Meta-UTAUT Approach. *Information Systems Frontiers*, *25*(4), 1299–1313. https://doi.org/10.1007/s10796-021-10181-1

Chen, Chiang, & Storey. (2012). Business Intelligence and Analytics: From Big Data to Big Impact. *MIS Quarterly*, *36*(4), 1165. https://doi.org/10.2307/41703503

Chen, L., & Nath, R. (2018). Business analytics maturity of firms: An examination of the relationships between managerial perception of IT, business analytics maturity and success. *Information Systems Management*, *35*(1), 62–77. https://doi.org/10.1080/10580530.2017.1416948

Chou, C., Bentler, P. M., & Satorra, A. (1991). Scaled test statistics and robust standard errors for non-normal data in covariance structure analysis: A Monte Carlo study. *British Journal of Mathematical and Statistical Psychology*, *44*(2), 347–357. https://doi.org/10.1111/j.2044-8317.1991.tb00966.x

Cody, W. F., Kreulen, J. T., Krishna, V., & Spangler, W. S. (2002). The integration of business intelligence and knowledge management. *IBM Systems Journal*, *41*(4), 697–713. https://doi.org/10.1147/sj.414.0697

Collins, C., Dennehy, D., Conboy, K., & Mikalef, P. (2021). Artificial intelligence in information systems research: A systematic literature review and research agenda. *International Journal of Information Management*, *60*, 102383. https://doi.org/10.1016/j.ijinfomgt.2021.102383

Compeau, D., Higgins, C. A., & Huff, S. (1999). Social Cognitive Theory and Individual Reactions to Computing Technology: A Longitudinal Study. *MIS Quarterly*, *23*(2), 145. https://doi.org/10.2307/249749

Cooil, B., Aksoy, L., & Keiningham, T. L. (2008). Approaches to Customer Segmentation. *Journal of Relationship Marketing*, *6*(3–4), 9–39. https://doi.org/10.1300/J366v06n03_02

Dahlgren, A., & Nilsson, V. (2019). *Business Analytics Maturity Model—An adaptation to the e-commerce industry*.

Dasgupta, S., & Gupta, B. (2013). Organization Culture Dimensions as Antecedents of Internet Technology Adoption. Em Y. K. Dwivedi, H. Z. Henriksen, D. Wastell, & R. De' (Eds.), *Grand Successes and Failures in IT. Public and Private Sectors* (Vol. 402, pp. 658–662). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-38862-0_49

Davenport, T. H., & Harris, J. G. (2007). *Competing on analytics: The new science of winning*. Harvard Business School Press.

Davenport, T. H., Harris, J., & Shapiro, J. (2010). Competing on talent analytics. *Harvard Business Review*, *88*(10), 52–58, 150.

Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly*, *13*(3), 319. https://doi.org/10.2307/249008

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1992). Extrinsic and Intrinsic Motivation to Use Computers in the Workplace [1]. *Journal of Applied Social Psychology*, *22*(14), 1111–1132. https://doi.org/10.1111/j.1559-1816.1992.tb00945.x

Dayal, U., Castellanos, M., Simitsis, A., & Wilkinson, K. (2009). Data integration flows for business intelligence. *Proceedings of the 12th International Conference on Extending Database Technology: Advances in Database Technology*, 1–11. https://doi.org/10.1145/1516360.1516362

De Bruin, T. (2005). *Understanding the Main Phases of Developing a Maturity Assessment Model*.

Dejkam, R., & Shahraki, A. (2017). Evaluation the Effect of Implementing Business Intelligence on Customer Relationship Management Success. *International Journal of Humanities and Applied Social Science*, *6*, 147–160.

Denison, D. R., & Mishra, A. K. (1995). Toward a Theory of Organizational Culture and Effectiveness. *Organization Science*, *6*(2), 204–223. https://doi.org/10.1287/orsc.6.2.204

Dinter, B. (2012). *The Maturing of a Business Intelligence Maturity Model*.

Divatia, A. S., Tikoria, J., & Lakdawala, S. (2021). Emerging trends and impact of business intelligence & analytics in organizations: Case studies from India. *Business Information Review*, *38*(1), 40–52. https://doi.org/10.1177/0266382120969265

Dwivedi, Y. K., Rana, N. P., Jeyaraj, A., Clement, M., & Williams, M. D. (2019). Re-examining the Unified Theory of Acceptance and Use of Technology (UTAUT): Towards a Revised Theoretical Model. *Information Systems Frontiers*, *21*(3), 719–734. https://doi.org/10.1007/s10796-017-9774-y

Elkhatibi, Y., Houda, G., & Redouane, B. (2024). Factors Influencing the Adoption of AI-Powered Chatbots in the Moroccan Banking Sector: An Extended UTAUT Model. *Journal of Logistics, Informatics and Service Science*. https://doi.org/10.33168/JLISS.2024.0730

Emmanuel Osamuyimen Eboigbe, Oluwatoyin Ajoke Farayola, Funmilola Olatundun Olatoye, Obiageli Chinwe Nnabugwu, & Chibuike Daraojimba. (2023). BUSINESS INTELLIGENCE TRANSFORMATION THROUGH AI AND DATA ANALYTICS. *Engineering Science & Technology Journal*, *4*(5), 285–307. https://doi.org/10.51594/estj.v4i5.616

Enehage and Khurana. (2020). *Bringing AI to business intelligence and analytics Enehage and Khurana*.

