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David Diolle

Brunel Business School

Academic year: 2022/2023

MASTER IN BUSINESS ADMINISTRATION (MBA)

Module Code: MB5537

Student ID: 2157780

A Strategic Approach to Enhancing Corporate Adoption of Data Science, Machine Learning, and Artificial Intelligence Technologies in the UK

An Empirical Investigation using the AI-Cocoon

Supervisor: Dr Ning Wu

Submission date: 20/04/2023

Word count: 11,992

ABSTRACT

As the fourth industrial revolution continues to unfold, Data Science and AI have emerged as a driver of innovation and growth in the corporate landscape. However, despite the promise of increased efficiency, cost savings, and improved decision-making, corporate users' adoption of AI technologies remains uneven and highly variable. In the United Kingdom, where the pace of technological change has been incredibly rapid, understanding the factors that shape AI-enabled tool adoption has become a critical priority for businesses seeking to remain competitive in a fast-changing global economy.

To this end, the present study draws on the numerous technology adoption theories to understand the influencing elements of acceptance and usage of AI technologies by UK corporate users. This research represents an exciting opportunity for future theoretical and empirical studies. It aims to provide further insights into the interplay between critical variables such as belief, attitude, intention and behaviour and their nuances with the complex exogenous factors that drive or inhibit the uptake of AI-enabled technologies in corporate settings.

Declaration

I hereby declare that any material in this dissertation not originating from my own work has been duly acknowledged. All research materials, encompassing research data, preliminary analyses, notes, and drafts, have been retained and can be provided upon request.

Acknowledgement

Last but not least…My deepest appreciation for the support to EmergeIQ… Dr Ning… The Brunel MBA team… and my family…

Their collective support was a beacon of light, guiding me through the challenges of this academic pursuit!

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Chapter 1: INTRODUCTION

1.1 Background and Context of the Study.

The Pandemic acted as a catalyst in businesses' accelerated adoption of Data Science and Artificial Intelligence (AI), and according to the Economist, all conditions seem to be aligned for this momentum to continue (Andronie et al., 2021; Nica et al., 2022; The Economist, 2023). This trend is supported by PWC (2022) and Harris Poll (2020), who found that companies are expected to accelerate their AI strategy further (Harris Poll. 2020, cited in Harvard Business Review, 2021; PWC, 2022). Meanwhile, McKinsey (2021) states that AI is leveraging the ROI of companies successfully adopting it. However, among the 'Data Science' technology adopters, a large section still needs to achieve the desired returns and success post-adoption (Braganza et al., 2017; Bley et al., 2022; MITsloanreview, 2019).

While these technologies have the potential to boost productivity and increase ROI significantly, the transition can be complicated (Gilliland et al., 2021). Robert Solow, a Nobel-prizewinning economist, noted that it took decades for the computer age to have a noticeable impact on productivity statistics, well after the first Silicon Valley integrated circuits. It was not until the mid-1990s that a computer-powered productivity boom eventually emerged (The Economist, 2023). This gap between technological innovation and economic impact is partly due to fine-tuning. Early steam engines, for example, were wildly inefficient and consumed prohibitively expensive coal piles. Similarly, the stunning performance of modern AI tools represents a significant improvement over those which sparked a boomlet of AI enthusiasts roughly a decade ago.

Adopting, implementing, and managing Data science requires companies to acquire an array of new skills and create new career profiles, such as data scientist, which combines engineering, statistics, and deep knowledge of business practices. Regrettably, these skills are among the most sought-after by employers nowadays (Cabrera-Sánchez & Villarejo-Ramos, 2019). These concerns are compiled with internal adoption challenges from the current workforce, intensified by competence deficiencies and resistance to change (Bakhshi et al., 2014; Yaqoob et al., 2016). Nevertheless, Data Science, AI, and Machine learning (ML) have the potential to improve employee decision-making significantly. This leads us to ask two key questions. First, what affects AI adoption? Second, why are so many companies not using these technologies yet?

This study is two folds. First, it aims to delve deeper into the reasons behind the factors influencing the acceptance and the challenges associated with adopting Data science, AI and ML technologies by corporate in the U.K. and second, it explores and proposes a framework that can help EmergeIQ (a cloud service provider), to predict and optimise the acceptance of a Leading-edge business model, "Data science as a service."

1.2 Rationale of Study.

The adoption of Data Science, AI and ML technologies (DMAT) has engendered a paradigm shift in the modus operandi of businesses, enabling them to process and analyse vast amounts of data in real-time to gain insights and add value to operations (Venkatesh, 2022). As argued earlier, the adoption of AI has been exponential, and the trend is expected to persist in the coming years (Alsheibani et al., 2018; Gartner, 2017; The Economist, 2023).

The rapid evolution of these technologies has created a new landscape, and DMAT is at the forefront of this transformation. As organisations strive to stay ahead of this curve, there is a growing need to understand the attitudes and beliefs of corporate users and what influences the adoption of these technologies (Nascimento & Meirelles, 2021). According to an article from The Economist, the different ways people respond to AI and algorithms are a burgeoning area of research (The Economist, 2023). This is due to the growing recognition of these technologies' value to organisations and the economy. Despite these recognitions, a paucity of research was observed in the context of the U.K.

In spite of the promising features of DMAT, the researcher observed that the literature covering adoption by businesses of different sizes, is lacklustre. The purpose of this study is to fill these gaps in the literature by critically reviewing empirical frameworks such as the Technology acceptance model (TAM), the Theory of reasoned action (TRA), the Theory of planned behaviour (TPB), Diffusion of Innovation (DoI) and the Unified Theory of acceptance and use of Technology (UTAUT) to understand the factors influencing and moderating the adoption of DMAT (Davis, 1985; Fishbein & Ajzen, 1977; Ajzen, 1991; Venkatesh et al., 2003).

The study will be conducted using a multimethod approach involving a case study, conversational interviews, multiple choice and Likert scale questions with individuals from different industries who have adopted or planning to adopt DMAT. The researcher will diagnose the case of EmergeIQ and collect data to investigate the key factors influencing the acceptance of DMAT technologies. The results are expected to provide valuable insights into the factors influencing DMAT adoption while informing the development of initiatives to support the diffusion of these technologies.

1.3 Significance of the Research

Enterprises have deployed predictive analytics, text mining, and automation for years. Nevertheless, as observed by the Solow paradox, they still experience process gaps that hold back insights and affect outcomes (McKinsey, 2021). The reason? Too often, advanced analytics capabilities require a complex array of point products to supplement big data platforms. These products are costly, not integrated, and need specialised skills to leverage productivity (IDC, 2022; Chen, Chiang, & Storey, 2018).

While large organisations can utilise this technology by investing heavily in expertise, smaller enterprises which compose 99.9% of all UK private sector, typically lack dedicated data science teams (Moscone et al., 2019). Whereas, in practice, they do exploit Business analytics to unveil opportunities (Dereli et al., 2020). Consequently, this study argues that understanding the factors that influence the adoption of DMAT is paramount.

In this light, our study endeavours to bridge the literature gap by providing an alternative framework that can be used against the backdrop of a rapidly evolving technological landscape. The findings of this research are likely to have important implications for businesses across a wide range of industries, from the decision-maker seeking to understand the potential benefits of AI adoption to the researcher interested in the latest insights into the factors shaping technology adoption. This study represents an essential step in understanding the role of AI in the workplace and the broader economy. It promises to offer a sophisticated and detailed analysis of the complex interplay between AI-enabled tools and human behaviour.

1.4 Scope and Limitations

In this research, scope refers to the conditions under which the study will be conducted and is closely connected to framing the problem parameters. As a pioneering startup, EmergeIQ faces limitations caused by uncertainty with its go-to-market strategy. Although historical models (cited in Chapter 1.2) were widely used in different contexts for technology adoption, they are considered techno-centric approaches and address adoption at an individual level (Oliveira and Martins, 2011; Benbasat & Barki, 2007). This study considers both the techno-economic and organisation-level factors that influence the perception of corporate users. Figure 1.4 illustrates the approach used throughout this research, delimiting the boundary between empirical literature and the theoretical evidence used to develop the AI-Cocoon (The proposed enterprise-context adoption framework).

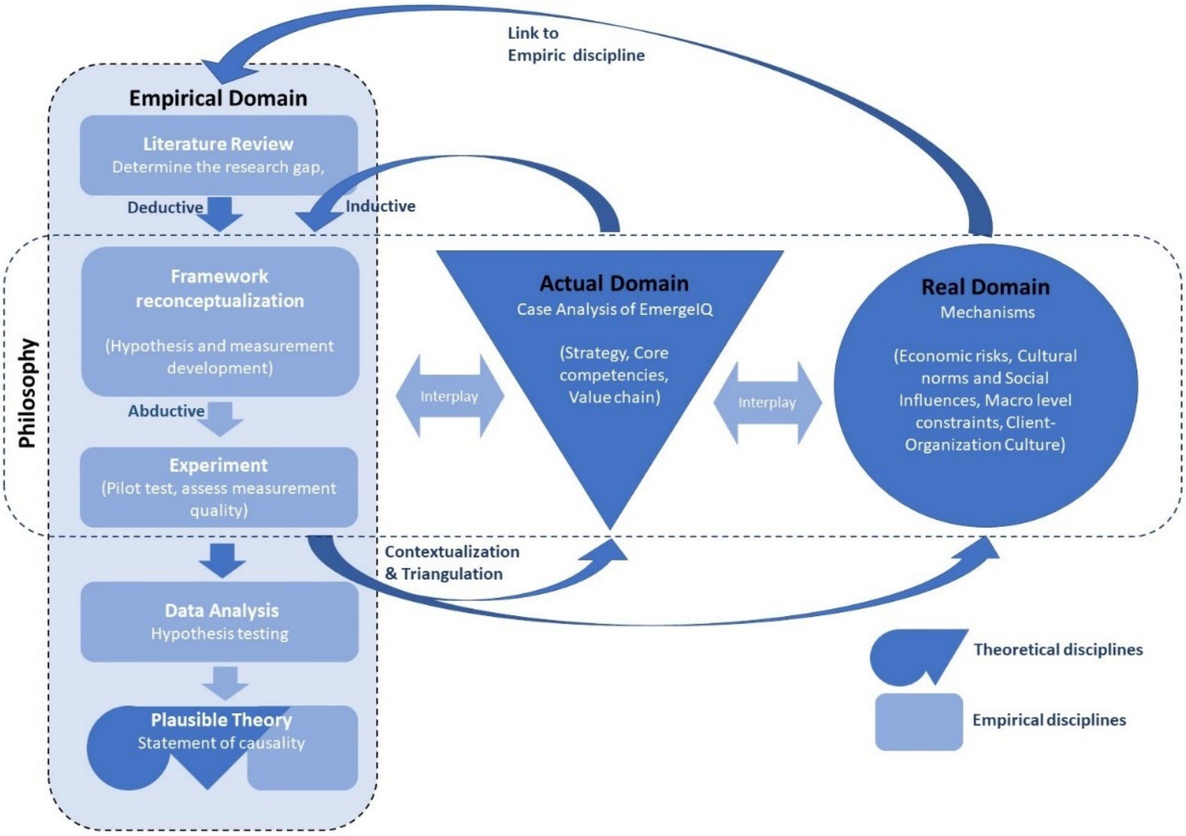


Figure 1.4: Proposed synthesis for the development of the framework

While employing an inductive approach in the present case studies generate numerous advantages, such as new concept generation and evidence examination, the sole use of an inductive approach cannot state causal inferences (Saunders et al., 2015). Additional research is needed to verify whether the study's findings could be generalised (Simon & Goes, 2013). In line with the conferred approach, this research attempts to investigate the findings from the case analysis by adopting a quantitative survey from previous empirical models to provide a plausible theory (as seen in Figure 1.4).

Limitations to this research lie in the case analysis of EmergeIQ and the population size, as they may not reflect the behaviour of a broader population or similar entities. Additionally, survey instruments distributed with time constraints can be perceived as problematic as participants with time restrictions are less likely to be considered (Simon & Goes, 2013). Moreover, objective questionnaires limit the response range, forcing participants to choose categories they may not consider themselves in (Delva et al., 2002).

Chapter 2: LITERATURE REVIEW

2.1 Overview of Data Science, Machine Learning and Artificial Intelligence Technologies

In recent years DMAT has undergone a revolution (The Economist, 2022). Reviewing the literature surrounding these technologies outlined a growing body of research on various aspects of DMAT, ranging from requirements elicitation (Wang et al. 2019) to technical aspects (Romanova et al. 2019) in a variety of settings, to include; healthcare (Pan et al. 2019), supply chain (Priore et al. 2019), hiring employees (Li et al., 2021; Van Esch et al., 2019), to the formulation of customer relations, marketing strategy, and performance management (Chatterjee et al., 2021; Davenport et al., 2020; Nica et al., 2021; Vlačić et al., 2021; Huang and Rust, 2020).

The literature also revealed that there is currently no widely accepted definition for DMAT due to the constant evolution in technological trends. McKinsey's 2020 global survey (e.g.) attempts to define AI based on specific use cases across various business functions, while Eurostat's Community Survey on ICT Usage and E-commerce in Enterprise defines AI based on technologies, such as ML and Natural language processing (NLP) (McKinsey 2020 & Eurostat, 2021. cited in Capital Economics, 2022). DMAT (Also referred to as AI-enabled tools and AI-powered tools) is an umbrella term used for this research and cuts across constituents such as AI, ML, NLP, Big Data Analytics (BDA), Business Intelligence, Computer vision and image processing (CVIP), Computer Science & Programming Skills, Mathematics, and Domain Knowledge (McCarthy, 1988; Collins et al., 2021).

As there is no consensus on a holistic definition for DMAT, and characterisation varies depending on contextual attributes. This study identified and selected a combination of five definitions of Data Science, ML and A.I. from relevant articles (refer to Appendix 2.1) to provide a Meta-level definition of DMAT based on existing literature.

Therefore, for this study's purposes, DMAT is defined as:

An interdisciplinary field that encompasses the cyclical capturing of (business) needs, data, and patterns to prepare, process, analyse, and predict insights that can be actuated into algorithm models for machine learning and human-like action and choice.

Additionally, this research uses a technology-based classification of A.I. that was developed based on existing literature and used by Capital Economics in a report commissioned by the U.K. Government and includes five main technology categories, namely: ML, NLP, CVIP, data management and analysis (DMA), and A.I. hardware (AIH), which are supported by business application examples (See Appendix 2.1.1) to facilitate understanding of the terminologies (Gov.uk, 2022; Capital Economics, 2022).

ML are algorithms that enable machines to learn and improve from experience without being explicitly programmed for each use case. It includes supervised, unsupervised, and reinforcement learning paradigms (Dhar, 2013; Goodfellow et al., 2016).
NLP use text and audio-based technologies to interpret written or spoken text, performing tasks from translation to chatbots (Indurkhya, & Damerau, 2010; Daniel & James, 2007).
CVIP enable machines to "see," understand, and extract information from visual stimuli, applied in facial recognition, image classification and augmented reality. (Szeliski, 2022; Wiley and Lucas, 2018)
DMA includes processes embedded in data management systems, such as database query optimisation and automatic data gathering, formatting, and processing, for use in forecasting exercises. (Capital Economics, 2022; Provost & Fawcett, 2013)
AIH includes autonomous machines, drones, and self-driving cars that orchestrate and coordinate computations for the AI process. (Kortenkamp et al., 2016; Capital Economics, 2022)

Table 2.1 Overview of the proposed category

2.2 Outsourcing solution.

The last decades have seen the emergence of Cloud computing as a new computing archetype that provides reliable, customisable, and dynamic computing environments to end-users, metamorphosing the process of provisioning computing infrastructure (Wang et al., 2010; Dillon et al., 2010; Etro, 2009). Shifting the infrastructure location to a more centralised and larger scale datacentre enables businesses to reduce the costs associated with managing software and hardware resources (Zhao et al., 2009).

Concepts like Infrastructure-as-a-Service, Platform-as-a-Service, and Software-as-a-Service have revolutionised computing on several layers (Zhao et al., 2014; Dillon et al., 2010). The symbiosis of these platforms, infrastructure and software has enabled new service models, namely, Analytics-as-a-Service, Data-Analysis-as-a-Service, and AI-as-a-Service, referred to as Data-science-as-a-service (DSaas) throughout this paper (Pohl et al., 2018).

DSaas refers to delivering DMAT capabilities and services in a service-oriented architecture through a network, typically the internet, to organisations through a cloud-based or external provider (Burns, 2021; Elshawi et al., 2018; Pohl et al., 2018). This approach allows businesses to access advanced DMAT capabilities without investing in expensive software or hiring specialised data scientists in-house (Burns, 2021; Pohl et al., 2018). DSaaS providers automate many services, including data preparation, analysis, modelling, and visualisation (Pohl et al., 2018) through DMAT to support multiple business functions, such as customer segmentation, predictive maintenance, and fraud detection.

2.3 Adoption challenges.

As discussed, DMAT has established itself as a transformative technology across various industries (Dasgupta and Wendler, 2019; Andronie et al., 2021; Nica et al., 2022). These technologies facilitate decision-making and problem-solving to increase organisation efficiency (Malone, 2018; Wilson and Daugherty, 2018) and can leverage decision-making by reducing the likelihood of biases and bounded rationality (Kahneman et al., 2016; Burton et al., 2019).

Despite numerous benefits, Studies have highlighted the gap in applying these technologies in businesses, caused by the need for more understanding of the interplay between humans and AI (Traumer et al., 2017; Kellogg et al., 2020; Henke and Kaka, 2018). A Deloitte (2020) report that surveyed AI projects found that most managers need help integrating DMAT with existing workers, processes, and systems due to missing organisational and AI capability requirements (Bley et al., 2022; Hupfer, 2020). According to Bley et al. (2022), companies that encounter difficulties deriving value from their DMAT endeavours tend to face organisational obstacles rather than technological ones.