Fetaji, M. (2023). Devising a Model AI-UTAUT by Combining Artificial Inteligence AI with Unified Theory of Acceptance and Use of Technology (UTAUT). *SAR Journal - Science and Research*, 182–187. https://doi.org/10.18421/SAR63-06

Fishbein, & Ajzen. (1975). *Belief, attitude, intention and behaviour: An introduction to theory and research*.

Fitrianie, S., Horsch, C., Beun, R. J., Griffioen-Both, F., & Brinkman, W.-P. (2021). Factors Affecting User's Behavioral Intention and Use of a Mobile-Phone-Delivered Cognitive Behavioral Therapy for Insomnia: A Small-Scale UTAUT Analysis. *Journal of Medical Systems*, *45*(12), 110. https://doi.org/10.1007/s10916-021-01785-w

Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, *18*(1), 39. https://doi.org/10.2307/3151312

Fraser, P., Moultrie, J., & Gregory, M. (2002). The use of maturity models/grids as a tool in assessing product development capability. *IEEE International Engineering Management Conference*, *1*, 244–249. https://doi.org/10.1109/IEMC.2002.1038431

Freeman, C., Burns, T., & Stalker, G. M. (1969). The Management of Innovation. *The Economic Journal*, *79*(314), 403. https://doi.org/10.2307/2230196

Fridin, M., & Belokopytov, M. (2014). Acceptance of socially assistive humanoid robot by preschool and elementary school teachers. *Computers in Human Behavior*, *33*, 23–31. https://doi.org/10.1016/j.chb.2013.12.016

Garikapati, D., & Shetiya, S. S. (2024). *Autonomous Vehicles: Evolution of Artificial Intelligence and Learning Algorithms* (arXiv:2402.17690). arXiv. http://arxiv.org/abs/2402.17690

Gauzelin, S., & Bentz, H. (2017). An examination of the impact of business intelligence systems on organizational decision making and performance: The case of France. *Journal of Intelligence Studies in Business*, *7*(2). https://doi.org/10.37380/jisib.v7i2.238

Gefen, D., & Straub, D. (2005). A Practical Guide To Factorial Validity Using PLS-Graph: Tutorial And Annotated Example. *Communications of the Association for Information Systems*, *16*. https://doi.org/10.17705/1CAIS.01605

Götz, O., Liehr-Gobbers, K., & Krafft, M. (2009). Evaluation of Structural Equation Models Using the Partial Least Squares (PLS) Approach. Em V. Esposito Vinzi, W. W. Chin, J. Henseler, & H. Wang (Eds.), *Handbook of Partial Least Squares* (pp. 691–711). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-540-32827-8_30

Grace, K., Salvatier, J., Dafoe, A., Zhang, B., & Evans, O. (2017). *When Will AI Exceed Human Performance? Evidence from AI Experts* (Versão 3). arXiv. https://doi.org/10.48550/ARXIV.1705.08807

Grover, P., Kar, A. K., & Dwivedi, Y. K. (2020). Understanding artificial intelligence adoption in operations management: Insights from the review of academic literature and social media discussions. *Annals of Operations Research*, *308*(1–2), 177–213. https://doi.org/10.1007/s10479-020-03683-9

Gursoy, D., Chi, O. H., Lu, L., & Nunkoo, R. (2019). Consumers acceptance of artificially intelligent (AI) device use in service delivery. *International Journal of Information Management*, *49*, 157–169. https://doi.org/10.1016/j.ijinfomgt.2019.03.008

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (Eighth edition). Cengage.

Hair, J. F., Sarstedt, M., & Ringle, C. M. (2017). Partial Least Squares Structural Equation Modeling. Em C. Homburg, M. Klarmann, & A. Vomberg (Eds.), *Handbook of Market Research* (pp. 1–40). Springer International Publishing. https://doi.org/10.1007/978-3-319-05542-8_15-1

Harfouche, A., Quinio, B., Skandrani, S., & Marciniak, R. (2017). *A Framework for Artificial Knowledge Creation in Organizations*.