Conversely, Ransbotham et al. (2019) argue that entities that successfully extract value from their AI pursuits exhibit a distinct pattern of organisational behaviour (Ransbotham, 2019). Exploring evidence of how to best increase acceptance of DMAT across domains and industries is therefore of empirical significance (Sharma, 2020; Chatterjee et al., 2021; Rana et al., 2022; Al-Nuaimi et al., 2022).

2.4 Technology Adoption Models.

While DMAT is a relatively new technology, the past fifty years have seen the rise of numerous theories and models to understand the influencing elements of acceptance and usage of technologies. During the 1970s, TRA was put forth, explaining a person's behavioural tendencies about attitudes and subjective norms (Fishbein & Ajzen, 1977). A decade later, TPB was proposed as an extension of TRA, assuming that specific parameters could control behaviours in context (Ajzen, 1991).

In a similar timeframe, Davis (1989) proposed TAM to explain the causal relationships between internal psychological variables such as attitudes, beliefs and behavioural intention on information technology. TAM is based on two user constructs, Perceived Usefulness and Perceived Ease of Use, which are widely accepted for understanding and predicting individual acceptance behaviours. Subsequent models include the combined TAM and TPB (C-TPB-TAM), which focus on the impact of experience on technology use (Venkatesh and Bala), and the TAM2/TAM 3 models as a theoretical extension of TAM that includes the perspectives of subjective norms and job relevance, in technology adoption.

The Unified Theory of Acceptance and use of technology (UTAUT) results from a comprehensive conceptual review of the technology acceptance models mentioned above, in addition to the Motivational Model, Innovation Diffusion Theory, Model of PC Utilization, and Social Cognitive Theory (Davis et al. 1992; Thompson et al., 1991; Moore & Benbasat, 2001; Compeau et al., 1999 Venkatesh, 2003; Bandura, 1986). UTAUT consists of six broad constructs deemed to be significant direct determinants of technology acceptance and include Performance expectancy (PE), Effort expectancy (EE), Social influence (SI), Facilitating conditions (FC), Behavioural intention (BI), and Use behaviour (UB). UTAUT2, as illustrated in Venkatesh et al. (2012), identifies additional constructs moderated by gender, age, and experience. UTAUT2 condenses the semiotics attributed by users to the technology, making it a valuable model for research design and methodology.

2.5 Limitation of current models.

Previous researchers evaluating technology acceptance have been criticised for their approaches, which limit its measures to use or intention of use (Venkatesh, 2022). Academics agree that these models need to be expanded to see the impact of introducing new technologies such as DMAT to corporate users. Contextualising these models to a corporate context will aid in understanding social and technological convergence (Bednar and Welch, 2020; Makarius et al., 2020).

The use of DMAT has always been contentious and controversial at both organisational and personal levels (Duan et al., 2019; Coa et al., 2021). While the potential of using AI to improve decision-making is increasingly recognised, there are concerns about how the algorithm's accuracy is perceived (Venkatesh, 2022). Researchers and practitioners have witnessed people's reluctance to use algorithms (Burton et al., 2019; Mahmud et al., 2022). This rejection is called algorithm aversion (Dietvorst et al., 2015; Jain et al., 2022) or Algorithm scepticism (Venkatesh, 2022). Mahmud et al. (2022) define it as "a behaviour of neglecting algorithmic decisions in favour of one's own or other's decisions, either consciously or unconsciously".

Organisations' negative perception of AI can be attributed to a poor understanding of how to use AI (Raisch and Krakowski, 2020) and to a lack of trust in AI systems due to its black box nature (Glikson and Woolley, 2020; Venkatesh, 2022). Many researchers have explored the factors that influence the adoption of AI by individual within organisations (Pumplun et al., 2019; Alsheibani et al., 2020; Pelau et al., 2021), but there is less evidence of how these technologies are adopted cross-industry (Nascimento & Meirelles, 2021).

2.6 The AI-Cocoon.

As argued in Chapter 1, technology use has become increasingly pervasive in today's business context, and many organisations see DMAT as an opportunity to leverage their capability and performance (Bley et al., 2022; The Economist, 2023). While previous Technology adoption models provide valuable insights, DMAT represents a distinctive challenge with its own characteristics and ambiguities. There is, therefore, an unequivocal need to model a framework that enables contextualisation of the factors influencing AI-powered tool adoption (Venkatesh, 2022). The proposed framework (refer to Figure 2.6) captures this complex interplay by associating findings from the case analysis with previous empirical research (See Figure 1.4).

2.6.1 Constructs derived from UTAUT.

Organisational Performance Expectancy (OPE) refers to the extent to which companies believe technology enhances job performance and aligns with PE (Venkatesh et al., 2003). This concept is related to the belief that employees using productivity technology, including AI-enabled tools, will experience improved performance (Chatterjee et al., 2020; Dwivedi et al., 2019; Jain et al., 2022). Effort Expectancy represents the perceived ease of using technology, with antecedents such as complexity and ease of use (Davis, 1989; Venkatesh et al., 2003; Cimperman et al., 2016; Andrews et al., 2021). In this context, EE pertains to corporates' attitudes towards adopting DMAT (Chatterjee and Bhattacharjee, 2020; Andrews et al., 2021).

Norms and Social Influencers (NSI) encompass the impact of peers and stakeholders on individual behaviour (Venkatesh et al., 2003). Influenced by perceived benefits, peer usage may encourage others to adopt the technology (Jain et al., 2022). H3 supports Chatterjee and Bhattacharjee (2020) by suggesting that NSI significantly influence perceived usefulness through internalizations. Organisational Facilitating Condition (OFC) examines the extent to which an individual perceives that the technical infrastructure supports new technologies, such as AI (Chatterjee et al., 2020; Jain et al., 2022; Venkatesh et al., 2003).

Lastly, cost and pricing structure can significantly impact technology use (Alhwaiti, 2023). Price Value (PV) is defined by Kwateng et al. (2018) as an individual's cognitive trade-off analysis comparing the perceived benefit to the monetary cost of using an innovative service, supporting the development of H5.

Hence, it can be hypothesised that:

H1. OPE positively impacts ATT toward DMAT
H2. EE positively influences ATT to adopt DMAT.
H3. NSI positively influences the BI to adopt DMAT.
H4 OFC positively influences the UB of DMAT.
H5. PV positively influences the BI to adopt DMAT.

2.6.2 DMAT-specific Constructs

Due to a relatively new application to corporate settings, the proposed framework (refer to figure 2.6) considers additional factors influencing DMAT adoption decisions based on the findings from the case analysis (see appendixes 2.6.1, to 2.6.4):

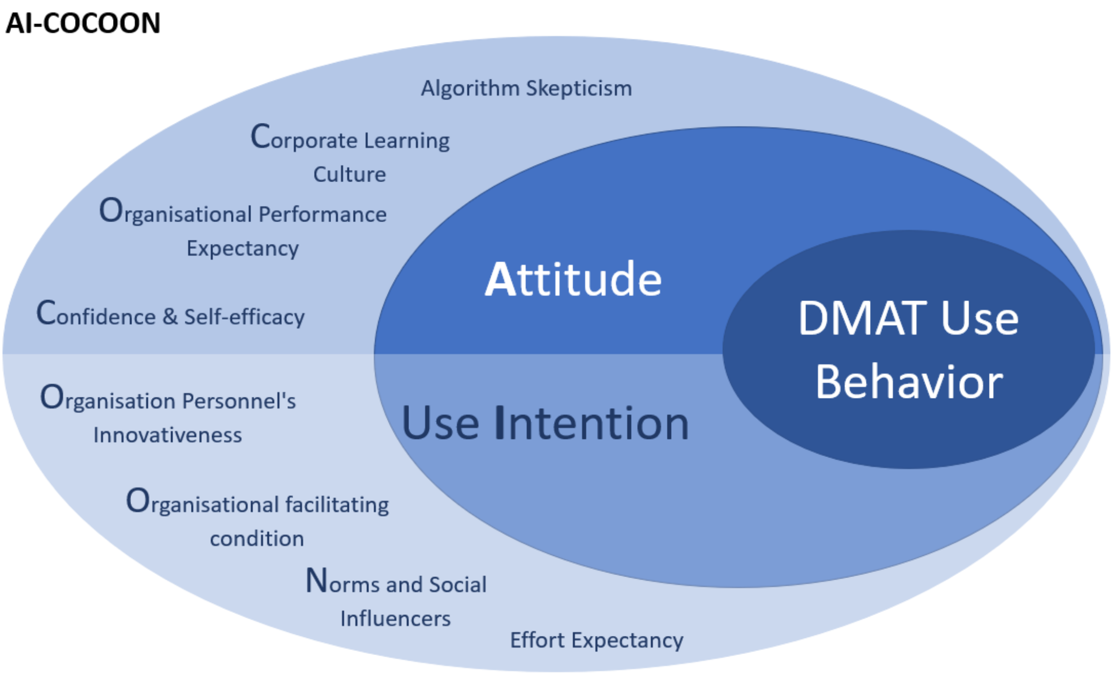


Figure 2.6 The AI-Cocoon (Revised)

Corporate Learning Culture (CLC) is interpreted as the degree to which a company's learning culture (including values, beliefs and practices) influences individuals' attitudes toward DMAT. Innovation-oriented environments prioritising continuous learning are expected to have high adoption rates and positive attitudes toward AI and innovation (Nascimento & Meirelles, 2021; Marsick and Watkins, 2003). This is because continuous learning promotes user adjustment to new systems, contributing to positive attitudes towards innovative technologies (Aladwani, 2001). Hence, continuous learning is proposed as a factor condition enhancing end users' attitudes toward knowledge and innovation (Marsick and Watkins, 2003), directly impacting their attitude toward DMAT.

Algorithm Scepticism (AS) questions the accuracy, fairness, and transparency of algorithms' impacts on attitude (ATT). The intricate design and limited explainability of DMAT can affect adoption (Cheatham et al., 2019; Jain et al., 2022). Venkatesh (2022) argues that AI's black-box nature offers little or no visibility to users, impeding adoption. Mahmud et al. (2022) support this argument, citing algorithmic opacity as a hindrance. While Research from Bigman and Gray (2018) states that the level of awareness about the expertise and efficiency of algorithms influences algorithmic aversion.

Organisation Personnel's Innovativeness (OPI) encompasses employees' inclination towards novelty and exploration (Hirschman, 1980). This concept is crucial for marketing, as it addresses individual differences in the adoption process (Aroean & Michaelidou, 2014). Since prior models neglected individual differences in the adoption process, incorporating this attribute into the AI-Cocoon is a valuable addition, as OPI is anticipated to play a significant, positive role in their intentions to adopt DMAT (Abu-Shanab and Pearson, 2009; Patil et al., 2020; Slade et al., 2015).

According to Social Cognitive theory (SCT), proposed by Bandura (1986), self-efficacy refers to people's assessments of their effectiveness or ability to organise and execute courses of action needed to achieve a specific outcome. In the context of DMAT, this relates to the participants' belief about their ability to master the use of AI-based technology, regardless of the potential results that could be achieved (Chao, 2019; Abu-Shanab & Pearson, 2009). Previous studies demonstrated that if users master using an AI-based system, it will influence their adoption intention (Nascimento & Meirelles, 2021).

ATT encompasses consumers' positive or negative evaluations of behaviour (Ajzen, 1991) and features in numerous IS/IT adoption theories such as TRA, TAM, and DTPB (Fishbein & Ajzen, 1975; Davis et al., 1989; Taylor & Todd, 1995). Dwivedi et al. (2019) argue that reintroducing attitude improves model variance in understanding the use of novel technology. Numerous studies confirm the relationship between attitude and behavioural intention (Chatterjee and Bhattacharjee, 2020; Andrew et al., 2021).

Venkatesh et al. (2003) established that behavioural intention is a perfect predictor of use. BI plays a formative role in UB (Ajzen, 1991). If an organisation's personnel exhibit BI toward DMAT systems, it is likely they will exhibit use behaviour and deploy the system (Andrews et al., 2021; Cao et al., 2021; Chatterjee et al., 2021). This research identifies the outcome variable as UB. Many studies have investigated and confirmed technology use as an outcome (Patil et al., 2020; Chatterjee et al., 2021).

Given the preceding discussion and considering that DMAT application to corporate setting is quite innovative, this study proposes these additional hypotheses:

H6. CLC positively impacts ATT toward DMAT
H7. AS negatively influences ATT to adopt DMAT.
H8. OPI positively influences BI toward DMAT.
H8a. BI mediates the relationship between OPI and UB
H9. CSE positively influences ATT toward DMAT.
H9a. ATT mediates the relationship between CSE and BI
H10. ATT positively influences BI toward DMAT
H11. BI positively influences UB toward DMAT

2.6.3 Moderating Effects

Previous research highlights risk perception, which encompasses uncertainties and potential adverse outcomes, as a vital factor affecting technology adoption (Cabrera-Sánchez and Villarejo-Ramos, 2020). In the context of DMAT, Security risks (SR) are defined as the perceived potential harm to individuals or an organisation's resources (Kalakota and Whinston, 1996) that can arise from attacks on computer networks or unauthorised access. Therefore, SR refers to the moderating effect of potential electronic fraud or hacker attacks on DMAT.

Additionally, DMAT presents risks of errors or unintended consequences, potentially resulting in financial losses (Bostrom et al., 2014) Biased AI algorithms or unexpected feedback loops may cause significant economic downfalls (Aljindi, 2015), while input error can introduce inaccuracies and inconsistencies, leading to incorrect predictions and financial loss (Davenport and Kalakota, 2019). Financial risk (FR) is conceptualised as individuals' perception of monetary risk associated with technology adoption (Featherman and Pavlou, 2003). Hence, it can be hypothesised that:

H12: SR moderates the effect of ATT, toward BI
H12a: SR moderates the effect of BI, toward UB
H13: FR moderates the effect of ATT, toward BI
H13a: FR moderates the effect of BI, toward UB

2.6.4 Demographic and Firmographic Moderators

Previous research explores the role of firm size in AI adoption (Nascimento & Meirelles, 2022), revealing both positive associations (Bresnahan et al., 2002) and insignificant relationships (Bayo-Moriones et al., 2013; Oliveira & Martins, 2011). Additionally, firm age can impact innovation activity (Cefis & Marsili, 2005) as older firms can optimise capabilities (Becker & Dietz, 2004), though conflicting evidence exists (Sørensen, & Stuart, 2000)

Researchers also posit that technology adoption and BI are moderated by age and gender (Venkatesh et al., 2003). Highly educated individuals are more inclined to embrace novel technologies (Venkatesh et al., 2003). While in contrast, older people may face difficulties absorbing new information, hindering adoption (Plude and Hoyer, 1985). According to Venkatesh and Morris (2000), Men exhibit greater tenacity in overcoming challenges than women, while experience enhances familiarity and knowledge structures, facilitating user learning (Alba and Hutchinson, 1987).

Hence this study posits that Gender (Hxb), Age (Hxc), Academic level (Hxd), Job seniority (Hxe), DMAT experience (Hxf), role with DMAT (Hxg), Firm size (Hxh) and Firm age (Hxi) moderate the observed and mediating variables toward UB (where “x” refers to the path label, see appendix 4.9 for hypotheses).

Thus, the AI-Cocoon support that:

$$UB=f\ (\alpha + \beta 1 \times OPE + \beta 2 \times EE + \beta 3 \times NSI + \beta 4 \times OFC + \beta 5 \times PV + \beta 6 \times CLC + \beta 7 \times AS + \beta 8 \times OPI + \beta 9 \times CSE + [\beta 12 \times SR + \beta 13 \times FR + \beta 14 \times D + \beta 15 \times F] + \varepsilon)$$

Where:

UB is the Dependant variable.
OPE, EE… and CSE are the constructs of the model.
[SR, FR… and D] are the moderators.
α is the intercept.
$\beta 1$, β…, to $\beta 15$ are the regression coefficients.
ε is the error term.

Chapter 3: RESEARCH METHODOLOGY

3.1 Research Philosophy

This chapter focuses on the most appropriate approach to examine the acceptance of DMAT and will discuss the methodology adopted for this research, including the underpinning philosophy. According to Lincoln and Guba (1985), research consists of four elements: methodology, ontology, epistemology, and axiology. As discussed throughout Chapter 1, this research seeks to identify the underlying causal mechanisms and structures that influence the adoption of DMAT by corporate users through a case study and a quantitative survey. This research method provides a comprehensive understanding of the multilevel factors influencing DMAT adoption while testing the hypothesis generated through the case study and previous empirical research.