Harter, D. E., Krishnan, M. S., & Slaughter, S. A. (2000). Effects of Process Maturity on Quality, Cycle Time, and Effort in Software Product Development. *Management Science*, *46*(4), 451–466. https://doi.org/10.1287/mnsc.46.4.451.12056

Heaton, J. (2018). Ian Goodfellow, Yoshua Bengio, and Aaron Courville: Deep learning: The MIT Press, 2016, 800 pp, ISBN: 0262035618. *Genetic Programming and Evolvable Machines*, *19*(1–2), 305–307. https://doi.org/10.1007/s10710-017-9314-z

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Hevner, A. R., & March, S. T. (2003). IT systems perspectives—The information systems research cycle. *Computer*, *36*(11), 111–113. https://doi.org/10.1109/MC.2003.1244541

Hogan, S. J., & Coote, L. V. (2014). Organizational culture, innovation, and performance: A test of Schein's model. *Journal of Business Research*, *67*(8), 1609–1621. https://doi.org/10.1016/j.jbusres.2013.09.007

Huang, M.-H., & Rust, R. T. (2018). Artificial Intelligence in Service. *Journal of Service Research*, *21*(2), 155–172. https://doi.org/10.1177/1094670517752459

Humphrey, W. S. (1988). Characterizing the software process: A maturity framework. *IEEE Software*, *5*(2), 73–79. https://doi.org/10.1109/52.2014

Im, I., Hong, S., & Kang, M. S. (2011). An international comparison of technology adoption. *Information & Management*, *48*(1), 1–8. https://doi.org/10.1016/j.im.2010.09.001

Isaac, O., Abdullah, Z., Aldholay, A. H., & Abdulbaqi Ameen, A. (2019). Antecedents and outcomes of internet usage within organisations in Yemen: An extension of the Unified Theory of Acceptance and Use of Technology (UTAUT) model. *Asia Pacific Management Review*, *24*(4), 335–354. https://doi.org/10.1016/j.apmrv.2018.12.003

Jain, R., Garg, N., & Khera, S. N. (2022). Adoption of AI-Enabled Tools in Social Development Organizations in India: An Extension of UTAUT Model. *Frontiers in Psychology*, *13*, 893691. https://doi.org/10.3389/fpsyg.2022.893691

Jordan, M. I., & Mitchell, T. M. (2015). Machine learning: Trends, perspectives, and prospects. *Science*, *349*(6245), 255–260. https://doi.org/10.1126/science.aaa8415

Joshi, A. V. (2020). *Machine Learning and Artificial Intelligence*. Springer International Publishing. https://doi.org/10.1007/978-3-030-26622-6

Kamakura, W. A. (2010). Common Methods Bias. Em J. Sheth & N. Malhotra (Eds.), *Wiley International Encyclopedia of Marketing* (1.ª ed.). Wiley. https://doi.org/10.1002/9781444316568.wiem02033

Keppels, J. (2018). *Qualitative Measurement of BI Maturity in a SME ICT Organisation*.

Kline, R. (2005). *Principles and Practice of Structural Equation Modeling (2nd Edition)*.

Kock, N., Lynn, G., Texas A&M International University, & Stevens Institute of Technology. (2012). Lateral Collinearity and Misleading Results in Variance-Based SEM: An Illustration and Recommendations. *Journal of the Association for Information Systems*, *13*(7), 546–580. https://doi.org/10.17705/1jais.00302

Kreutzer, R. T., & Sirrenberg, M. (2020). *Understanding Artificial Intelligence: Fundamentals, Use Cases and Methods for a Corporate AI Journey*. Springer International Publishing. https://doi.org/10.1007/978-3-030-25271-7

Kriemadis, T., Pelagidis, T., & Kartakoullis, N. (2012). The role of organizational culture in Greek businesses. *EuroMed Journal of Business*, *7*(2), 129–141. https://doi.org/10.1108/14502191211245570

Leach, L., & Henson, R. K. (2007). *Multiple Linear Regression Viewpoints*. https://www.glmj.org/archives/MLRV_2007_33_1.pdf#page=4

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, *521*(7553), 436–444. https://doi.org/10.1038/nature14539

Liddy, E. D. (2001). *Natural Language Processing*.

M. Olszak, C., & Ziemba, E. (2007). Approach to Building and Implementing Business Intelligence Systems. *Interdisciplinary Journal of Information, Knowledge, and Management*, *2*, 135–148. https://doi.org/10.28945/105

Ma, L., & Sun, B. (2020). Machine learning and AI in marketing – Connecting computing power to human insights. *International Journal of Research in Marketing*, *37*(3), 481–504. https://doi.org/10.1016/j.ijresmar.2020.04.005

Mahara, T., Iyer, L. S., Matta, V., & Alagarsamy, S. (2021). Effect of Organizational Culture during Crises on adoption of virtual classrooms: An extension of UTAUT model. *Journal of Information Technology Case and Application Research*, *23*(3), 213–239. https://doi.org/10.1080/15228053.2021.1965818

Makarius, E. E., Mukherjee, D., Fox, J. D., & Fox, A. K. (2020). Rising with the machines: A sociotechnical framework for bringing artificial intelligence into the organization. *Journal of Business Research*, *120*, 262–273. https://doi.org/10.1016/j.jbusres.2020.07.045

Mensah, I. K., & Khan, M. K. (2024). Unified Theory of Acceptance and Use of Technology (UTAUT) Model: Factors Influencing Mobile Banking Services' Adoption in China. *Sage Open*, *14*(1), 21582440241234230. https://doi.org/10.1177/21582440241234230

Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J. (2019). Big data analytics and firm performance: Findings from a mixed-method approach. *Journal of Business Research*, *98*, 261–276. https://doi.org/10.1016/j.jbusres.2019.01.044

Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management*, *58*(3), 103434. https://doi.org/10.1016/j.im.2021.103434

Mishra, A. N., & Pani, A. K. (2021). Business value appropriation roadmap for artificial intelligence. *VINE Journal of Information and Knowledge Management Systems*, *51*(3), 353–368. https://doi.org/10.1108/VJIKMS-07-2019-0107

Montesdioca, G. P. Z., & Maçada, A. C. G. (2015). Measuring user satisfaction with information security practices. *Computers & Security*, *48*, 267–280. https://doi.org/10.1016/j.cose.2014.10.015

Moore, G. C., & Benbasat, I. (1991). Development of an Instrument to Measure the Perceptions of Adopting an Information Technology Innovation. *Information Systems Research*, *2*(3), 192–222. https://doi.org/10.1287/isre.2.3.192

Musto, S., & Maguire, C. (2021). *The Total Economic Impact™ Of IBM Watson Natural Language Processing (NLP) Solutions Cost Savings And Business Benefits Enabled By IBM Watson Natural Language Processing (NLP) Solutions*.

Negash, S., & Gray, P. (2003). Business Intelligence. Em *Commun Assoc Inf Sys* (Vol. 13).

Norzelan, N. A., Mohamed, I. S., & Mohamad, M. (2024). Technology acceptance of artificial intelligence (AI) among heads of finance and accounting units in the shared service industry. *Technological Forecasting and Social Change*, *198*, 123022. https://doi.org/10.1016/j.techfore.2023.123022

O'Leary, D. E. (2014). Embedding AI and Crowdsourcing in the Big Data Lake. *IEEE Intelligent Systems*, *29*(5), 70–73. https://doi.org/10.1109/MIS.2014.82

Oliveira, T., Faria, M., Thomas, M. A., & Popovič, A. (2014). Extending the understanding of mobile banking adoption: When UTAUT meets TTF and ITM. *International Journal of Information Management*, *34*(5), 689–703. https://doi.org/10.1016/j.ijinfomgt.2014.06.004

Pancić, M., Ćućić, D., & Serdarušić, H. (2023). Business Intelligence (BI) in Firm Performance: Role of Big Data Analytics and Blockchain Technology. *Economies*, *11*(3), 99. https://doi.org/10.3390/economies11030099

Parsons, T. (1960). *Structure and Process in Modern Societies*.

Paschen, J., Kietzmann, J., & Kietzmann, T. C. (2019). Artificial intelligence (AI) and its implications for market knowledge in B2B marketing. *Journal of Business & Industrial Marketing*, *34*(7), 1410–1419. https://doi.org/10.1108/JBIM-10-2018-0295

Paulk, M. C., Curtis, B., Chrissis, M. B., & Weber, C. V. (1993). Capability maturity model, version 1.1. *IEEE Software*, *10*(4), 18–27. https://doi.org/10.1109/52.219617

Pencheva, I., Esteve, M., & Mikhaylov, S. J. (2020). Big Data and AI – A transformational shift for government: So, what next for research? *Public Policy and Administration*, *35*(1), 24–44. https://doi.org/10.1177/0952076718780537

Perifanis, N.-A., & Kitsios, F. (2023). Investigating the Influence of Artificial Intelligence on Business Value in the Digital Era of Strategy: A Literature Review. *Information*, *14*(2), 85. https://doi.org/10.3390/info14020085

Ping Teoh, A., Rajendran, M., & Kin Lim, E. (2014). Predictors and Outcome of Business Intelligence System Implementation: A Perspective of Manufacturers in Malaysia. *Research Journal of Applied Sciences, Engineering and Technology*, *8*(18), 1980–1993. https://doi.org/10.19026/rjaset.8.1190

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Popovič, A., Hackney, R., Coelho, P. S., & Jaklič, J. (2012). Towards business intelligence systems success: Effects of maturity and culture on analytical decision making. *Decision Support Systems*, *54*(1), 729–739. https://doi.org/10.1016/j.dss.2012.08.017

Prairie View A&M University, Ramakrishnan, T., Khuntia, J., University of Colorado, Kathuria, A., Indian School of Business, Saldanha, T. J. V., & University of Georgia. (2019). An Integrated Model of Business Intelligence & Analytics Capabilities and Organizational Performance. *Communications of the Association for Information Systems*, *46*(1), 722–750. https://doi.org/10.17705/1CAIS.04631

Raj, R. (2021). *Supervised, Unsupervised and Semi-supervised Learning*. https://www.enjoyalgorithms.com/blogs/supervised-unsupervised-and-semisupervised-learning

Raza, S. A., Qazi, W., Khan, K. A., & Salam, J. (2021). Social Isolation and Acceptance of the Learning Management System (LMS) in the time of COVID-19 Pandemic: An Expansion of the UTAUT Model. *Journal of Educational Computing Research*, *59*(2), 183–208. https://doi.org/10.1177/0735633120960421