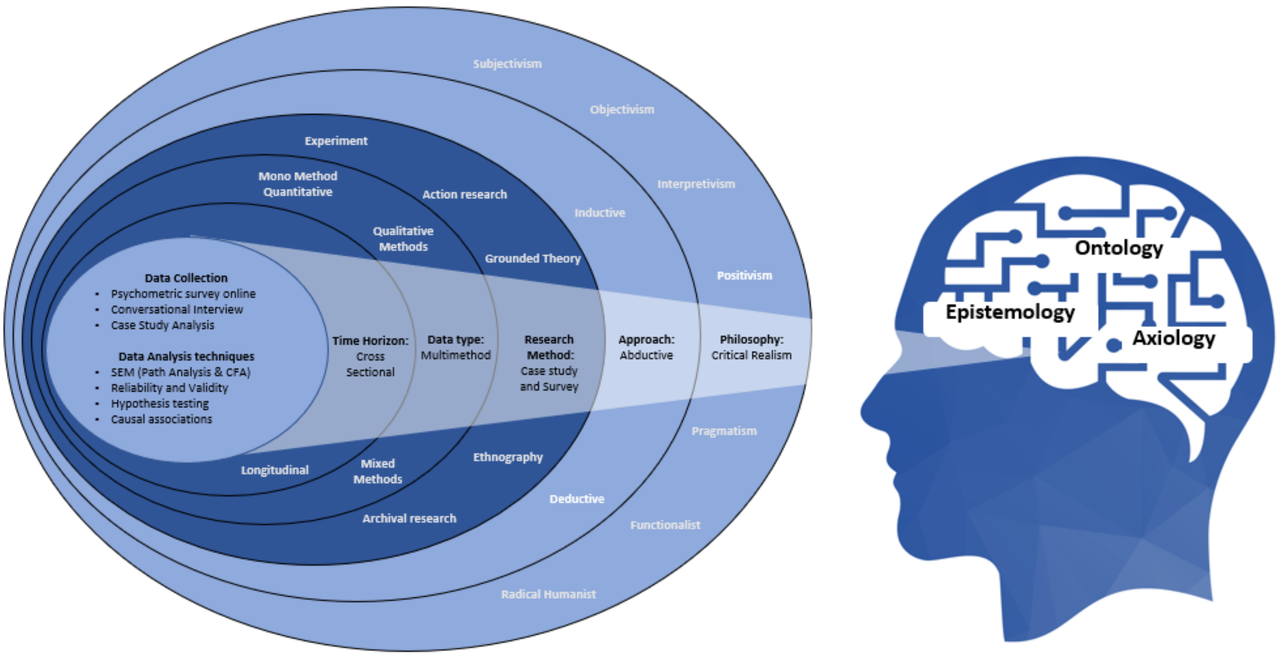


Figure 4.1 The research perspective, adapted from Saunders et al. (2012)

This research uses an abductive approach, where a modified theory is developed from observations, events exploration, and patterns explanation. The theory is then examined with data collection and analysis (Saunders et al., 2015). Findings from the abductive approach are considered merely best predictions based on incomplete observations and work out a plausible theory to explain their occurrence (Bell et al., 2019). This methodology aligns with Critical realism, which Saunders et al. (2015) define as a "philosophical stance where what we experience are some of the manifestations of the things in the real world, rather than the actual things" (Saunders et al., 2015, p. 714). It is a philosophical approach that bridges the nuances between ontology and epistemology by providing a theoretical framework explaining the relationship between reality, knowledge, and human perception.

Ontologically, critical realism posits that an objective reality exists independently of our perceptions and interpretations. This reality is structured and organised in specific ways, and our knowledge of it is limited by our ability to access it (Saunders et al., 2009). Critical realism argues that while our perceptions of reality are always mediated by social, cultural, and historical factors, objective reality exists beyond these factors (Bhaskar et al., 1998; Collier, 1994). Epistemologically, the adopted philosophy emphasises the importance of scientific inquiry to access objective reality. Critical realism recognises that our knowledge of reality is always partial and incomplete but argues that it is possible to develop theories and explanations that are more or less true (Saunders et al., 2009; Bhaskar et al., 1998). Critical realism acknowledges that our social and cultural contexts shape our perceptions of reality but argues that we can still strive for objectivity by developing rigorous scientific methods and theories grounded in empirical evidence.

As seen in Figure 4.1, this perspective aligns with the abductive approach by providing a rigorous and systematic way to investigate the underlying causal mechanisms and provides the required depth to understand the structures contributing to DMAT adoption by recognising the importance of multilevel studies (Saunders et al., 2009; Collier, 1994).

3.2 EmergeIQ case study

EmergeIQ is a pioneer startup that provides cloud-based solutions in DMAT to clients in the United Kingdom. The company boasts a global team comprising approximately 25 highly skilled professionals with a unique blend of technical and business expertise. They specialise in offering bespoke DMAT solutions tailored to clients' requirements (Refer to Appendix 2.6.1). The organisation's cloud-based algorithm library optimises user operations to provide its clients with a competitive edge. The product offerings cater for businesses of all sizes on a subscription basis, enabling customers to benefit from DMAT expertise at a feasible price on an ongoing basis.

Interviewing the Chief Technical Officer (CTO) revealed that the challenges of providing bespoke DMAT solutions underlie complex cost structures and the need to understand the linkages between developers and clients (See Appendix 2.6.2). The CTO argues that the company aims to provide value through cost-effective solutions that can be reused and provide clients with positive financial ROI. He argues that clients may initially be hesitant to adopt data science and believe that educating clients would increase the incentive to adopt their products.

This point of view is supported by the Chief Data Officer's observations (CDO), who argue that their clients often struggle with defining their requirements, particularly for user interfaces, which leads to unnecessary iterations. This issue is a common challenge for business-based technology projects, not just for DMAT. According to the CDO, the company can only strive by focusing on efficiency and cost-effectiveness, adding the minimum innovation required to add value, and aligning their ventures' outcomes with clients' needs (See Appendix 2.6.2). The CDO also observe that large organisation trends to adopt DMAT with less difficulty and believe that the industry type may also impact adoption.

Using third-party APIs allows EmergeIQ to adapt quickly to client requirements, as these can be changed easily. Despite their innovative approach to business optimisation (Refer Appendix 2.6.1), EmergeIQ recognises a need to understand what influences the adoption of their technologies to leverage their unique value proposition. This challenge is compounded by the complexity of the industry terminologies, which require some adjustments to be more readily understood from an end-user perspective (Refer to Appendix 2.1.1).

As argued by EmergeIQ, the organisation must optimise its Technology-Client fit to develop its market. Their experience in various domains enables them to deploy and adapt to project needs at a competitive cost. However, there is still a pressing need to understand the factors influencing the adoption of this cutting-edge offering. The case analysis support that the underlying potential challenge could lie in understanding the organisations' stakeholders and adapting scopes to the human challenges associated with project implementation (See Appendix 2.6.4).

3.3 Research and Survey Design

The paucity of research on UK-tailored adoption frameworks for DMAT fostered the development of the suggested model in Figures 2.6 and 4.8, which led to the hypothesis developed in Chapter 2.6. The survey aims to collate information for 32 variables, including ATT, BI, and UB, each measured by three items derived from Fishbein & Ajzen (1977) and Venkatesh et al. (2003), which have been slightly altered to fit this research (Refer to Appendix 2.1.2). The study will use a cross-sectional design, which involves collecting data at a single time from a sample population based in the U.K., making underlying relationships accessible by simultaneously measuring multiple factors (Hinzmann and Bogatzki, 2020).

A web-based questionnaire was developed, with a 5-point Likert scale ranging from strongly disagree (1) to strongly agree (5), in line with Venkatesh’s psychometric scale

(Venkatesh et al., 2003). The primary reason for choosing surveys in a quantitative approach is that they are time-effective in gaining a representative insight into the population's opinion (Saunders et al., 2009). Additionally, Web-based self-completion questionnaires enable reaching many participants within a short time horizon (Saunders et al., 2009).

The survey questions result from previous research on technology adoption and the observations from EmergeIQ case analysis (Refer appendixes 2.6.1, 2.6.2, 2.6.3, 2.6.4). Questions were formulated per Bryman's guidelines and reviewed by a panel of 5 specialists working with DMAT solutions to check for apparent bias (Bryman, 2016). The questionnaire was revised in response to the feedback and piloted twice with 40 professionals in the U.K. to test the understandability of the questions. Revisions were made to the survey from 27th January 2023 to 31st January 2023.

3.4 Survey Strategy and Limitation

EmergeIQ agreed to support the research by providing access to its customer database to conduct the survey. The questionnaire will also be distributed electronically to 596 individuals that work in the UK via email and 691 participants through social media platforms. Data will also be collected face-to-face at Conferences and events venues through convenience sampling, and a total of 205 questionnaires were collected.

The questionnaire (refer to Appendixes 2.1.1 and 2.1.2) was divided into four sections: where the first section collates information on the frequency, purpose and type of technology used. The second section concentrates on demographic and firmographic information and classifies a series of information such as employee title, academic level, industry type and firm size. The third section (refer to Appendix 2.1.2) measures the manifest and mediating variables of the proposed framework and their effects on the model's dependent variable, UB. The last section encompasses categorical questions to identify the stage of DMAT implementation and the factors influencing the choice and type of suppliers. Questions were logically arranged to inform participants of the constitutes of DMAT (Refer to item 4 from Appendix 2.1.1) and to optimise the response rate. Items measuring the same construct were placed in a non-sequential manner to obtain reliable results and reduce respondent bias (Ajzen, 2006).

Nominal and ordinal scales were combined to collect data at a single point in time to investigate the causal relationship between belief-attitude-intention-behaviour (Lin et al., 2013; Bryman, 2016). Additional interaction variables were proposed based on the pattern observed in the case study and previous empirical frameworks on AI adoption (See Appendix 2.6.4). This includes perceived risks associated with adopting DMAT, such as Financial and Security risks, and additional factors that take into consideration novelty and product specific attributes.

Potential limitations to this study reside in the closed-ended questions used throughout the survey. The researcher's complete control of the investigation can cause missed individual perceptions and experiences (Bryman, 2012). Another limitation is rooted in convenience sampling, which may not accurately represent the UK population and limit generalisation and inferences (Bornstein & Putnick., 2016). As discussed in Chapter 2, DMAT delves into a collection of innovative products with shared characteristics but differing purposes and applications. While efforts were made to clarify the meaning and application of these technologies, the researcher acknowledges the constraints posed by the participants' subjective interpretation of the semantics, lexical, and pragmatic elements (Martinez, 2023). To alleviate these limitations, the researcher intends to achieve an adequate sample size, ensuring the survey instrument's validity and reliability, by targeting a minimum ratio of 5:1 for each direct relationship but preferably 10:1 for CFA, as recommended by Hair et al. (2017), and DeVellis (2017).

3.5 Data Analysis

To derive meaningful conclusions, it is essential that the data fulfils the quality criteria and that an appropriate analytical method is chosen (Easterby-Smith et al., 2015). Missing data is a commonly encountered issue in data analysis (Tabachnick & Fidell, 2007) and arises when some respondents failed to provide complete responses to all questions (Little & Rubin, 2014). This problem can result in a smaller sample size, reducing statistical power and causing biased estimates (Enders, 2010). In this study, out of the 205 collected surveys, only 120 respondents fully completed the survey, while 14 provided partial responses to the psychometric scale section.

To address this issue, data were imputed per Sharif's (2021) guidelines in SPSS v26. Additionally, using the Mahalanobis distance measurement method in SPSS Amos, nine multivariate outliers were identified from the imputed sample of 134 respondents and subsequently removed. The Mahalanobis distance has gained widespread recognition for effectively detecting statistical errors, as highlighted by Jiang and Zhang (2018). This method's appeal can be attributed to its robustness, mathematical tractability, affine invariance, and computational efficiency (Barnett & Lewis, 1974).

Additionally, Items with high correlation were assessed for multicollinearity using the Variance Inflation Factor (VIF) and tolerance values in SPSS v26 (Gaskin, 2020). The measurement model was also evaluated regarding internal consistency, convergent validity, and discriminant validity (Sharif, 2021). For this purpose, Internal consistency and Confirmatory factor analysis (CFA) was carried out in SPSS and AMOS software (Refer to Appendix 3.5).

Internal consistency was evaluated by Cronbach's alpha (also known as Alpha coefficient) and Composite reliability (CR). The importance of internal consistency in the development of scales cannot be overstated, as it is widely acknowledged that instruments with high levels of internal consistency are more dependable (DeVellis, 2006; Nunnally & Bernstein, 1994). The alpha coefficient measures the "correlations among the items (of a scale)" (DeVellis, 2006, p.52). High correlations between items would imply a high alpha (implying that Items are interrelated and measure the same variable) (Hair et al.,2010). This means that the scale can then be deemed unidimensional; in other words, the items within the scale measure the same core subject. Therefore, to ensure the internal consistency of the AI-Cocoon, all constructs composing the model were measured by the alpha coefficient. This process also allowed for a preliminary evaluation of the (redundant or repetitive) items within the scale for possible exclusion (Clark & Watson, 1995). Finally, all analysis results will be presented in tables, graphs, and narrative form (Creswell & Creswell, 2017).

3.6 Ethical Considerations

In the context of this research, ethics is defined as the appropriate behaviour of the people who come in touch with the investigation or are affected by it, including consent, confidentiality, and privacy requirements (Saunders et al., 2007). The survey will be conducted anonymously, and findings will be stored in a secure, password-protected Brunel network for the duration of the research in line with the Ethical approval from the Research Ethics Committee, granted on the 24th of February 2023. Copies of the approval letter, participant information sheet, signed consent forms, and other email agreements can be found in Appendix 3.6. Finally, the respondents were allowed to withdraw from the survey without restriction at any point in time.

Chapter 4: RESULTS

4.1 Primary Analysis

An initial evaluation was conducted to examine the distribution of the variables before the analyses (Sharif, 2021; Tabachnick and Fidell, 2013). Figures (See appendix 2.1.2) outline that the skewness (-1.2 to 0.373) and Kurtosis values (-1.165 to 3.408) lie within the acceptable ranges of -2/+2 and -7/+7, as recommended by Hair et al. (2010) and is therefore considered to exhibit a normal distribution and deemed suitable for further analysis (Bryne, 2010; Kline, 2011).

4.2 Descriptive Statistics

The breakdown of the respondents' characteristics outlines that the most prominent groups within the age distribution are those aged between 25-34 (30.7%) and 35-44 (32.1%). Most respondents are male (58.6%), while 37.9% are female. In terms of academic qualifications, most hold a master's degree (43.6%), followed by bachelor's degree holders (35.0%) and PhDs (10.7%). Professionally, middle management positions are the most prevalent (41.4%), with 23.6% being officers and 13.6% senior executives.

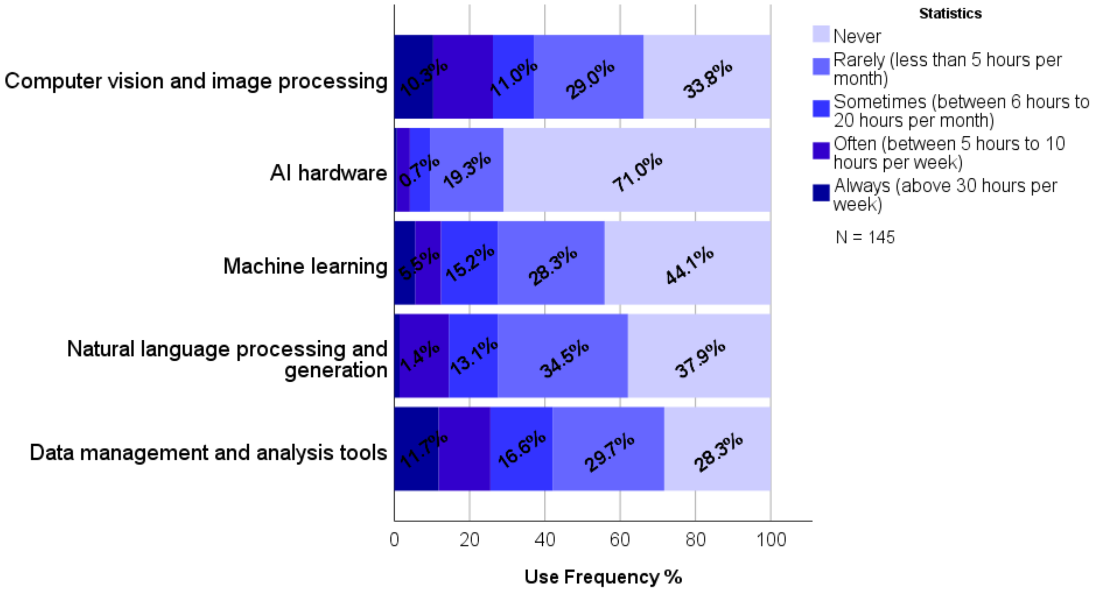


Figure 4.2.1 Use frequency of DMAT

DMAT experience is predominantly between 1 to 4 years (35.7%), with 30.7% having less than one year of experience. Most respondents are end users/administrators (48.6%), followed by DMAT decision influencers (20.7%). As seen in Figure 4.2.1, most respondents never used AI hardware for work purposes (71.0%), while DMA was the most used tool, with 72% using it on varied frequencies (from occasionally to always). Usage frequency of other tools differs, with a larger percentage of respondents reporting using DMAT rarely or occasionally.

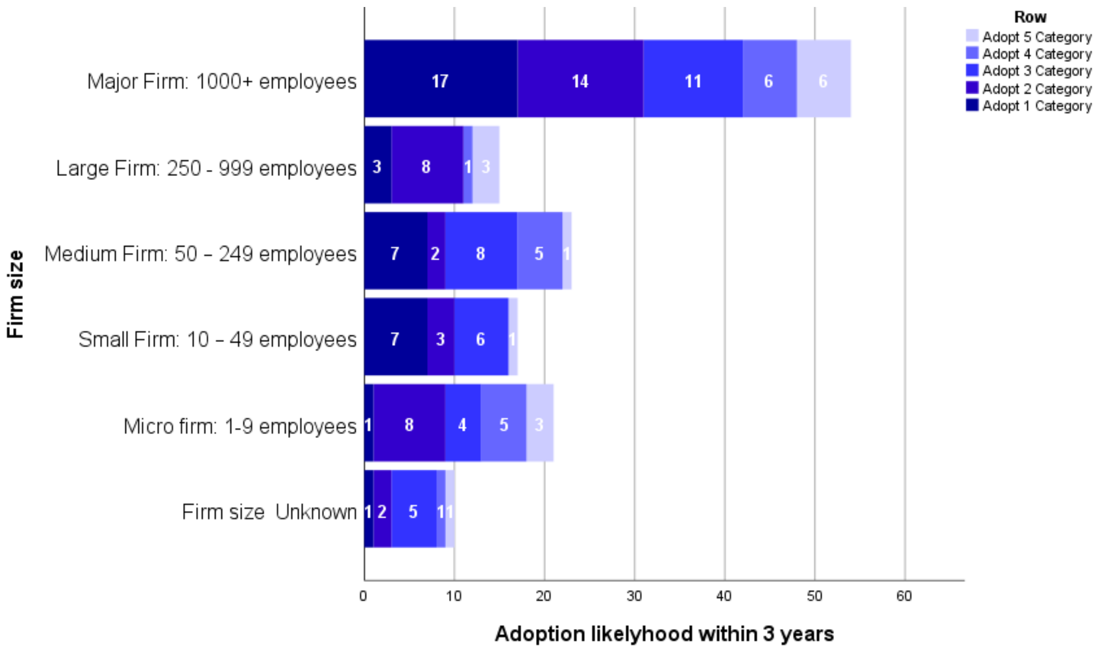


Figure 4.2.2 Likelihood of adoption

The participant's distribution is skewed towards larger organisations, with 38.6% working for companies with over 1000 employees. Figure 4.2.2 outlines the likelihood of DMAT adoption by Firm size and Category. Firm age is more evenly distributed, with the largest group comprising companies older than 50 years (28.6%) and the smallest being those less than one year of operation (4.3%). Figure 4.2.3 ranks the participants' preferred considerations (Attributes) by differentiated personas when purchasing or subscribing to DMAT from DSaas providers. The analysis revealed that Implementation stage is skewed toward pre-implementation stages (61.6%). Other descriptive data related to the respondents' industry, and motivation can be found in Appendixes 4.2.1 to 4.2.6.

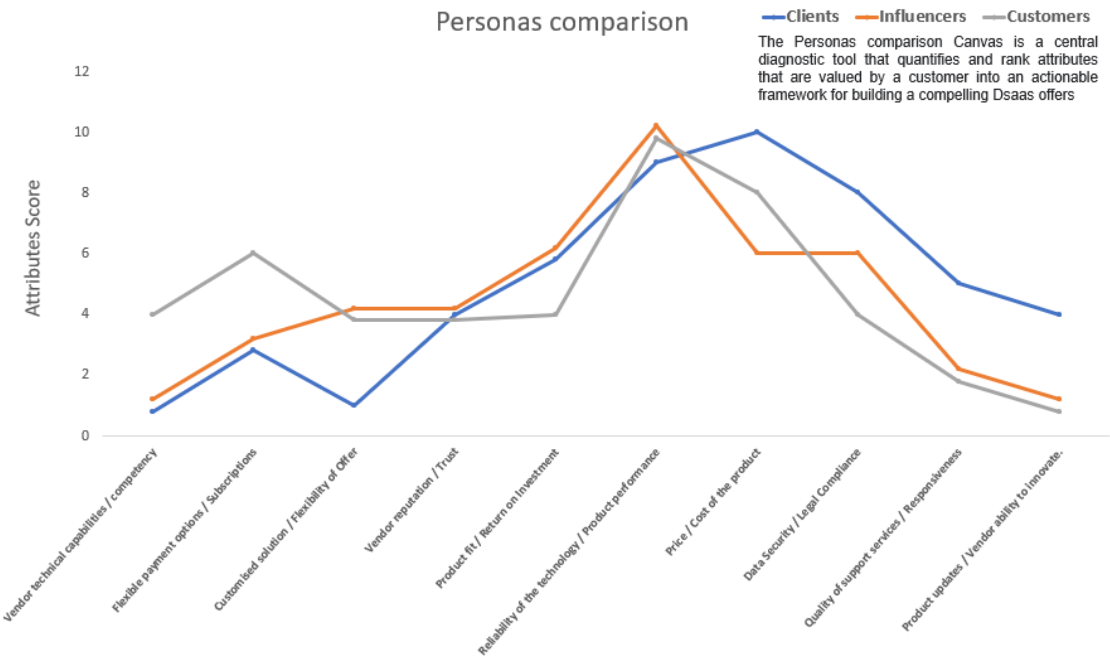


Figure 4.2.3 Canvas comparing Users' preferred attributes.

4.3 Measurement model analysis

A Confirmatory Factor Analysis (CFA) was conducted with the measurement items to assess the model using goodness-of-fit guidelines set out by Hair et al. (2010). Table 4.3 presents the model fit summary for the measurement, initial and revised models, including various fit indices, categorised as absolute, incremental, and parsimony fit (Hair et al., 2009; Kline, 2011). The measurement model's degree of freedom (df) is 560, and Chi-Square (X^2) value is 746.72. Chi-square is a popular measure to evaluate the overall model fit (Hooper et al., 2008) and measures the discrepancy between expected and observed covariances in the data (Rappaport et al., 2020). For the absolute fit indices, the Root Mean Square Error of Approximation (RMSEA) is 0.052, which falls within the acceptable fit interval of 0.05 to 0.08, as suggested by Hair et al. (2009) and Meyers et al. (2005). The Standardized Root Mean Square Residual (SRMR) is 0.05 and can be considered a good fit as it is less than the recommended value of 0.09 (Hair et al., 2009; Sharif, 2021).

In terms of incremental fit indices, the Comparative Fit Index (CFI) is 0.936, which falls within the acceptable fit interval of 0.90 to 0.95 (Hair et al., 2009; Hatcher, 1994). CFI is among the most reported fit indices in the literature, as it is one of the least affected by sample size (Hooper et al., 2008), supporting its selection as one of the preferred indices to evaluate the AI-Cocoon. IFI and TLI are 0.939 and 0.919, respectively, which exceeds the threshold of 0.90, indicating a good model fit (Meyers et al., 2005). For parsimony fit indices, the Parsimonious Normed Fit Index (PNFI) is 0.632, falling above the recommended threshold of 0.5, suggesting a parsimonious fit (Meyers et al., 2009). Additionally, the parsimony-Adjusted Comparative Fit Index (PCFI) is 0.745 exceeding the minimum threshold of 0.5 and is close to the optimal value of 1, indicating a good fit as per Meyers et al. (2009).

Lastly, the normed Chi-square (CMIN/DF) value is 1.333, which is considered a good fit as it is below the recommended threshold of 3.0 (Hair et al., 2009; Marsh & Hocevar, 1985). CMIN/DF is often preferred to Chi-square as it is the minimum discrepancy per degree of freedom and divides the Chi-square by DF (X^2/DF), norming the Chi-square, making it less dependent on sample size (Kline, 2011; Marsh & Hocevar, 1985). As argued above, the model demonstrates an adequate to good fit according to various fit indices and adheres to the recommendation of Jaccard and Wan (1996).

Model fit summary for the final measurement model.

Fit Measure	Measurement Model	Initial Model	Revised Model	Acceptable Fit Interval	Reference
Degree of Freedom (df)	560	405	316	To report if N between 100 and 200	Tabachnik & Fidell (1996)
Chi-Square (X^2)	746.72	527.87	371.44*		
Absolute Fit Indices					
Root mean square error of approximation	0.052	0.049	0.038	0.05 ≤ RMSEA CFI ≤ 0.08	Hair et al. (2009); Meyers et al.,
Standardized Root Mean Square Residual	0.050	0.050	0.051	<0.09	Hair et al. (2009); Sharif (2018)
Incremental Fit Indices					
Comparative Fit Indices (CFI)	0.936	0.948	0.972	0.90 ≤ CFI ≤ 0.95	Hair et al. (2009); Hatcher
Incremental Fit Index (IFI)	0.939	0.950	0.973	> 0.90	Meyers et al. (2005)
Tucker Lewis coefficient (TLI)	0.919	0.936	0.967	> 0.90	Hair et al. (2009)
Parsimony Fit Indices					
Parsimonious Normed Fit Index (PNFI)	0.632	0.666	0.705	> 0.5	Meyers et al. (2009)
Parsimony-Adjusted Comparative fit Index	0.745	0.774	0.813	> 0.5; Close to 1 Good	Meyers et al, (2009); Arbuckle
CMIN/DF	1.333	1.303	1.175	<3.0 Good; < 5.0 Sometime Permissible	Hair et al. (2009); Marsh & Hocevar (1985)
				N=125	* p = 0.017

Jaccord and Wan (1996) recommends reporting at least three fit tests (One Absolute, One Relative, and One parsimonious)
Sharif(2021) recommend reporting Chi-Square, and it df and two incremental fit indices, RMSEA and SRMR.

Table 4.3 Model fit summary for the measurement and structural models

4.4 Validity and Reliability of the Model

Table 4.4.1 shows that the Cronbach alpha of all constructs is higher than 0.70, ranging from 0.701 to 0.881, in line with Hair et al. (2009) recommendations.

Construct	Indicators	Cronbach's α	Factor Loading	CR	AVE
Organisational Performance Expectancy	PE1 PE2* PE3	0.759	0.877 0.810* 0.697	0.769	0.627
Effort Expectancy	EE1 EE2 EE3	0.848	0.784 0.832 0.810	0.850	0.654
Norms and Socio Influencers	SI1 SI2 SI3	0.714	0.738 0.630 0.667	0.720	0.462†
Organisation Facilitating Conditions	FC1* FC2 FC3	0.701	0.620* 0.594 0.908	0.733	0.589
Price Value	PV1 PV2	0.801	0.744 0.900	0.809	0.682
Corporate Learning Culture	LC1 LC2 LC3*	0.856	0.785 0.953 0.823*	0.864	0.762
Algorithm Scepticism	AS1 AS2 AS3 AS4*	0.823	0.749 0.876 0.749 0.758*	0.821	0.606
Security risk	SR1 SR2 SR3	0.850	0.774 0.786 0.858	0.848	0.651
Financial risk	FR1 FR2 FR3	0.845	0.709 0.847 0.859	0.848	0.653
Organisation Personnel Innovativeness	PI1 PI2 PI3* PI4*	0.756	0.774 0.786 0.922* 0.683*	0.757	0.608

Confidence & Self-efficacy	SE1* SE2* SE3 SE4	0.789	0.626* 0.537* 0.754 0.879	0.802	0.671
Data-Driven Expertise	DD1* DD2* DD3* DD4*	0.850	0.932 0.794 0.562* 0.782*	0.856	0.750
Attitude	ATT1 ATT2 ATT3	0.881	0.780 0.890 0.860	0.882	0.713
Behaviour Intention	BI1 BI2 BI3	0.913	0.926 0.898 0.842	0.862	0.677
Use behaviour	UB1 UB2 UB3	0.853	0.843 0.738 0.880	0.919	0.791

* Removed due to multicollinearity
† Below threshold but kept

Table 4.4.1 Reliability and Convergent validity assessment

	CR	AVE	MSV	UB	OPE	EE	NSI	OFC	PV	SR	FR	AS	CLC	OPI	CSE	DD	ATT	BI
UB	0.919	0.791	0.669	**0.889**														
PE	0.769	0.627	0.457	0.675	**0.792**													
EE	0.850	0.654	0.453	0.636	0.614	**0.809**												
NSI	0.720	0.462*	0.454	0.674	0.631	0.673	**0.680**											
OFC	0.733	0.589	0.327	0.359	0.484	0.507	0.572	**0.767**										
PV	0.809	0.682	0.244	0.343	0.358	0.280	0.284	0.359	**0.826**									
SR	0.848	0.651	0.610	-0.337	-0.270	-0.202	-0.227	-0.124	0.062	**0.807**								
FR	0.848	0.653	0.610	-0.294	-0.301	-0.138	-0.021	-0.090	-0.019	0.781	**0.808**							
AS	0.821	0.606	0.569	-0.265	-0.291	-0.296	-0.134	-0.294	-0.123	0.754	0.753	**0.779**						
CLC	0.864	0.762	0.255	0.358	0.226	0.255	0.412	0.284	0.355	-0.079	-0.184	-0.210	**0.873**					
OPI	0.757	0.608	0.507	0.660	0.519	0.490	0.482	0.318	0.467	-0.152	-0.131	-0.103	0.233	**0.780**				
CSE	0.802	0.671	0.659	0.812	0.571	0.607	0.511	0.356	0.373	-0.154	-0.171	-0.166	0.347	0.607	**0.819**			
DD	0.856	0.750	0.558	0.747	0.565	0.587	0.535	0.458	0.253	-0.343	-0.253	-0.246	0.310	0.712	0.727	**0.866**		
ATT	0.882	0.713	0.669	0.818	0.676	0.573	0.618	0.415	0.348	-0.392	-0.401	-0.443	0.505	0.460	0.786	0.722	**0.845**	
BI	0.862	0.677	0.658	0.811	0.608	0.588	0.569	0.494	0.494	-0.195	-0.148	-0.226	0.310	0.669	0.713	0.622	0.654	**0.823**

† AVE < 0.50, below threshold but kept in the model

Table 4.4.2 Discriminant validity table

Factor loadings and average variance extracted (AVE) were used as indicators of convergent validity, with a threshold of 0.60 for factor loadings and 0.50 for AVE (Hair et al., 2010). All items used have factor loadings and AVE above the recommended threshold, except Norms and Socio Influencers, with an AVE slightly below the recommended threshold with a value of 0.462. Sharif (2021) argues that AVE is a too strict measure for convergence validity. He argues that an AVE of 0.462 can be accepted, provided CR is > AVE and CR is > 0.7. Overall, the remaining items exhibited solid convergent validity. Therefore, the survey measures were deemed to have good convergent validity.

Discriminant validity was evaluated by measuring the cross-loadings and checking the Fornell-Larcker criterion (Fornell and Larcker, 1981). This criterion evaluates the extent to which a latent variable is distinct from other latent variables in the model by comparing the square root of the AVE for each construct with the correlations between the constructs (Fornell & Larcker, 1981). Discriminant validity is established when the square root of the AVE for a construct is higher than its correlation with any other construct in the model (Hair et al., 2009). Sharif (2021) argues that for the criterion to be fulfilled, the AVE of each construct must be greater than the MSV, which is the case for each construct in Table 4.4.2.

4.5 Initial Structural Model Results

We employed SEM to concurrently test the study hypotheses, including the direct and indirect effects (refer to Appendix 4.5) with a maximum likelihood estimation method, which accounted for measurement errors and the interrelationships between constructs. Our findings indicate significant total effects of CLC, OPE and CSE on attitude ($p=0.002$, $p=0.014$, and $p<0.001$, respectively), with positive low-to-moderate path coefficients (see Table 4.5 for the initial model's results).

A negative association emerged between AS and ATT ($\beta=-0.222$, $p=0.001$), supporting H7, while H2, H3, and H5 were rejected due to non-significant effects of EE, NSI, and PV on ATT ($p=0.730$, $p=0.142$, and $p=0.254$, respectively).

Path coefficients between OPI and ATT towards BI were significant and positive ($\beta=0.265$ and $\beta=0.350$, $p<0.05$), moderately contributing to BI and supporting H8 and H10. The coefficient of determination (R^2) for BI was 0.816, with independent variables accounting for 81.6% of the variance. Table 4.5 reveals CSE as the strongest influence on ATT, while ATT was found as the strongest influence on BI. H4 and H11 were also supported, demonstrating positive impacts on DMAT usage ($\beta=0.213$, $p=0.011$ and $\beta=0.565$, $p<0.001$, respectively).

Hypothesis	Path	β	S.E	C.R.	p-value	Results	Contribution
H1	**OPE → ATT**	0.218	0.102	2.454	0.014	Supported	Moderately Low
H2	**EE → BI**	0.033	0.114	0.346	0.730*	Not Supported	
H3	**NSI → BI**	0.146	0.136	1.468	0.142*	Not Supported	
H4	**OFC → UB**	0.213	0.070	2.545	0.011	Supported	Moderately Low
H5	**PV → BI**	-0.080	0.072	-1.140	0.254*	Not Supported	
H6	**CLC → ATT**	0.218	0.063	3.156	0.002	Supported	Moderately Low
H7	**AS → ATT**	-0.222	0.070	-3.187	0.001	Supported	Moderately Low
H8	**OPI → BI**	0.265	0.106	2.773	0.006	Supported	Moderately Low
H9	**CSE → ATT**	0.458	0.118	3.666	***	Supported	Moderate
H10	**ATT → BI**	0.350	0.139	3.005	0.003	Supported	Moderately Low
H11	**BI → UB**	0.565	0.081	4.837	***	Supported	Moderate

*** ($p < 0.001$) * Not sig ($p > 0.05$)

Table 4.5 Result of Initial Model

4.6 Alteration to the AI-Cocoon

The initial model, while broadly supporting the hypotheses, remains susceptible to potential misspecification, which could result in the rejection of H2, H3, and H5. According to Kline (2015), "Models are always provisional, subject to revision and modification" (p. 447). To address these inaccuracies, the initial model was modified to accommodate recent findings from Nascimento & Meirelles (2022) to enhance the model's explanatory power and accuracy. Therefore, in line with AI2M, this research proposes that EE and OPE positively influence NSI toward BI, replacing H2 and H5 with the hypotheses below:

H1a: OPE positively influences NSI toward intention to use DMAT.

H2a: EE positively influences NSI toward intention to use DMAT.

The new results revealed varying levels of support for the revised model, with differences in the path coefficients (β) and parameters (SE and CR). Comparing the findings with the initial model revealed that while H2 was previously rejected, EE contribution toward BI is now supported in the forms of H2a (EE → NSI) and H3 (NSI → BI). This suggests that EE and OPE influence NSI toward BI, unlike the initial model, where its influence on BI was found not significant. All other previously supported hypotheses remain supported with different levels of contributions, significance, and reliability (refer to the β, CR and SE in Table 4.6), translating into an improved model fit index that explains 73.2% of the variance in use behaviour (R^2=0.732).