Reznikov, R. (2023). *Council Post: How Natural Language Processing Is Revolutionizing Business Operations*. Forbes.

https://www.forbes.com/sites/forbestechcouncil/2023/05/16/how-natural-language-processing-is-revolutionizing-business-operations/

Riemenschneider, C. K., Hardgrave, B. C., & Davis, F. D. (2002). Explaining software developer acceptance of methodologies: A comparison of five theoretical models. *IEEE Transactions on Software Engineering*, *28*(12), 1135–1145. https://doi.org/10.1109/TSE.2002.1158287

Rikhardsson, P., & Yigitbasioglu, O. (2018). Business intelligence & analytics in management accounting research: Status and future focus. *International Journal of Accounting Information Systems*, *29*, 37–58. https://doi.org/10.1016/j.accinf.2018.03.001

Ringle, C., Wende, S., & Will, A. (2005). *SmartPLS 2.0. Retrieved from http://www.smartpls.de*.

Sashkin, M., & Rosenbach, W. E. (1996). *ORGANIZATIONAL CULTURE ASSESSMENT QUESTIONNAIRE*.

Savage, N. (2020). How AI is improving cancer diagnostics. *Nature*, *579*(7800), S14–S16. https://doi.org/10.1038/d41586-020-00847-2

Schein, E. H. (2004). *Organizational Culture and Leadership*.

Schmidt, R., Möhring, M., & Zimmermann, A. (2020). *Value Creation in Connectionist Artificial Intelligence – A Research Agenda*.

Schminke, M., Cropanzano, R., & Rupp, D. E. (2002). Organization structure and fairness perceptions: The moderating effects of organizational level. *Organizational Behavior and Human Decision Processes*, *89*(1), 881–905. https://doi.org/10.1016/S0749-5978(02)00034-1

Shin, D.-H. (2009). Towards an understanding of the consumer acceptance of mobile wallet. *Computers in Human Behavior*, *25*(6), 1343–1354. https://doi.org/10.1016/j.chb.2009.06.001

Silic, M., & Back, A. (2013). *Organizational Culture Impact on Acceptance and Use of Unified Communications & Collaboration Technology in Organizations*. https://aisel.aisnet.org/bled2013/28

Slevitch, L. (2011). Qualitative and Quantitative Methodologies Compared: Ontological and Epistemological Perspectives. *Journal of Quality Assurance in Hospitality & Tourism*, *12*(1), 73–81. https://doi.org/10.1080/1528008X.2011.541810

Sullivan, Y., & Fosso Wamba, S. (2024). Artificial intelligence and adaptive response to market changes: A strategy to enhance firm performance and innovation. *Journal of Business Research*, *174*, 114500. https://doi.org/10.1016/j.jbusres.2024.114500

Suša Vugec, D., Bosilj Vukšić, V., Pejić Bach, M., Jaklič, J., & Indihar Štemberger, M. (2020). Business intelligence and organizational performance: The role of alignment with business process management. *Business Process Management Journal*, *26*(6), 1709–1730. https://doi.org/10.1108/BPMJ-08-2019-0342

Syam, N., & Sharma, A. (2018). Waiting for a sales renaissance in the fourth industrial revolution: Machine learning and artificial intelligence in sales research and practice. *Industrial Marketing Management*, *69*, 135–146. https://doi.org/10.1016/j.indmarman.2017.12.019

Taylor, S., & Todd, P. A. (1995). Understanding Information Technology Usage: A Test of Competing Models. *Information Systems Research*, *6*(2), 144–176. https://doi.org/10.1287/isre.6.2.144

Thompson, R. L., Higgins, C. A., & Howell, J. M. (1991). Personal Computing: Toward a Conceptual Model of Utilization. *MIS Quarterly*, *15*(1), 125. https://doi.org/10.2307/249443

Tratica. (2018). *Artificial Intelligence Market Forecasts. 315 Consumer, Enterprise, Government, and Defense Use Cases for Machine Learning, Deep Learning, Natural Language Processing, Computer Vision, Machine Reasoning, and Strong AI across 30 Industry Sectors.* https://www.tractica.com/research/artificial-intelligence-market-forecasts/

Tschang, F. T., & Almirall, E. (2021). Artificial Intelligence as Augmenting Automation: Implications for Employment. *Academy of Management Perspectives*, *35*(4), 642–659. https://doi.org/10.5465/amp.2019.0062

Turban, E. (Ed.). (2007). *Decision support and business intelligence systems* (8. ed., Pearson internat. ed). Pearson Prentice Hall.