Hypothesis	Path	β	S.E	C.R.	p-value	Results	Contribution
H1	**OPE → ATT**	0.261	0.107	2.791	0.005	Supported	Moderately Low
H1a	**OPE → NSI**	0.371	0.134	2.732	0.006	Supported	Moderately Low
H2a	**EE → NSI**	0.473	0.117	3.470	***	Supported	Moderate
H3	**NSI → BI**	0.192	0.111	2.377	0.017	Supported	Low
H4	**OFC → UB**	0.196	0.065	2.370	0.018	Supported	Low
H6	**CLC → ATT**	0.219	0.067	3.010	0.003	Supported	Moderately Low
H7	**AS → ATT**	-0.235	0.072	-3.285	0.001	Supported	Moderately Low
H8	**OPI → BI**	0.225	0.096	2.610	0.009	Supported	Moderately Low
H9	**CSE → ATT**	0.519	0.093	5.202	***	Supported	Moderate
H10	**ATT → BI**	0.347	0.132	3.127	0.002	Supported	Low
H11	**BI → UB**	0.587	0.081	5.010	***	Supported	Moderate

Model Fit Indices: CMIN/DF: 1.175 IFI: 0.973, CFI: 0.972, PCFI: 0.813, RMSEA: 0.0: *** ($p < 0.001$)

Table 4.6 Result of Revised Model

4.7 Mediation Analysis

This study explored the mediation role of BI and ATT by bootstrapping the sample size to 2000 at 95% confidence level. According to Baron & Kenny (1986), a Mediation analysis is conducted when a middle variable (e.g., BI) could function as a mediator, affecting the relationship between the predictor (e.g., OPI) and the endogenous variable (e.g., UB). In the context of the structural path evaluation in SEM, the mediator variable is understood to have absorbing effects on the independent variable towards the dependent variable (Hair et al., 2010).

	Standardised Coefficient				
Hypothesis	**Path**	**β**	**p-value**	**Hypothesis**	**Results**
H8a	OPI → BI→UB			BI mediates the relationship between OPI and UB	Full Mediation
	Total Effect	0.359	0.011*		
	Indirect Effect	0.132	0.054†		
	Direct Effect	0.227	0.149		
H9a	CSE → ATT→ BI			ATT mediates the relationship between CSE and BI	Partial mediation
	Total Effect	0.494	0.027*		
	Indirect Effect	0.180	0.048*		
	Direct Effect	0.313	0.056†		

*Sig ($p < 0.05$)

†Quasi Sig ($p < 0.10$)

Table 4.7 Result of mediation analysis

Reviewing the literature on technology adoption suggests that partial mediation is most witnessed between constructs, meaning that the introduced mediator only mediates a part of the effect on the outcome (Gunzler et al., 2013). In this analysis, partial mediation was confirmed in the effect of CSE on BI, mediated through Attitude, as the lower and upper limits of the confidence interval (0.094; 0.743) did not include zero, mediation was found at a 5% significance level, accepting H9a (refer table 4.7). While full mediation can be considered between OPI and UB through BI due to a statistically not significant direct effect result (P=0.149).

4.8 Moderation Analysis

The current study aimed to investigate the impact of attitudes toward the behaviour intention and use of DMAT while considering the moderating effects of continuous variables such as SR and FR (Gaskin, 2011). The analysis revealed no significant moderating effect between SR interaction with ATT and BI toward UB. However, results demonstrate that the relationship between BI and UB significantly differs between a low and high level of FR, supporting H13a.

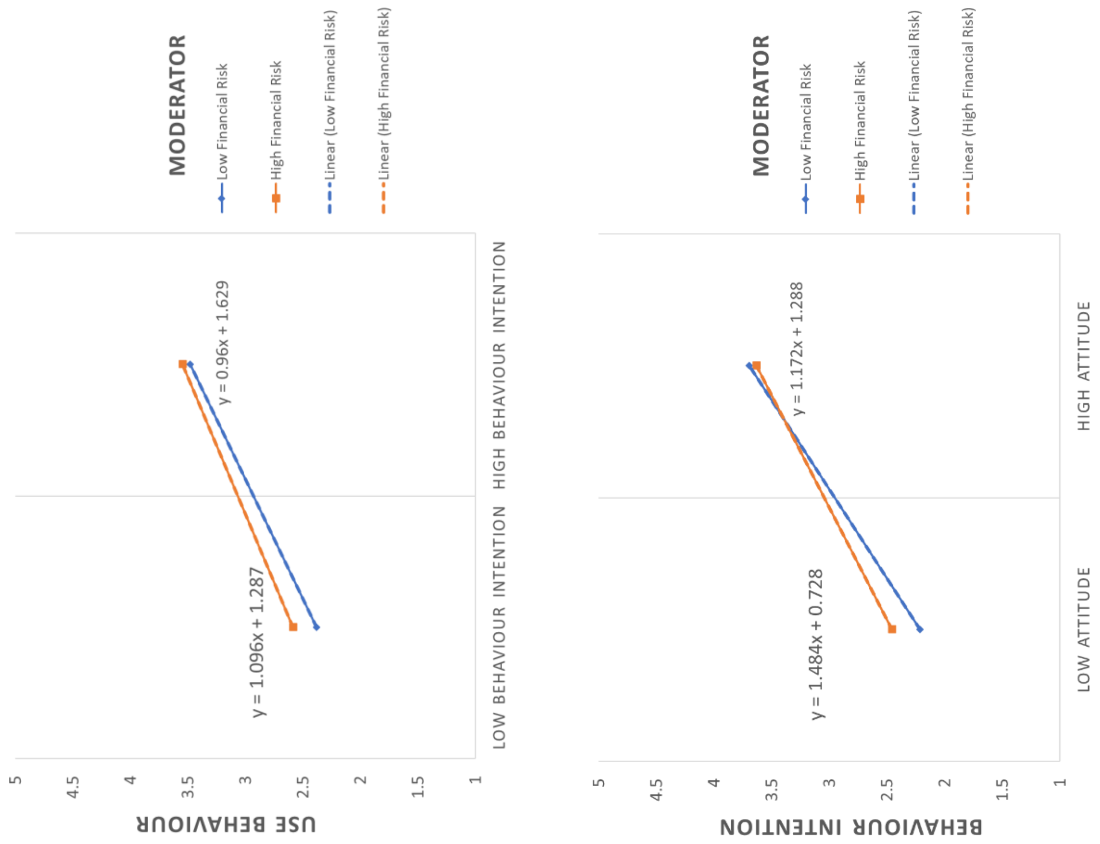


Figure 4.8 Interaction plots of the moderating effect of Financial Risk (Gaskin, 2019).

As illustrated in Figure 4.8, an interaction effect was observed between ATT and BI when moderated by FR (Sharif, 2021). Figures demonstrate that when FR is low, a unit change in individuals' attitudes will lead to a significantly stronger increase in BI, which means that at low FR levels, the effect of a change in ATT would generate a substantially more considerable increase in BI. In contrast, during high FR situations, a unit increase in attitude would result in a proportionately smaller increase in BI due to the steepness of the gradients. Gaskins (2019) posits that this occurs when FR dampens the positive association between ATT and BI. These results support H13 and H13a, while H12 and H12a were rejected.

4.9 Control Variables

The final step of the analysis was to understand the effects of the control variables on the AI-Cocoon. All hypotheses outlined in Chapter 2.6.4 were tested. Due to limitations caused by the sample size, the initial group composition was reorganised into composite groups (Refer to Appendix 4.9 for group composition and hypotheses). Two separate path models were estimated for each moderator, and their respective path coefficients were compared using Z-scores (Gaskin, 2011). Significant differences were supported for:

Hypothesis	Path	Gender Hxb	Age Hxc	Academic Hxd	Job Hxe	Experience Hxf	Role Hxg	Firm Size Hxh	Firm Age Hxi
H1y	**OPE → ATT**	-0.429	-1.358	2.059**	-1.83*	0.522	1.167	-0.160	-0.034
H1ay	**OPE → NSI**	1.319	-0.766	1.772*	0.108	-0.116	0.479	-1.758*	-0.787
H2ay	**EE → NSI**	-1.817*	0.643	-1.430	3.493***	0.300	-0.487	1.149	0.674
H3y	**NSI → BI**	2.522**	2.585***	1.594	1.8*	0.549	-2.271**	-0.867	-2.107**
H4y	**OFC → UB**	-0.239	0.642	-1.701*	2.887***	2.03**	1.761*	-0.298	0.727
H6y	**CLC → ATT**	1.197	1.867*	-0.742	-0.617	-0.285	-1.114	1.042	0.59
H7y	**AS → ATT**	1.424	0.99	0.125	-0.412	-0.409	1.069	0.189	-0.573
H8y	**OPI → BI**	-3.191***	-0.898	-0.235	-0.299	1.329	-0.197	1.630	1.606
H9y	**CSE → ATT**	-0.094	2.65***	-2.943***	3.908***	-0.672	-1.158	-0.944	-0.794
H10y	**ATT → BI**	0.501	-3.073***	0.807	-2.21**	-0.980	1.805*	0.126	-0.818
H11y	**BI → UB**	-1.043	-1.884*	-0.553	0.560	-1.871*	0.449	-0.645	-2.923***

*** Sig < 0.001, ** Sig < 0.05, * Sig < 0.10

Note: "y" and "x" represent the corresponding control variable (b, c..i)and path (1, 1a...11)

Table 4.9 Z-scores of the Multigroup analysis using critical

Hypothesis H2ab, relating EE to NSI, revealed a stronger relationship for males (β = 0.523, p < 0.001), as opposed to females (β = 0.044, p = 0.843). H3b and H8b were also found to be statistically different (Z < 0.05). While the older age group (35 and above) showed statistically different results for H3c, H6c, H9c, H10c, and H11c as compared to younger participants (18 to 35 years old)

Hypotheses H1d and H1ad (See appendix 4.9), manifested stronger path coefficients for participants with Master degree and above. In contrast, Z-scores for H4d and H9d were found to be significantly different, with p<0.05 for participants with lower academic's qualifications (Secondary to Bachelor)

H1e, H2ae, H3e, H4e, H9e, and H10e were all supported when using Job seniority as a control variable. While H4f and H11f were supported for experience as a moderator.

End Users and DMAT specialists (referred to as the Customers) displayed weaker relationships for ATT → BI, and OFC → UB. While H3g (NSI → BI) had a negative effect on participant influencing or managing DMAT's spending (referred to as Influencers and Clients).

As seen in Table 4.9, comparing Firm Size and Age reveal a significant difference (Z-score > 1.96) for H1ah, H3i and H11i. The results demonstrated that larger firms (above 250 employees) manifested a more pronounced association between EE and NSI. Conversely, the relationship between OPE and NSI was more influential for smaller firms (Refer to the dotted line in Figure 4.9).

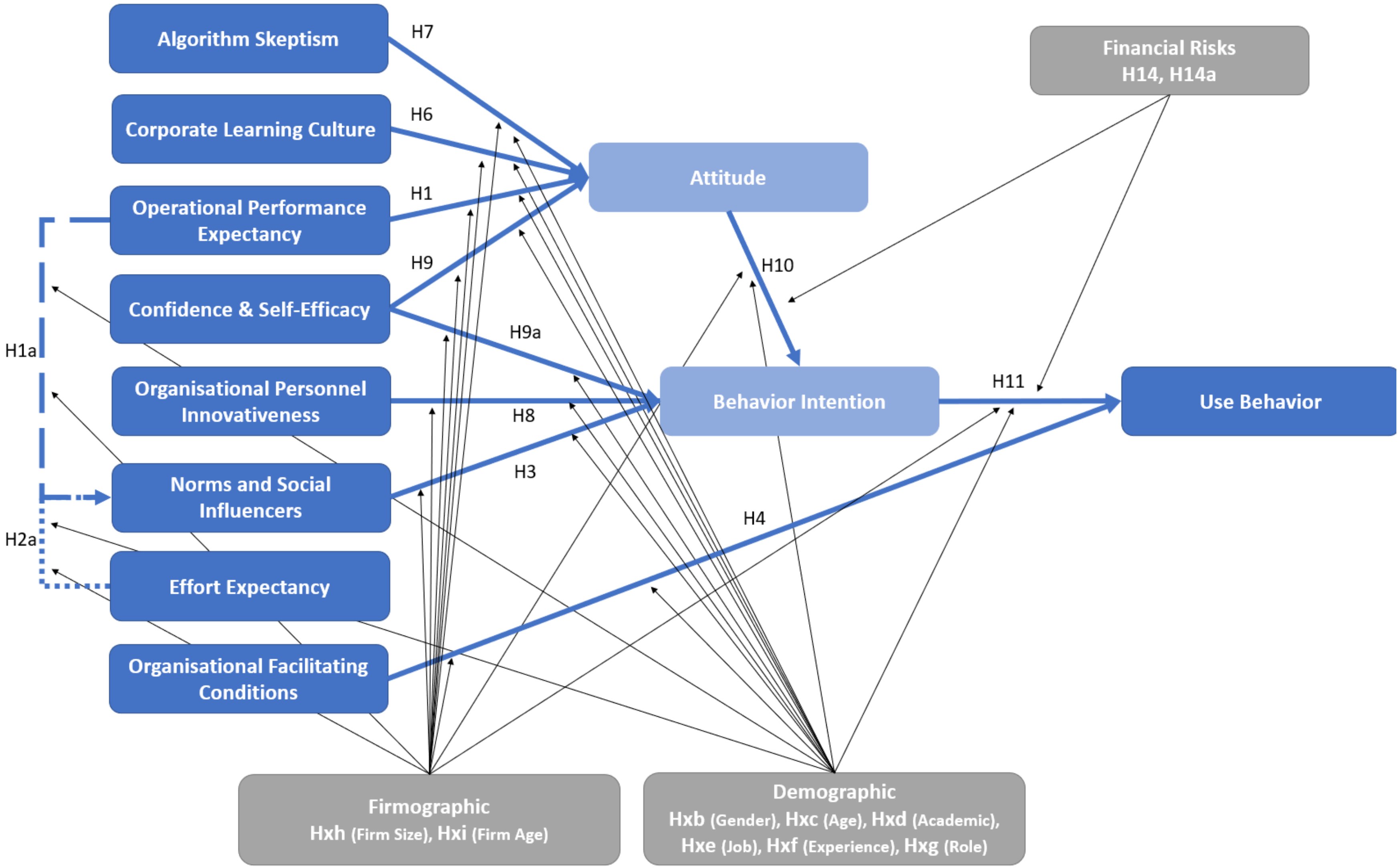


Figure 4.9 The moderating effect of the demographics, firmographics, and financial risks on the AI-Cocoon path analysis

Chapter 5: DISCUSSION AND CONCLUSIONS

6.1 Discussion of Results

The AI-Cocoon expands on previous research by integrating concepts from established technology adoption models such as UTAUT (Venkatesh et al., 2003), TAM (Davis, 1989), SCT (Bandura, 1986), and TRA (Fishbein & Ajzen, 1977) to include DMAT-specific paradigms (Jain et al., 2022; Nascimento & Meirelles, 2022). This comprehensive framework shapes the factors influencing individuals' attitudes and adoption intention by contextualising concepts that are specific to the technology attributes (such as CLC, AS, OPI, and CSE) with existing literature while recognising the moderating effects of demographics and firmographics variables (Chao, 2019; Chatterjee and Bhattacharjee, 2020).

The statistical analysis demonstrates varying levels of support for the hypothesised relationships. The path analysis revealed that OPE positively impacts attitudes towards DMAT use, aligning with previous research from Andrew et al. (2021), Chatterjee et al. (2021), Handoko & Lantu (2021), and Cao et al. (2021). This suggests that corporates who perceive AI-powered tools' positive impact on job performance are likelier to adopt them. The study also reveals that OFC positively influences use behaviour toward DMAT (H4), in agreement with the findings from Venkatesh et al. (2003) and Jain et al. (2022). Surprisingly, as opposed to previous studies on Technology adoption, EE, NSI, and PV did not have significant effects on ATT toward DMAT within the initial model (Venkatesh, 2003; Fishbein & Ajzen, 1977).

Revising the model to incorporate the findings from Nascimento & Meirelles (2022) demonstrated that EE ($\beta = 0.473$, $p < 0.001$) indirectly influences behaviour intention through the mediation of NSI. In addition to an improved statistical effect of EE, the revision enhances the model fit indices, suggesting improved accuracy and a more robust representation of the model relationships. The revised model exhibited moderate to strong effects (CSE → ATT and BI → UB), while other constructs revealed only low to moderately low support (NSI → BI and OPE → ATT). This heterogeneity in the strength of the relationships suggests that some factors may be more influential in shaping individuals' attitudes and intentions toward DMAT adoption than others.

For instance, the strong relationship between CSE and ATT ($\beta = 0.519$, $p < 0.001$) implies that enhancing individuals' CSE might yield more significant improvements in their attitudes toward DMAT than solely focusing on OPE ($\beta = 0.261$, $p = 0.005$). Our findings also highlight that attitude plays a decisive role in Use behaviour. While omitted by Venkatesh (2003), ATT was found to significantly impacts BI (H10). This leads to construe that DSaas providers would find it helpful and beneficial to shape the attitude of stakeholders to mould their intention toward DMAT use (Chatterjee and Bhattacharjee, 2020).

Analysing the moderating effects of demographic and firmographic variables provides a comprehensive understanding of the underlying dynamics of DMAT adoption. Significant differences were observed for 26 of the proposed moderation hypotheses. Results demonstrate that the effect of NSI toward BI is moderated by 5 out of 8 proposed control variables. In contrast, the moderating effects of AS toward ATT were not supported for either Demographic or Firmographic variables. It is important to note that the moderating variable results should be interpreted with caution, as the sample size of the composite groups was relatively small, which could subsequently affect the statistical power and the generalizability of the findings (Cohen, 1992; Bryman, 2016).

6.2 Comparison with Previous Research

This study contributes to the existing literature on technology adoption by proposing a comprehensive framework, the AI-Cocoon, which captures the unique characteristics of AI-powered tool adoption. The research identifies the most critical antecedents of DMAT adoption and tests the interrelations among those antecedents. The findings of this study suggest that utilisation of previous technology acceptance models such as TPB, TAM and UTAUT may not apply to studying DMAT as they mainly focus on established technologies (Those skewing toward the Maturity stage of their lifecycle) in a B2C context (Rogers, 2003).

Comparing the findings of this study with previous research reveals some interesting contrasts and similarities. For instance, the significant relationships between CLC, OPE, and CSE on ATT are consistent with prior studies, emphasising the importance of these factors in shaping users' attitudes toward technology adoption (Bandura, 1986; Chatterjee and Bhattacharjee, 2020). However, although prior research has confirmed the positive effect of social influence on user technology acceptance (Martins et al., 2014; Venkatesh et al., 2003), these studies only test its direct effect without supporting evidence that explains the underlying mechanisms. The result of this study diverges from the existing literature and supports those of Nascimento & Meirelles (2022), who argue that EE and OPE positively influence NSI toward DMAT adoption.

Furthermore, OFC was found to have a low impact on UB ($\beta = 0.196$, $p = 0.018$), which aligns with the findings in UTAUT. In contrast to Venkatesh (2003), OPI positively contributes to BI ($\beta = 0.225$, $p = 0.009$), in line with the findings from Patil et al. (2020), Lu et al. (2005) and Yuen & Ma (2008). However, as discussed in Chapter 4.7, the direct effect of OPI on UB may not always be significant. Previous research argues that this could be due to the presence of moderating factors such as perceived risk (Featherman & Pavlou, 2003), social influence (Venkatesh et al., 2003), and facilitating conditions (Thong et al., 2006).

The negative association between AS and ATT supports the risk aversion hypothesis (H7), which has been documented in the literature (Jain et al., 2022). The study also contributes to the literature by supporting that individuals with negative perceptions of DMAT are less likely to adopt and use it. As shown in the result of this study, AS has a moderately low negative impact on attitude (β = -0.235, $p < 0.001$). Furthermore, the study addresses the gap in the literature by applying these concepts in an organisational setting.

Additionally, the mediation analysis confirmed the importance of BI and ATT as mediators between the predictor variables and actual usage behaviour, consistent with prior research (Ajzen, 1991; Venkatesh et al., 2003). Whereas the moderation analysis contributes to understanding the boundary conditions among the variables affecting DMAT adoption by highlighting the role of demographic and firmographics variables in the complex interplay between individual and technology adoption.

In contradiction to existing literature, this study found no significant moderating effect between SR interaction with ATT and BI toward UB but confirmed that FR dampens the positive relationship between ATT and BI in line with Featherman, & Pavlou, (2003). These findings suggest that the moderating effects of continuous variables differ across studies and contexts (Hair et al., 2010). Regrettably, the model does not address potential barriers to DMAT adoption that may arise from exogenous factors such as Data availability and economic and legal environments, which could influence attitudes and intentions to use DMAT (prompting to the proposal of the Meta-model, referred to in Appendix 6.2).

6.3 Recommendations

The AI-Cocoon unfold the causal relationships that trigger the adoption of DMAT to offer the background needed to design effective adoption strategies. As discussed in Chapter 4.6, the framework explains 73% of the variance in use behaviour. It demonstrates that the adoption of DMAT is influenced by the complex interplay between the extrinsic and intrinsic motivators that drive attitudes and intentions to use DMAT. Therefore, this study argues that organisations should consider using the AI-Cocoon findings when implementing AI-enabled tools.

The study findings outlined several recommendations for organisations seeking to promote using DMAT. First, organisations should focus on enhancing Attitude and CSE, as these factors play a crucial role in the adoption process (β = 0.347, p= 0.002 and β = 0.313, p= 0.056, respectively). They should also aim to improve CLC and OPE to strengthen the attitudes toward DMAT, as these factors significantly influence users' behaviours. Thus, organisations should invest in training programs and resources to improve skills and self-efficacy using novel technology (Bandura, 1986). These can be achieved by providing practical training, role model speeches, and immersive technical visits to boost confidence and self-efficacy, subsequently leading to a higher adoption intention (Mckinsey, 2019).

Second, organisations should address Algorithm scepticism by creating an environment that encourages adopting AI-enabled tools through the fostering of positive social influences. These can be addressed through increased transparency, education and with effective communications about DMAT's benefits and limitations (Burrell, 2016).

Organisations should educate users about AI's capabilities, and their potential impact on team management and performance to reduce AI aversion (Jain et al., 2022). As outlined in the result discussion, there may be situations where individuals with high OPI have strong intentions to use DMAT but need help with actual usage. In these cases, external factors, such as CLC, NSI, management support, or user training, may help in the relationship between OPI and UB (Brown et al., 2002).

The dampening effect of FR, suggest that DSaas providers and organisations should aim to mitigate FR by developing transparent and ethical AI frameworks, investing in establishing clear regulations and governance structures (Mckinsey, 2019). Previous research revealed that firm size could significantly impact the relationships between various factors influencing performance (Wu, 2020). For instance, participants from smaller firms appear to be more influenced by OPE and CSE, while participants from larger firms seem to prioritise OFC, CLC, and OPI (refer to Appendix 4.9). Understanding these differences can help DSaas providers and organisations develop tailored strategies to encourage DMAT adoption across firms of different sizes.

The study also highlights the importance of considering user demographics when analysing behaviour intention. The results of the multigroup analysis show varying strengths in the relationships among the constructs moderated by gender, age, education, job position, and role with DMAT. Tailoring DMAT adoption strategies to different demographic groups can significantly increase adoption (Kapoor et al., 2018). One of the ways this could be achieved involves providing adequate facilitating conditions. For example, companies should ensure that the necessary infrastructure, support, and resources are available to facilitate the adoption and use of DMAT subject to the user level of education, job seniority, experience, and their role with regards to DMAT (Z-scores are -1.701, 2.887, 2.030, 1.761 respectively). Other ways this can be achieved include differentiating users into statistically different personas (refer to Appendixes 6.3.1 and 6.3.2) and align the offering based on each personas preferred attributes.

Additionally, organisations should leverage the effect of norms and social influencers by recognising the role of EE (β = 0.473, $p < 0.001$) and OPE (β = 0.371, p= 0.006) in influencing BI. Firms should invest in enhancing Effort expectancy and Performance expectancy of DMAT and involve influential individuals to promote the use of the technology (Cheung & Lee., 2012). While this study has revealed new insights that articulate the hidden rationale for the development of positive behavioural intentions toward DMAT, it is essential to highlight that the survey focused mainly on a population based in the UK. Therefore, the generalizability of the model is still unknown (Srite & Karahanna., 2006). Future studies could expand the sample size and scope by conducting further research with the public, preferably a cross-national sample, to assess the generalizability of the AI-Cocoon.

Furthermore, the cross-sectional design used in this study may have limited the ability to observe change patterns of subjects across time, which may have caused misidentification of the relationships between variables (Podsakoff et al., 2012). Longitudinal study designs provide opportunities to validate the AI-Cocoon stability over time (Petter et al., 2008). Researchers could also explore additional constructs, such as organisational and management attributes, affective dimensions, anthropomorphism and data accessibility, to further refine the AI-Cocoon (Gursoy et al., 2019).

6.4 Theoretical Contribution

This study contributes to the growing body of literature on DMAT adoption. The AI-Cocoon contributes to the developing literature on AI-powered tools by offering a comprehensive framework that can be tailored to the unique traits of DMAT users (Bhattacherjee & Sanford, 2009). By incorporating additional DMAT-specific constructs and moderators, the model addresses the gaps in previous research and provides a more nuanced understanding of the factors influencing adoption. This conceptual model extends the applicability of well-established technology adoption theories, by providing a valuable foundation for future research in the field of AI adoption, thereby progressing the theoretical knowledge in this domain (Davis, 1989; Venkatesh et al., 2003; Bandura, 1986).

Whilst the model highlights the importance of using contextual attributes observed from the case analysis, it may need further refinement to capture the full range of exogenous factors influencing DMAT adoption. By concentrating primarily on individual within a UK corporate context, the research may inadvertently neglect the importance of broader circumstantial elements that may influence adoption. Potential research should refine the model by accounting for these multilevel forces (Refer to Appendix 6.2) and explore the potential interactions between these factors at different levels of analysis (Yoo et al., 2012; Tarhini, et al., 2015)

6.5 Conclusion

This study developed and tested a theoretical model to explain the interplay influencing the use behaviour of DMAT. The case analysis and the review of previous empirical studies identified eight predictors that significantly influence AI-tool adoption.

The findings from this research support the model's ability to explain a significant amount of the variance in adoption, offering important implications for organisations seeking to implement AI-powered tools. By understanding the factors that drive adoption, DSaas providers and organisations can devise effective strategies to ensure the successful integration of DMAT. The AI-Cocoon shares similarities with other empirical models in identifying the belief-attitude-intention-use causal relationships and includes exogenous elements affecting the adoption process to improve the model's accuracy. However, the study also emphasises that organisations should critically evaluate the relevance of each recommendation within their unique contexts and be prepared to adapt their strategies as required, underscoring the absence of a one-size-fits-all solution (Rogers, 2003).

The author encourages future research to build upon these findings, to further refine the AI-Cocoon as a powerful scale, that gauge's adoption strategies.

List of Acronyms:

AI: Artificial Intelligence

AIH: Artificial Intelligence Hardware

AMOS: Analysis of Moment Structures

AS: Algorithm Scepticism

ATT: Attitude

AVE: Average Variance Extracted

BDA: Big Data Analytics

BI: Behavioural Intention

CDO: Chief Data Officer

CFA: Confirmatory Factor Analysis

CFI: Comparative Fit Index

CLC: Corporate Learning Culture

CMIN/DF: normed Chi-square

CR: Composite Reliability

CSE: Confidence and Self-efficacy

CTO: Chief Technical Officer

CVIP: Computer Vision and Image Processing

D: Demographics

DF: Degree of Freedom

DMA: Data Management and Analysis

DMAT: Data Science, Machine Learning, and Artificial Intelligence Technologies

DOI: Diffusion of Innovation

DSaas: Data-science-as-a-service

EE: Effort Expectancy

F: Firmographics

FC: Facilitating Conditions

FR: Financial Risk

ICT: Information and Communication Technology

IDC: International Data Corporation

IFI: Incremental Fit Index

ML: Machine Learning

NLP: Natural Language Processing

NSI: Norms and Social Influencers

OFC: Organisational Facilitating Condition

OPE: Organisational Performance Expectancy

OPI: Organisation Personnel's Innovativeness

PCFI: parsimony-Adjusted Comparative Fit Index

PE: Performance Expectancy

PNFI: Parsimonious Normed Fit Index

PV: Price Value

PWC: Price Water Coppers

RMSEA: Root Mean Square Error of Approximation

SCT: Social Cognitive theory

SE: Standard Error

SEM: Structural Equation Modelling

SI: Social Influence

SPSS: Statistical Package for the Social Sciences

SR: Security Risks

SRMR: Standardized Root Mean Square Residual

TAM: Technology Acceptance Model

TLI: Tucker-Lewis Index

TPB: Theory of Planned Behaviour

TRA: Theory of Reasoned Action

UB: Use Behaviour

UTAUT: Unified Theory of Acceptance and Use of Technology

References:

Abu-Shanab, E. and Pearson, J.M., 2009. Internet banking in Jordan: An Arabic instrument validation process. Int. Arab J. Inf. Technol., 6(3), pp.235-244.

Ajzen, I., 1991. The theory of planned behavior. Organizational behavior and human decision processes, 50(2), pp.179-211.

Ajzen, I., 2006. Constructing a theory of planned behavior questionnaire.

Aladwani, A.M., 2001. Change management strategies for successful ERP implementation. Business Process management journal, 7(3), pp.266-275.

Alba, J.W. and Hutchinson, J.W., 1987. Dimensions of consumer expertise. Journal of consumer research, 13(4), pp.411-454.

Alhwaiti, M., 2023. Acceptance of Artificial Intelligence Application in the Post-Covid Era and Its Impact on Faculty Members' Occupational Well-being and Teaching Self Efficacy: A Path Analysis Using the UTAUT 2 Model. Applied Artificial Intelligence, 37(1), p.2175110.

Aljindi, A., 2015. Information security, artificial intelligence and legacy information systems. Northcentral University.

AL-Nuaimi, M.N., Al Sawafi, O.S., Malik, S.I., Al-Emran, M. and Selim, Y.F., 2022. Evaluating the actual use of learning management systems during the covid-19 pandemic: an integrated theoretical model. Interactive Learning Environments, pp.1-26.

Alsheibani, S., Cheung, Y. and Messom, C., 2018. Artificial Intelligence Adoption: AI-readiness at Firm-Level. PACIS, 4, pp.231-245.

Alsheibani, S., Messom, C., Cheung, Y. and Alhosni, M., 2020. Artificial Intelligence Beyond the Hype: Exploring the Organisation Adoption Factors.

Andrews, J.E., Ward, H. and 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), p.102437.

Andronie, M., Lăzăroiu, G., Iatagan, M., Uță, C., Ștefănescu, R. and Cocoșatu, M., 2021. Artificial intelligence-based decision-making algorithms, internet of things sensing networks, and deep learning-assisted smart process management in cyber-physical production systems. Electronics, 10(20), p.2497.

Arbuckle, J. L.., 2003. Amos 5.0 update to the Amos user's guide. SmallWaters Corporation.

Aroean, L. and Michaelidou, N., 2014. Are innovative consumers emotional and prestigiously sensitive to price?. Journal of Marketing Management, 30(3-4), pp.245-267.

Bakhshi, H., Mateos-Garcia, J. and Whitby, A., 2014. Model workers: How leading companies are recruiting and managing their data talent. Engineering and Technology, 48.

Bandura, A., 1986. Social foundations of thought and action. Englewood Cliffs, NJ, 1986(23-28).

Baraldi, A.N. and Enders, C.K., 2010. An introduction to modern missing data analyses. Journal of school psychology, 48(1), pp.5-37.

Barnett, V. and Lewis, T., 1994. Outliers in statistical data (Vol. 3, No. 1). New York: Wiley.

Baron, R.M. and Kenny, D.A., 1986. The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. Journal of personality and social psychology, 51(6), p.1173.

Bayo-Moriones, A., Billón, M. and Lera-López, F., 2013. Perceived performance effects of ICT in manufacturing SMEs. Industrial Management & Data Systems, 113(1), pp.117-135.

Becker, S., Bryman, A. and Ferguson, H. eds., 2012. Understanding research for social policy and social work: themes, methods and approaches. policy press.

Becker, W. and Dietz, J., 2004. R&D cooperation and innovation activities of firms—evidence for the German manufacturing industry. Research policy, 33(2), pp.209-223.

Bednar, P.M. and Welch, C., 2020. Socio-technical perspectives on smart working: Creating meaningful and sustainable systems. Information Systems Frontiers, 22(2), pp.281-298.

Bell, E., Bryman, A., & Harley, B., 2019. Business Research Methods (5th ed.). Oxford University Press

Benbasat, I. and Barki, H., 2007. Quo vadis TAM?. Journal of the association for information systems, 8(4), p.7.

Bhaskar, R., Collier, A., Lawson, T. and Norrie, A., 1998. Critical realism. In Proceedings of the standing conference on realism and human sciences, Bristol, UK (Vol. 4, pp. 1-0).

Bhattacherjee, A. and Sanford, C., 2009. The intention–behaviour gap in technology usage: the moderating role of attitude strength. Behaviour & information technology, 28(4), pp.389-401.

Bigman, Y.E. and Gray, K., 2018. People are averse to machines making moral decisions. Cognition, 181, pp.21-34.

Bley, K., Fredriksen, S.F.B., Skjærvik, M.E. and Pappas, I.O., 2022, September. The role of organizational culture on artificial intelligence capabilities and organizational performance. In The Role of Digital Technologies in Shaping the Post-Pandemic World: 21st IFIP WG 6.11 Conference on e-Business, e-Services and e-Society, I3E 2022, Newcastle upon Tyne, UK, September 13–14, 2022, Proceedings (pp. 13-24). Cham: Springer International Publishing.

Bostrom, N., Yudkowsky, E. and Frankish, K., 2014. The Cambridge handbook of artificial intelligence. The ethics of artificial intelligence. Frankish, K., Ramsey, WM (eds.), Cambridge University Press, Cambridge, UK, 316, p.334.

Braganza, A., Brooks, L., Nepelski, D., Ali, M. and Moro, R., 2017. Resource management in big data initiatives: Processes and dynamic capabilities. Journal of Business Research, 70, pp.328-337.

Bresnahan, T.F., Brynjolfsson, E. and Hitt, L.M., 2002. Information technology, workplace organization, and the demand for skilled labor: Firm-level evidence. The quarterly journal of economics, 117(1), pp.339-376.

Brown, S.A., Massey, A.P., Montoya-Weiss, M.M. and Burkman, J.R., 2002. Do I really have to? User acceptance of mandated technology. European journal of information systems, 11(4), pp.283-295.

Bryman, A., 2016. Social research methods. Oxford university press.

Bryne, B. M., 2010. Structural Equation Modeling with AMOS: Basic Concepts, Applications, and Programming. 2nd ed. New York: Routledge.

Burns, 2021. data science as a service (DSaaS) Availaible from https://www.techtarget.com/searchbusinessanalytics/definition/data-science-as-a-service-DSaaS#:~:text=Ed%20Burns-,What%20is%20Data%20Science%20as%20a%20Service%3F,clients%20for%20their%20business%20use. (Accessed 14 October 2022)

Burrell, J., 2016. How the machine 'thinks': Understanding opacity in machine learning algorithms. Big data & society, 3(1), p.2053951715622512.

Burton, J., Stein, M., and Jensen, T. (2019). A systematic review of algorithm aversion in augmented decision making. J. Behav. Decis. Mak. 33, 220–239. doi: 10.1002/bdm.2155

Cabrera-Sánchez, J.P. and Villarejo-Ramos, A.F., 2020. Factors affecting the adoption of big data analytics in companies. Revista de Administração de Empresas, 59, pp.415-429.