Ukhalkar, Mr. P., Parakh, Dr. S., Phursule, Dr. R., & Sanu, Mrs. L. (2021). Augmented Analytics and Modern Business Intelligence Adoption to Maximize Business Value. *Journal of University of Shanghai for Science and Technology*, *23*(3). https://doi.org/10.51201/Jusst12685

Venkatesh, Morris, Davis, & Davis. (2003). User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly*, *27*(3), 425. https://doi.org/10.2307/30036540

Venkatesh, V. (2021). Adoption and use of AI tools: A research agenda grounded in UTAUT. *Annals of Operations Research*, *308*(1–2), 641–652. https://doi.org/10.1007/s10479-020-03918-9

Vidgen, R., Shaw, S., & Grant, D. B. (2017). Management challenges in creating value from business analytics. *European Journal of Operational Research*, *261*(2), 626–639. https://doi.org/10.1016/j.ejor.2017.02.023

Vimalkumar, M., Sharma, S. K., Singh, J. B., & Dwivedi, Y. K. (2021). 'Okay google, what about my privacy?': User's privacy perceptions and acceptance of voice based digital assistants. *Computers in Human Behavior*, *120*, 106763. https://doi.org/10.1016/j.chb.2021.106763

Wamba-Taguimdje, S.-L., Fosso Wamba, S., Kala Kamdjoug, J. R., & Tchatchouang Wanko, C. E. (2020). Influence of artificial intelligence (AI) on firm performance: The business value of AI-based transformation projects. *Business Process Management Journal*, *26*(7), 1893–1924. https://doi.org/10.1108/BPMJ-10-2019-0411

Wanda, P., & Stian, S. (2015). The Secret of my Success: An exploratory study of Business Intelligence management in the Norwegian Industry. *Procedia Computer Science*, *64*, 240–247. https://doi.org/10.1016/j.procs.2015.08.486

Wang, K., Ruan, Q., Zhang, X., Fu, C., & Duan, B. (2024). Pre-Service Teachers' GenAI Anxiety, Technology Self-Efficacy, and TPACK: Their Structural Relations with Behavioral Intention to Design GenAI-Assisted Teaching. *Behavioral Sciences*, *14*(5), 373. https://doi.org/10.3390/bs14050373

Warrick, D. D. (2017). What leaders need to know about organizational culture. *Business Horizons*, *60*(3), 395–404. https://doi.org/10.1016/j.bushor.2017.01.011

Westerman, G., Tannou,M., Bonnet, D., Ferraris, P., &McAfee, A. (2012). *The digital advantage: How digital leaders outperform their peers in every industry (pp. 2-23). Massachusetts: MIT Sloan Management and Capgemini Consulting.*

Xu, Y., Schneier, F., Heimberg, R. G., Princisvalle, K., Liebowitz, M. R., Wang, S., & Blanco, C. (2012). Gender differences in social anxiety disorder: Results from the national epidemiologic sample on alcohol and related conditions. *Journal of Anxiety Disorders*, *26*(1), 12–19. https://doi.org/10.1016/j.janxdis.2011.08.006

Yeoh, W., & Koronios, A. (2010). Critical success factors for business intelligence systems. *Journal of Computer Information Systems*, *50*.

Yin, R. K. (2009). *Case study research: Design and methods* (4th ed). Sage Publications.

Zohuri, B. (2020). From Business Intelligence to Artificial Intelligence. *Modern Approaches on Material Science*, *2*(3). https://doi.org/10.32474/MAMS.2020.02.000137

APPENDIX A - BI&A MATURITY MEASURES

ID	DIMENSION	ITEM A	ITEM B
BI1	The scope of business intelligence systems use.	BI is used in an isolated manner by individuals.	BI is used in all (wherever needed) organizational units, hierarchical levels, and application areas.
BI2	The level of data architecture maturity	Business data management is not addressed in our organization. There are non-existing or heterogeneous semantics	Internal (both structured and unstructured) and external data are fully integrated, and requirements (e.g. data quality) are met.
BI3	The impact of business intelligence	BI is not considered to have a relevant impact.	Decision-making is based on BI and BI is perceived as having a critical impact on organizational performance.
BI4	The level of technical architecture maturity of BI	No dedicated BI storage is used.	Enterprise-wide data warehouse is used.
BI5	The level of data management maturity	Data integration is manual.	Data integration is automated; dedicated tools for data management and integration are used.
BI6	Type of BI tools used within the organization	We do not use any specific BI tool; manual analysis is performed.	A broad range of BI tools and techniques is used, such as reporting tools, ad hoc analytics (OLAP), in memory analytics, planning, alerts, forecasts, scorecards, mobile BI, data mining, predictive analytics, and other advanced techniques of analysis and visualization.
BI7	The organizational structure related to BI	There are no specifically defined roles and organizational units for BI.	A BI (business data analytics or similar) competence center with a comprehensive spectrum of tasks and competences exists.
BI8	The level of maturity of BI processes	No explicit processes related to BI are defined.	BI specific processes are defined and actively managed.
BI9	The level of the profitability assessment of BI	There is no profitability assessment of BI.	A cross-project and benefit-oriented profitability assessment of BI takes place.
BI10	The level of BI strategy	No BI strategy exists in our organization.	A dedicated BI strategy exists and clearly reflects the business/IT alignment.

APPENDIX B - SURVEY

No.	Original Statements	Adapted Statements	Author(s)
Performance expectancy (PE)			
PE1	I would find the system useful in my job.	I would find the system with AI useful in my job.	(Venkatesh et al., 2003)
PE2	Using the system enables me to accomplish tasks more quickly.	Using the system with AI enables me to accomplish tasks more quickly.	
PE3	Using the system increases my productivity.	Using the system with AI increases my productivity.	
PE4	If I use the system, I will increase my chances of getting a raise	If I use the system with AI, I will increase my chances of getting a raise.	
Effort Expectancy (EE)			
EE1	My interaction with the system is clear and understandable.	My interaction with the system with AI would be clear and understandable.	(Venkatesh et al., 2003)
EE2	It would be easy for me to become skilful at using the system.	It would be easy for me to become skilful at using the system with AI.	
EE3	I would find the system easy to use.	I would find the system with AI easy to use.	
EE4	Learning to operate the system is easy for me.	Learning to operate the system with AI is easy for me.	
Social Influence (SI)			
SI1	People who influence my behaviour think that I should use the system.	People who influence my behaviour think that I should use the system with AI	(Venkatesh et al., 2003)
SI2	People who are important to me think that I should use the system.	People who are important to me think that I should use the system with AI.	
SI3	The senior management of this business has been helpful in the use of the system.	The senior management of this business has been helpful in the use of the system with AI.	
SI4	In general, the organization has supported the use of the system.	In general, the organization has supported the use of the system with AI.	
Facilitating conditions (FC)			
FC1	I have the resources necessary to use the system.	I have the resources necessary to use the system with AI.	(Venkatesh et al., 2003)
FC2	I have the knowledge necessary to use the system.	I have the knowledge necessary to use the system with AI.	
FC3	The system is not compatible with other systems I use.	The system with AI is not compatible with other systems I use.	
FC4	A specific person (or group) is available for assistance with system difficulties.	A specific person (or group) is available for assistance with system with AI difficulties.	
Organizational Culture (OC)			
OC1	In this organization people and teams are often expected to reach goals which they believe are unattainable	In this organization people and teams are often expected to reach goals which they believe are unattainable	(Sashkin & Rosenbach, 1996)
OC2	This company has a long-term purpose and direction.	This company has a long-term purpose and direction.	(Denison & Mishra, 1995)
OC3	In this organization people believe they can influence and affect their workplace through their ideas and involvement.	In this organization people believe they can influence and affect their workplace through their ideas and involvement.	(Sashkin & Rosenbach, 1996)
AI intention to use (AI)			
AI1	I intend to use the system in the next 12 months.	I intend to use the system with AI in the next 12 months.	(Venkatesh et al., 2003)
AI2	I predict I would use the system in the next 12 months.	I predict I would use the system with AI in the next 12 months.	
AI3	I plan to use the system in the next 12 months.	I plan to use the system with AI in the next 12 months	
BI&A Maturity (BIA)			
BIA1	BI is used in all (wherever needed) organizational units, hierarchical levels, and application areas.	BI&A is used in all (wherever needed) organizational units, hierarchical levels, and application areas.	(Dinter, 2012)
BIA2	Internal (both structured and unstructured) and external data are fully integrated, and requirements (e.g. data quality) are met.	Internal (both structured and unstructured) and external data are fully integrated, and requirements (e.g. data quality) are met.	
BIA3	Decision-making is based on BI is perceived as having a critical impact on organizational performance.	Decision-making is based on BI&A is perceived as having a critical impact on organizational performance.	
BIA4	BI specific processes are defined and actively managed.	BI&A specific processes are defined and actively managed.	

No.	Original Statements	Adapted Statements	Author(s)
BIA5	A dedicated BI strategy exists and clearly reflects the business/IT alignment.	A dedicated BI&A strategy exists and clearly reflects the business/IT alignment.	
BIA6	A BI competence center with a comprehensive spectrum of tasks and competences exists.	A BI&A competence center with a comprehensive spectrum of tasks and competences exists.	
Firm Performance (FP)			
FP1	We perform much better than our main competitors in terms of profitability	We perform much better than our main competitors in terms of profitability	(Mikalef et al., 2019)
FP2	We perform much better than our main competitors in terms of rapid response to market demand	We perform much better than our main competitors in terms of rapid response to market demand	
FP3	We perform much better than our main competitors in terms of increasing customer satisfaction	We perform much better than our main competitors in terms of increasing customer satisfaction	
FP4	We perform much better than our main competitors in terms of providing better product and service quality	We perform much better than our main competitors in terms of providing better product and service quality	
FP5	We perform much better than our main competitors in terms of in reducing operating costs	We perform much better than our main competitors in terms of in reducing operating costs	
AI use (AU)			
AU1	What is your actual frequency of use of systems?	What is your actual frequency of use of systems?	(Im et al., 2011)
AU2	What is your actual frequency of use of systems?	What is your actual frequency of use of AI systems?	