Cao, G., Duan, Y., Edwards, J.S. and Dwivedi, Y.K., 2021. Understanding managers' attitudes and behavioral intentions towards using artificial intelligence for organizational decision-making. Technovation, 106, p.102312.

Capital Economics 2022. AI Activity in UK Businesses Report, Capital Economics and DCMS, January 2022. [online] Available from https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/1045381/AI_Activity_in_UK_Businesses_Report__Capital_Economics_and_DCMS__January_2022__Web_accessible_.pdf. (Accessed: 2 February 2022).

Cefis, E. and Marsili, O., 2005. A matter of life and death: innovation and firm survival. Industrial and Corporate change, 14(6), pp.1167-1192.

Chao, C.M., 2019. Factors determining the behavioral intention to use mobile learning: An application and extension of the UTAUT model. Frontiers in psychology, 10, p.1652.

Chatterjee, S. and Bhattacharjee, K.K., 2020. Adoption of artificial intelligence in higher education: A quantitative analysis using structural equation modelling. Education and Information Technologies, 25, pp.3443-3463.

Chatterjee, S., Rana, N.P., Dwivedi, Y.K. and Baabdullah, A.M., 2021. Understanding AI adoption in manufacturing and production firms using an integrated TAM-TOE model. Technological Forecasting and Social Change, 170, p.120880.

Chatterjee, S., Rana, N.P., Khorana, S., Mikalef, P. and Sharma, A., 2021. Assessing organizational users' intentions and behavior to AI integrated CRM systems: a Meta-UTAUT approach. Information Systems Frontiers, pp.1-15.

Cheatham, B., Javanmardian, K. and Samandari, H., 2019. Confronting the risks of artificial intelligence. McKinsey Quarterly, 2(38), pp.1-9.

Chen, H., Chiang, R.H. and Storey, V.C., 2012. Business intelligence and analytics: From big data to big impact. MIS quarterly, pp.1165-1188.

Cheung, C.M. and Lee, M.K., 2012. What drives consumers to spread electronic word of mouth in online consumer-opinion platforms. Decision support systems, 53(1), pp.218-225.

Cimperman, M., Brenčič, M.M. and Trkman, P., 2016. Analyzing older users' home telehealth services acceptance behavior—applying an Extended UTAUT model. International journal of medical informatics, 90, pp.22-31.

Clark Schaefer Hackett, 2023. Reasons to Outsource Data Analytics. Available at : https://www.cshco.com/articles/6-reasons-to-outsource-data-analytics/#:~:text=When%20you%20outsource%20your%20data,benefit%20of%20your%20bottom%20line (Accessed: 6 January 2023)

Clark, L.A. and Watson, D., 2016. Constructing validity: Basic issues in objective scale development.

Cohen, J., 1988. Statistical power analysis for the behavioral sciences and eii.

Collier, A., 1994. Critical realism: an introduction to Roy Bhaskar's philosophy.

Collins, C., Dennehy, D., Conboy, K. and Mikalef, P., 2021. Artificial intelligence in information systems research: A systematic literature review and research agenda. International Journal of Information Management, 60, p.102383.

Compeau, D., Higgins, C.A. and Huff, S., 1999. Social cognitive theory and individual reactions to computing technology: A longitudinal study. MIS quarterly, pp.145-158.

Creswell, J.W. and Creswell, J.D., 2017. Research design: Qualitative, quantitative, and mixed methods approaches. Sage publications..

Daniel, J. and James H, M., 2007. Speech and language processing: An introduction to natural language processing, computational linguistics, and speech recognition. prentice hall.

Dasgupta, A. and Wendler, S., 2019. AI adoption strategies. no, 9, pp.1-13.

Davenport, T. and Kalakota, R., 2019. The potential for artificial intelligence in healthcare. Future healthcare journal, 6(2), p.94.

Davenport, T., Guha, A., Grewal, D. and Bressgott, T., 2020. How artificial intelligence will change the future of marketing. Journal of the Academy of Marketing Science, 48, pp.24-42.

Davis, F.D., 1985. A technology acceptance model for empirically testing new end-user information systems: Theory and results (Doctoral dissertation, Massachusetts Institute of Technology).

Davis, F.D., 1989. Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS quarterly, pp.319-340.

Davis, F.D., Bagozzi, R.P. and Warshaw, P.R., 1992. Extrinsic and intrinsic motivation to use computers in the workplace 1. Journal of applied social psychology, 22(14), pp.1111-1132.

Delva, M.D., Kirby, J.R., Knapper, C.K. and Birtwhistle, R.V., 2002. Postal survey of approaches to learning among Ontario physicians: implications for continuing medical education. Bmj, 325(7374), p.1218.

Dereli, S.E., Korthaus, A., Scheepers, H. and Ahmed, A., 2020. The Role of Business Analytics for Competitive Advantage of Small and Medium Enterprises.

DeVellis, R. F., 2006. Scale development: Theory and applications. Sage Publications.

DeVellis, R. F., 2017. Scale Development: Theory and Applications (4th ed.). Thousand Oaks, CA: Sage.

DeVellis, R.F. and Thorpe, C.T., 2021. Scale development: Theory and applications. Sage publications.

Dietvorst Berkeley, J. and Simmons Joseph, P., 2015. Massey Cade. 2015. Algorithm aversion: People erroneously avoid algorithms after seeing them err. Journal of Experimental Psychology: General, 144(1), p.114.

Dillon, T., Wu, C. and Chang, E., 2010, April. Cloud computing: issues and challenges. In 2010 24th IEEE international conference on advanced information networking and applications (pp. 27-33). Ieee.

Donoho, D., 2017. 50 years of data science. Journal of Computational and Graphical Statistics, 26(4), pp.745-766.

Duan, Y., Edwards, J.S. and Dwivedi, Y.K., 2019. Artificial intelligence for decision making in the era of Big Data–evolution, challenges and research agenda. International journal of information management, 48, pp.63-71.

Dwivedi, Y.K., Rana, N.P., Jeyaraj, A., Clement, M. and 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, pp.719-734.

El Naqa, I. and Murphy, M.J., 2015. What is machine learning? (pp. 3-11). Springer International Publishing.

Elshawi, R., Sakr, S., Talia, D. and Trunfio, P., 2018. Big data systems meet machine learning challenges: towards big data science as a service. Big data research, 14, pp.1-11

Etro, F., 2009. The economic impact of cloud computing on business creation, employment and output in Europe. Review of Business and Economics, 54(2), pp.179-208.

Featherman, M.S. and Pavlou, P.A., 2003. Predicting e-services adoption: a perceived risk facets perspective. International journal of human-computer studies, 59(4), pp.451-474.

Fishbein, M. and Ajzen, I., 1977. Belief, attitude, intention, and behavior: An introduction to theory and research.

Fornell, C. and Larcker, D.F., 1981. Structural equation models with unobservable variables and measurement error: Algebra and statistics.

Gartner. 2017. "Applying Artificial Intelligence to Drive Business Transformation: A Gartner Trend Insight Report," pp. 2-7.

Gaskin, J., 2012. Group Differences. In Gaskination's Statictics. [Online} http://statwiki.kolobkreations.com (Accessed: 2 March 2023).

Gaskins, J., 2020. Multicollinearity in SPSS. [online] www.youtube.com. Available at: https://www.youtube.com/watch?v=U8Ldpisthso (Accessed: 2 March 2023).

Gilliland, M., Tashman, L. and Sglavo, U., 2021. Business forecasting: the emerging role of artificial intelligence and machine learning. John Wiley & Sons.

Glikson, E. and Woolley, A.W., 2020. Human trust in artificial intelligence: Review of empirical research. Academy of Management Annals, 14(2), pp.627-660.

Goodfellow, I., Bengio, Y. and Courville, A., 2016. Deep learning. MIT press.

Gunzler, D., Chen, T., Wu, P. and Zhang, H., 2013. Introduction to mediation analysis with structural equation modeling. Shanghai archives of psychiatry, 25(6), p.390.

Gursoy, D., Chi, O.H., Lu, L. and Nunkoo, R., 2019. Consumers acceptance of artificially intelligent (AI) device use in service delivery. International Journal of Information Management, 49, pp.157-169.

Hair Jr, J.F., Matthews, L.M., Matthews, R.L. and Sarstedt, M., 2017. PLS-SEM or CB-SEM: updated guidelines on which method to use. International Journal of Multivariate Data Analysis, 1(2), pp.107-123.

Hair, J. F., Black, W. C., Babin, B. J., and Anderson, R. E. 2010. Multivariate Data Analysis. 7th ed. Upper Saddle River, NJ: Prentice Hall.

Hair, J.F., 2009. Multivariate data analysis.

Handoko, B.L. and Lantu, J.E., 2021, July. UTAUT 2 Model for Predicting Auditor's Blockchain Technology Adoption. In The 2021 12th International Conference on E-business, Management and Economics (pp. 82-89).

Harvard Business Review, 2021. AI Adoption Skyrocketed Over the Last 18 Months. Available at https://hbr.org/2021/09/ai-adoption-skyrocketed-over-the-last-18-months (Accessed: 06.09.22)

Harvard Business Review, 2021. AI Doesn't Have to Be Too Complicated or Expensive for Your Business. [Online] Available from https://hbr.org/2021/07/aidoesnt-have-to-be-too-complicated-or-expensive-for-your-business. (Accessed: 6 September 2022)

Hatcher, L. and O'Rourke, N., 2013. A step-by-step approach to using SAS for factor analysis and structural equation modeling. SAS institute.

Hatcher, L., 1994. A step-by-step approach to using the SAS system for factor analysis and structural equation modeling. SAS Institute.

Henke, N., and Kaka, N., 2018. Crossing the frontier: how to apply AI for impact. McKinsey & Company

Hinzmann, J. and Bogatzki, K., 2020. Acceptance of autonomous delivery vehicles for last-mile delivery in Germany: extension of the technology acceptance model to an autonomous delivery vehicles acceptance model.

Hooper, D., Coughlan, J. and Mullen, M., 2008, September. Evaluating model fit: a synthesis of the structural equation modelling literature. In 7th European Conference on research methodology for business and management studies (pp. 195-200).

Huang, M.H. and Rust, R.T., 2021. A strategic framework for artificial intelligence in marketing. Journal of the Academy of Marketing Science, 49, pp.30-50.

Hupfer, S., 2020. Talent and workforce effects in the age of AI. Available from: https://www2.deloitte.com/uk/en/insights/focus/cognitive-technologies/ai-adoption-in-the-workforce.html (Accessed: 2 December 2022).

Indurkhya, N. and Damerau, F.J., 2010. Handbook of natural language processing. Chapman and Hall/CRC.

International Data Corporation, 2022. 4 Ways to Unlock Transformative Business Outcomes from Analytic Investments. Available at https://www.alteryx.com/resources/whitepaper/4-ways-to-unlock-transformative-business-outcomes-from-analytic-investments (Accessed: 23 August 2022)

J. McCarthy, 2007. What Is Artificial Intelligence? Retrieved from Computer Science Department Stanford University, [Online] Available from http://www-formal.stanford. edu/jmc/whatisai.pdf. (Accessed: 2 February 2022).

Jaccard, J. and Wan, C.K., 1996. LISREL approaches to interaction effects in multiple regression (No. 114). sage.

Jackson, P.R., Thorpe, R. and Easterby-Smith, M., 2015. Management and business research. Management and Business Research, pp.1-400.Easterby-Smith, M., Thorpe, R., & Jackson, P. R. (2012). Management Research (4th ed.). SAGE Publications Ltd.

Jägare, U., 2019. Data science strategy for dummies. John Wiley & Sons.

Jain, R., Garg, N. and Khera, S.N., 2022. Adoption of AI-Enabled Tools in Social Development Organizations in India: An Extension of UTAUT Model. Frontiers in Psychology, 13.

Jiang, C. and Zhang, S.B., 2018. A novel adaptively-robust strategy based on the Mahalanobis distance for GPS/INS integrated navigation systems. Sensors, 18(3), p.695.

Kalakota, R. and Whinston, A.B., 1996. Frontiers of electronic commerce. Addison Wesley Longman Publishing Co., Inc..

Kanhemann, D., Rosenfield, A., Gandhi, M., and Blaser, T., 2016. Noise: How to Overcome the High, Hidden Cost of Inconsistent Decision Making. Harvard Business Review. Available online at: https://hbr.org/2016/10/noise (Accessed: 15 April 2022)

Kaplan, A. and Haenlein, M., 2019. Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. Business Horizons, 62(1), pp.15-25.

Kapoor, K.K., Tamilmani, K., Rana, N.P., Patil, P., Dwivedi, Y.K. and Nerur, S., 2018. Advances in social media research: Past, present and future. Information Systems Frontiers, 20, pp.531-558.

Kellogg, K., Valentine, M., and Christin, A., 2020. Algorithms at Work: The New Contested Terrain of Control. Acad. Manag. Ann. 14, 366–410. doi: 10.5465/ annals.2018.0174

Kline, R. B., 2011. Principles and Practice of Structural Equation Modeling. 3rd ed. New York: The Guilford Press.

Kline, R.B., 2015. Principles and practice of structural equation modeling: Guilford publications. Principles and practice of structural equation modeling: Guilford publications.

Kortenkamp, D., Simmons, R. and Brugali, D., 2016. Robotic systems architectures and programming. Springer handbook of robotics, pp.283-306.

Kurup, S. and Gupta, V., 2022. Factors Influencing the AI Adoption in Organizations. Metamorphosis, 21(2), pp.129-139.

Kwateng, K.O., Atiemo, K.A.O. and Appiah, C., 2018. Acceptance and use of mobile banking: an application of UTAUT2. Journal of enterprise information management.

Li, L., Lassiter, T., Oh, J. and Lee, M.K., 2021, July. Algorithmic hiring in practice: Recruiter and HR Professional's perspectives on AI use in hiring. In Proceedings of the 2021 AAAI/ACM Conference on AI, Ethics, and Society (pp. 166-176).

Lin, H.C., Ho, C.F. and Yang, H., 2022. Understanding adoption of artificial intelligence-enabled language e-learning system: An empirical study of UTAUT model. International Journal of Mobile Learning and Organisation, 16(1), pp.74-94.

Lin, P.C., LU, H.K. and Liu, S.C., 2013. Towards an Education Behavioral Intention Model For E-Learning Systems: An Extension Of UTAUT. Journal of Theoretical & Applied Information Technology, 47(3).

Lincoln, Y. S., & Guba, E. G., 1985. Establishing Trustworthiness. In Naturalistic Inquiry. SAGE Publications Inc

Little, R.J.A. and Rubin, D.B., 2014. Incomplete data. John Wiley & Sons, Inc.

Lu, J., Yao, J.E. and Yu, C.S., 2005. Personal innovativeness, social influences and adoption of wireless Internet services via mobile technology. The journal of strategic Information Systems, 14(3), pp.245-268.

Mahmud, H., Islam, A.N., Ahmed, S.I. and Smolander, K., 2022. What influences algorithmic decision-making? A systematic literature review on algorithm aversion. Technological Forecasting and Social Change, 175, p.121390.

Makarius, E.E., Mukherjee, D., Fox, J.D. and Fox, A.K., 2020. Rising with the machines: A sociotechnical framework for bringing artificial intelligence into the organization. Journal of Business Research, 120, pp.262-273.

Malone, T.W., 2018. How human-computer'Superminds' are redefining the future of work. MIT Sloan management review, 59(4), pp.34-41.

Marsh, H.W. and Hocevar, D., 1985. Application of confirmatory factor analysis to the study of self-concept: First-and higher order factor models and their invariance across groups. Psychological bulletin, 97(3), p.562.

Marsick, V.J. and Watkins, K.E., 2003. Demonstrating the value of an organization's learning culture: the dimensions of the learning organization questionnaire. Advances in developing human resources, 5(2), pp.132-151.

Martinez, I., 2023. Data Skeptic. A Survey of Data Science Methodologies. [online] Google Podcasts. Available at: https://podcasts.google.com/feed/aHR0cHM6Ly9kYXRhc2tlcHRpYy5saWJzeW4uY29tL3Jzcw/episode/MGNiZmNiOTUtMDRhYi00M2IwLThjOWQtZjBiZmM1MDQwNGJh?ep=14 (Accessed: 31 Mar. 2023).

Martins, C., Oliveira, T. and Popovič, A., 2014. Understanding the Internet banking adoption: A unified theory of acceptance and use of technology and perceived risk application. International journal of information management, 34(1), pp.1-13.

McCarthy, J., 1988. Mathematical logic in artificial intelligence. Daedalus, pp.297-311.

McKinsey & Company, 2018. Crossing the frontier: How to apply AI for impact. Available from: https://www.mckinsey.com/~/media/mckinsey/business%20functions/mckinsey%20analytics/our%20insights/crossing%20the%20frontier%20how%20to%20apply%20ai%20for%20impact/crossing-the-frontier-collection.ashx (Accessed: 2 February 2023).

McKinsey, 2019. Confronting the risks of artificial intelligence. Available from: https://www.mckinsey.com/capabilities/quantumblack/our-insights/confronting-the-risks-of-artificial-intelligence (Accessed: 3 January 2023)

Mckinsey, 2021. AI adoption and impact. Availaible from: https://www.mckinsey.com/capabilities/quantumblack/our-insights/global-survey-the-state-of-ai-in-2021 (Accessed: 6 September 2022)

Meyers, L. S., Gamst, G., & Guarino, A. J., 2009. Performing data analysis using IBM SPSS. Wiley.

Meyers, L.S., Gamst, G. and Guarino, A.J., 2016. Applied multivariate research: Design and interpretation. Sage publications.

Mikalef, P. and 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), p.103434.

Mohr, L.A., Eroğlu, D. and Ellen, P.S., 1998. The development and testing of a measure of skepticism toward environmental claims in marketers' communications. Journal of consumer affairs, 32(1), pp.30-55.