APPENDIX C - CROSS-LOADINGS

	AI	AU	BIA	EE	FC	FP	OC	PE	SI	AI x BIA
AI1	**0.941**	0.69	0.286	0.41	0.503	0.168	0.252	0.557	0.45	-0.32
AI2	**0.953**	0.698	0.284	0.38	0.465	0.217	0.293	0.486	0.403	-0.356
AI3	**0.982**	0.745	0.28	0.41	0.496	0.218	0.255	0.535	0.398	-0.328
AU1	0.742	**1**	0.313	0.376	0.409	0.181	0.222	0.43	0.328	-0.307
BIA1	0.245	0.254	**0.822**	0.122	0.082	0.376	0.327	0.181	0.078	-0.324
BIA2	0.243	0.279	**0.818**	0.102	0.004	0.509	0.452	0.073	0.015	-0.303
BIA3	0.233	0.263	**0.877**	0.137	0.062	0.377	0.428	0.135	0.083	-0.268
BIA4	0.202	0.207	**0.919**	0.067	0.054	0.387	0.43	0.11	0.026	-0.297
BIA5	0.259	0.256	**0.855**	0.108	0.119	0.403	0.515	0.134	0.052	-0.264
BIA6	0.319	0.333	**0.853**	0.072	0.181	0.443	0.463	0.134	0.055	-0.277
EE1	0.351	0.291	0.06	**0.785**	0.308	0.03	0.113	0.576	0.534	0.112
EE2	0.346	0.318	0.069	**0.873**	0.524	0.119	0.113	0.408	0.309	0.003
EE3	0.286	0.302	0.096	**0.874**	0.464	0.123	0.073	0.376	0.315	0.024
EE4	0.422	0.365	0.163	**0.892**	0.576	0.209	0.11	0.394	0.387	-0.083
FC2	0.509	0.409	0.099	0.552	**1**	0.147	0.119	0.294	0.261	-0.197
FP1	0.147	0.1	0.389	0.147	0.137	**0.821**	0.385	0.088	0.079	0.054
FP2	0.088	0.036	0.411	0.043	0.086	**0.802**	0.373	0.031	-0.036	-0.026
FP3	0.165	0.137	0.43	0.127	0.096	**0.865**	0.433	0.118	0.054	-0.106
FP4	0.242	0.209	0.467	0.12	0.135	**0.922**	0.445	0.126	0.104	-0.103
FP5	0.233	0.279	0.358	0.18	0.168	**0.784**	0.275	0.081	0.165	-0.062
OC2	0.249	0.207	0.483	0.1	0.083	0.442	**0.896**	0.223	0.046	-0.043
OC3	0.25	0.19	0.435	0.117	0.129	0.38	**0.896**	0.323	0.136	-0.089
PE1	0.525	0.487	0.246	0.39	0.269	0.154	0.334	**0.85**	0.396	-0.196
PE2	0.366	0.315	0.048	0.487	0.201	0.045	0.174	**0.893**	0.449	0.041
PE3	0.511	0.302	0.065	0.477	0.282	0.067	0.262	**0.879**	0.482	0.034
SI1	0.434	0.335	0.082	0.395	0.253	0.084	0.115	0.47	**0.956**	-0.046
SI2	0.391	0.286	0.027	0.474	0.243	0.08	0.076	0.492	**0.945**	0.036
AI x BIA	-0.349	-0.307	-0.337	0.01	-0.197	-0.061	-0.074	-0.057	-0.008	1

APPENDIX D - HETEROTRAIT-MONOTRAIT RATIO OF CORRELATIONS

	AU	BIA	EE	FC	FP	OC	PE	SI
AU	0.770							
BIA	0.325	0.321						
EE	0.459	0.397	0.127					
FC	0.537	0.409	0.101	0.582				
FP	0.225	0.192	0.530	0.165	0.157			
OC	0.349	0.255	0.607	0.147	0.137	0.554		
PE	0.611	0.457	0.158	0.597	0.312	0.116	0.367	
SI	0.500	0.346	0.064	0.511	0.276	0.117	0.122	0.582

APPENDIX E - RESPONDENTS CHARACTERISTICS

Measure	Value	Frequency	%
Gender	Male	88	60,3
	Female	58	39,7
Education	Prefer not to say	1	0,7
	High School	7	4,8
	Doctoral degree	6	4,1
	Bachelor’s degree	59	44
	Master’s degree	73	50
Age	18-25	79	54,1
	26-35	45	30,8
	36-45	14	9,6
	46-55	7	4,8
	56 +	1	0,7

APPENDIX F - COLLINEARITY STATISTICS (VIF)

Items	VIF
AI1	2.939
AI2	2.939
AU1	1.000
BIA1	2.424
BIA2	2.345
BIA3	3.499
BIA4	4.686
BIA5	3.090
BIA6	2.956
EE1	1.679
EE2	2.487
EE3	2.805
EE4	2.818
FC2	1.000
FP1	2.253
FP2	2.058
FP3	3.338
FP4	4.513
FP5	2.069
OC2	1.581
OC3	1.581
PE1	1.728
PE2	2.866
PE3	2.388
SI1	2.861
SI2	2.861
AI x BIA	1.000

NOVA Information Management School
Instituto Superior de Estatística e Gestão de Informação

Universidade Nova de Lisboa