Moore, G.C. and Benbasat, I., 1991. Development of an instrument to measure the perceptions of adopting an information technology innovation. Information systems research, 2(3), pp.192-222.

Nascimento, A. and Meirelles, F., 2021. An Artificial Intelligence Adoption Model for Large and Small Businesses. Available at SSRN 4194043.

Nica, E., Sabie, O.M., Mascu, S. and Luţan, A.G., 2022. Artificial intelligence decision-making in shopping patterns: consumer values, cognition, and attitudes. Economics, Management and Financial Markets, 17(1), pp.31-43.

Nica, E., Stan, C.I., Luțan, A.G. and Oașa, R.Ș., 2021. Internet of things-based real-time production logistics, sustainable industrial value creation, and artificial intelligence-driven big data analytics in cyber-physical smart manufacturing systems. Economics, Management, and Financial Markets, 16(1), pp.52-63.

Nunnally, J.C. and Bernstein, I.H., 1994. The theory of measurement error. Psychometric theory, 3(1), pp.209-247.

Oliveira, T. and Martins, M.F., 2011. Literature review of information technology adoption models at firm level. Electronic journal of information systems evaluation, 14(1), pp.pp 110-121.

Pallant, J. (2020). SPSS Survival Manual: A Step by Step Guide to Data Analysis using IBM SPSS. 7th ed. London: Routledge.

Pan, J., Ding, S., Wu, D., Yang, S. and Yang, J., 2019. Exploring behavioural intentions toward smart healthcare services among medical practitioners: a technology transfer perspective. International Journal of Production Research, 57(18), pp.5801-5820.

Patil, P., Tamilmani, K., Rana, N.P. and Raghavan, V., 2020. Understanding consumer adoption of mobile payment in India: Extending Meta-UTAUT model with personal innovativeness, anxiety, trust, and grievance redressal. International Journal of Information Management, 54, p.102144. doi:https://doi.org/10.1016/j.ijinfomgt.2020.102144.

Pelau, C., Dabija, D.C. and Ene, I., 2021. What makes an AI device human-like? The role of interaction quality, empathy and perceived psychological anthropomorphic characteristics in the acceptance of artificial intelligence in the service industry. Computers in Human Behavior, 122, p.106855.

Petter, S., Straub, D. and Rai, A., 2007. Specifying formative constructs in information systems research. MIS quarterly, pp.623-656.

Plude, D.J. and Hoyer, W.J., 1986. Age and the selectivity of visual information processing. Psychology and aging, 1(1), p.4.

Podsakoff, P.M., MacKenzie, S.B. and Podsakoff, N.P., 2012. Sources of method bias in social science research and recommendations on how to control it. Annual review of psychology, 63, pp.539-569.

Pohl, M., Bosse, S. and Turowski, K., 2018. A Data-Science-as-a-Service Model. In CLOSER (pp. 432-439).

Poole, D.L. and Mackworth, A.K., 2010. Artificial Intelligence: foundations of computational agents. Cambridge University Press.

Price Water Coopers, 2022. PwC 2022 AI Business Survey. [Online] Available from https://www.pwc.com/us/en/tech-effect/ai-analytics/ai-business-survey.html (Accessed: 6 September 2022).

Priore, P., Ponte, B., Rosillo, R. and de la Fuente, D., 2019. Applying machine learning to the dynamic selection of replenishment policies in fast-changing supply chain environments. International Journal of Production Research, 57(11), pp.3663-3677.

Provost, F. and Fawcett, T., 2013. Data Science for Business: What you need to know about data mining and data-analytic thinking. " O'Reilly Media, Inc.".

Pumplun, L., Tauchert, C. and Heidt, M., 2019. A new organizational chassis for artificial intelligence-exploring organizational readiness factors.

Putnick, D.L. and Bornstein, M.H., 2016. Measurement invariance conventions and reporting: The state of the art and future directions for psychological research. Developmental review, 41, pp.71-90.

Raisch, S. and Krakowski, S., 2021. Artificial intelligence and management: The automation–augmentation paradox. Academy of management review, 46(1), pp.192-210.

Rana, N.P., Chatterjee, S., Dwivedi, Y.K. and Akter, S., 2022. Understanding dark side of artificial intelligence (AI) integrated business analytics: assessing firm's operational inefficiency and competitiveness. European Journal of Information Systems, 31(3), pp.364-387.

Ransbotham, 2019. Pioneers Combine Strategy, Organizational Behavior, and Technology. [Online] Available from: https://sloanreview.mit.edu/projects/winning-with-ai/ (Accessed: 10 September 2022)

Rappaport, L.M., Amstadter, A.B. and Neale, M.C., 2020. Model fit estimation for multilevel structural equation models. Structural Equation Modeling: A Multidisciplinary Journal, 27(2), pp.318-329.

Rogers, E.M., 2003. Diffusion of innovations. NY. NY.

Romanova, T., Stoyan, Y., Pankratov, A., Litvinchev, I., Avramov, K., Chernobryvko, M., Yanchevskyi, I., Mozgova, I. and Bennell, J., 2021. Optimal layout of ellipses and its application for additive manufacturing. International Journal of Production Research, 59(2), pp.560-575.

Saunders, M., Lewis, P. and Thornhill, A. 2015. Research Methods for Business Students (7th edn). London: Prentice Hall.

Saunders, M., Lewis, P. and Thornhill, A., 2009. Research methods for business students. Pearson education.

Schwab, K., 2017. The fourth industrial revolution. Currency.

Sharif, S., 2021, SEM with AMOS: From Zero to Hero (10: Univariate and multivariate outliers) [online] Available at:

https://www.youtube.com/watch?v=MvhNMS8xIt8&list=PL2z_Hka9ws8E9wkWimjnWTqOuMS715B9r&index=13 (Accessed: 2 March 2023).

Sharif, S., 2021, SEM with AMOS: From Zero to Hero (19: Construct reliability and validity assessment) [online] Available at: https://www.youtube.com/watch?v=bACJxpFwdNQ&list=PL2z_Hka9ws8E9wkWimjnWTqOuMS715B9r&index=26 (Accessed: 6 March 2023).

Sharif, S., 2021, SEM with AMOS: From Zero to Hero (21: Mediation and moderation in plain language). [online] Available at: https://www.youtube.com/watch?v=eTLCZDat-_Q&list=PL2z_Hka9ws8E9wkWimjnWTqOuMS715B9r&index=31 (Accessed: 5 March 2023).

Sharif, S., 2021. SEM with AMOS: From Zero to Hero (19: Construct reliability and validity assessment). [online] Available at: https://www.youtube.com/watch?v=bACJxpFwdNQ&list=PL2z_Hka9ws8E9wkWimjnWTqOuMS715B9r&index=25 (Accessed: 2 March 2023).

Sharma, R., 2020. Artificial Intelligence, Machine Learning and the Reconstruction of Employee Psychology. NHRD Netw. J. 13, 472-479. doi: 10.1177/2631454120971912

Simon, M.K. and Goes, J., 2013. Scope, limitations, and delimitations.

Slade, E.L., Dwivedi, Y.K., Piercy, N.C. and Williams, M.D., 2015. Modeling consumers' adoption intentions of remote mobile payments in the United Kingdom: extending UTAUT with innovativeness, risk, and trust. Psychology & marketing, 32(8), pp.860-873.

Sørensen, J.B. and Stuart, T.E., 2000. Aging, obsolescence, and organizational innovation. Administrative science quarterly, 45(1), pp.81-112.

Srite, M. and Karahanna, E., 2006. The role of espoused national cultural values in technology acceptance. MIS quarterly, pp.679-704.

Šumak, B., Polancic, G. and Hericko, M., 2010, February. An empirical study of virtual learning environment adoption using UTAUT. In 2010 Second international conference on mobile, hybrid, and on-line learning (pp. 17-22). IEEE.

Szeliski, R., 2022. Computer vision: algorithms and applications. Springer Nature.

Tabachnick, B. G., and Fidell, L. S., 2013. Using Multivariate Statistics. 6th ed. Boston, MA: Pearson.

Tabachnick, B.G. and Fidell, L.S., 2007. Allyn & Bacon.

Tai, Y.M. and Ku, Y.C., 2013. Will stock investors use mobile stock trading? A benefit-risk assessment based on a modified UTAUT model. Journal of Electronic Commerce Research, 14(1), p.67.

Tarhini, A., Hone, K. and Liu, X., 2015. A cross-cultural examination of the impact of social, organisational and individual factors on educational technology acceptance between B ritish and L ebanese university students. British Journal of Educational Technology, 46(4), pp.739-755.

Taylor, S. and Todd, P.A., 1995. Understanding information technology usage: A test of competing models. Information systems research, 6(2), pp.144-176.

The Economist, 2023. The AI boom: lessons from history. [Online] Available from https://www.economist.com/finance-and-economics/2023/02/02/the-ai-boom-lessons-from-history (Accessed: 1 February 2023).

The Economist, 2023. The relationship between AI and humans. [Online] Available from https://www.economist.com/business/2023/02/02/the-relationship-between-ai-and-humans (Accessed: 2 February 2023).

The Economist, 2023. The relationship between AI and humans. Available from https://www.economist.com/business/2023/02/02/the-relationship-between-ai-and-humans (Accessed: 8 December 2022)

The Economist., 2023. The Economist Podcasts. Bot the difference: AI and the future of search. [online] Google Podcasts. Available at: https://podcasts.google.com/feed/aHR0cHM6Ly9yc3MuYWNhc3QuY29tL3RoZWVjb25vbWlzdGFsbGF1ZGlv/episode/NjNlMzgwZWY5YmE4MzQwMDExNDgzZDZm?ep=14 (Accessed: 28 February 2023).

Thompson, R.L., Higgins, C.A. and Howell, J.M., 1991. Personal computing: Toward a conceptual model of utilization. MIS quarterly, pp.125-143.

Traumer, F., Oeste-ReiSS, S., and Leimeister, J. M., 2017. “Towards a future reallocation of work between humans and machines-taxonomy of tasks and interaction types in the context of machine learning,” in Proceedings of the International Conference on Information Systems (ICIS), Seoul. doi: 10.2139/ssrn.3159131

Twum, K.K., Ofori, D., Keney, G. and Korang-Yeboah, B., 2022. Using the UTAUT, personal innovativeness and perceived financial cost to examine student’s intention to use E-learning. Journal of Science and Technology Policy Management, 13(3), pp.713-737.

Van der Veer, K., Ommundsen, R., Yakushko, O., Higler, L., Woelders, S. and Hagen, K.A., 2013. Psychometrically and qualitatively validating a cross-national cumulative measure of fear-based xenophobia. Quality & Quantity, 47, pp.1429-1444.

Van Esch, P., Black, J.S. and Ferolie, J., 2019. Marketing AI recruitment: The next phase in job application and selection. Computers in Human Behavior, 90, pp.215-222.

Venkatesh, V. and Bala, H., 2008. Technology acceptance model 3 and a research agenda on interventions. Decision sciences, 39(2), pp.273-315.

Venkatesh, V., 2022. Adoption and use of AI tools: a research agenda grounded in UTAUT. Annals of Operations Research, pp.1-12.

Venkatesh, V., Morris, M.G., Davis, G.B. and Davis, F.D., 2003. User acceptance of information technology: Toward a unified view. MIS quarterly, pp.425-478.

Venkatesh, V., Thong, J.Y. and Xu, X., 2012. Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. MIS quarterly, pp.157-178.

Villarejo Ramos, Á.F. and Cabrera-Sánchez, J.P., 2019. Factors affecting the adoption of big data analytics in companies.

Vinciotti, V., Tosetti, E., Moscone, F. and Lycett, M., 2019. The effect of interfirm financial transactions on the credit risk of small and medium-sized enterprises.

Vlačić, B., Corbo, L., e Silva, S.C. and Dabić, M., 2021. The evolving role of artificial intelligence in marketing: A review and research agenda. Journal of Business Research, 128, pp.187-203.

Wang, L., Von Laszewski, G., Younge, A., He, X., Kunze, M., Tao, J. and Fu, C., 2010. Cloud computing: a perspective study. New generation computing, 28, pp.137-146.

Wang, Z., Chen, C.H., Zheng, P., Li, X. and Khoo, L.P., 2021. A graph-based context-aware requirement elicitation approach in smart product-service systems. International Journal of Production Research, 59(2), pp.635-651.

Wiley, V. and Lucas, T., 2018. Computer vision and image processing: a paper review. International Journal of Artificial Intelligence Research, 2(1), pp.29-36.

Wilson, H.J. and Daugherty, P.R., 2018. Collaborative intelligence: Humans and AI are joining forces. Harvard Business Review, 96(4), pp.114-123.

Wu, N., 2020. Small Is Beautiful or Big Is Better: How Much Do Industry and Family Ownership Matter in Firms of Different Sizes?. European Management Review, 17(4), pp.977-991.

Yaqoob, I., Hashem, I.A.T., Gani, A., Mokhtar, S., Ahmed, E., Anuar, N.B. and Vasilakos, A.V., 2016. Big data: From beginning to future. International Journal of Information Management, 36(6), pp.1231-1247.

Yoo, Y., Henfridsson, O.,& Lyytinen, K. (2012). Research commentary - The new organizing logic of digital innovation: An agenda for information systems research. Information Systems Research, 21(4), 724-735.

Yuen, A.H. and Ma, W.W., 2008. Exploring teacher acceptance of e-learning technology. Asia-Pacific Journal of Teacher Education, 36(3), pp.229-243.

Zhao, G., Liu, J., Tang, Y., Sun, W., Zhang, F., Ye, X. and Tang, N., 2009. Cloud computing: A statistics aspect of users. In Cloud Computing: First International Conference, CloudCom 2009, Beijing, China, December 1-4, 2009. Proceedings 1 (pp. 347-358). Springer Berlin Heidelberg.

Zhao, L., Sakr, S., Liu, A., Bouguettaya, A., Zhao, L., Sakr, S., Liu, A. and Bouguettaya, A., 2014. Cloud computing. Cloud data management, pp.9-20.

Appendix 2.1

Definition	Author(s)
The science and engineering of making intelligent machines. Computational agents that act intelligently and perceive their environments in order to take actions that maximize chances of success	McCarthy, (20070 Poole and Mackworth (2010)
Data science is an interdisciplinary academic field that uses statistics, scientific computing, scientific methods, processes, algorithms and systems to extract or extrapolate knowledge and insights from noisy, structured, and unstructured data	Donoho, (2017); Dhar, (2013)
Machine learning is the science of getting computers to learn, without being explicitly programmed. It is a subfield of artificial intelligence that involves developing algorithms that can automatically identify patterns in data and then use those patterns to make predictions or decisions. Machine learning algorithms can be divided into three broad categories: supervised learning, unsupervised learning, and reinforcement learning	El Naga & Murphy, (2015)
Data Science' is a cyclical process of capturing the business needs and acquiring the relevant data, storage, security, privacy, preparation, pre-processing, analytics; generating and communicating insights; and finally, actuating these actionable insights (Jägare 2019)	Jagare, (2019)

Appendix 2.1.1

Questionnaire items

2. Please choose the frequency of use for each type of Data Science and AI technology* you are currently using (Never, Rarely, Sometimes, Often, Always):

- ☐ Data management and analysis tools (SAAP, ERP, CRM, app-based data management)
- ☐ Natural language processing and generation (Sentiment analysis, Chatbot and Digital voice assistant)
- ☐ Machine learning (Product recommendation, fraud and anomalies prevention)
- ☐ AI hardware (Self-driving vehicles, Autonomous robots)
- ☐ Computer vision and image processing (Object detection, image segmentation, and face recognition)

3. Please indicate why you are currently using Data Science and AI technologies* at work (Can be more than one):

- ☐ Improve decision making.
- ☐ Reduce risk.
- ☐ Enhance customer experience.
- ☐ Security, Anomaly and Fraud detection
- ☐ Optimise revenue.

- Reduce processing / Lead time.
- Cost saving
- Improve quality.
- Increase production capacity.
- Forecasting / Predictive analysis
- Differentiate from competitors.
- Ease work (Life-work balance)

4. Please indicate which new technologies (from the applications e.g listed) you most likely to adopt within the next 3 years (can be more than one):

- Automate administrative work / Restaurant operations processes (Data management and analysis tools)
- Business Intelligence / Clinical decision support / Compliance management (Data management and analysis tools)
- Image and Video enhancement & Generation / Agricultural soil analysis (Computer vision and image processing)
- Optimise pricing / agricultural yield / Fish detection and tracking (Machine learning)
- Fraud detection and risk management / Weather forecast for irrigation optimisation (Machine learning)
- Revenue and Business model expansion, Predictive fishing / 24/7 operations / Pest monitoring (AI Hardware)
- Predictive modelling of maintenance of ships and agricultural equipment (AI Hardware)
- Research & Development and anomaly detection (Machine learning)
- Recommender system / Customer experience enhancement / Personalised medical treatment plan (Machine learning)
- Automate repetitive and time-consuming tasks (AI Hardware)
- Automate text classification, C.V, Legal and clinical document classification (Natural language processing)
- Automate warehouse management / Medication production line (AI Hardware)
- Chatbots for hotels / retail stores (Natural language processing)
- Analyse customer feedback / Sentiment Analysis (Natural language processing)
- Tracking customer behaviour / Optimising product display (Computer vision and image processing)
- Facial and Object recognition for surveillance system, soil analysis / Medical imaging (Computer vision and image processing)
- Driver assistance system, Surgical assistance / Virtual reality for entertainments (Computer vision and image processing)
- Data visualisation tools, disease outbreak / Route analysis (Data management and analysis tools)
- Other (please specify the category)
- None of the above

5 Age:

- 18- 24
- 25 -34
- 35 - 44
- 45- 54
- 55 >

6. Gender:

- Male
- Female
- Non-binary/third gender

- Prefer not to say.

7. Academic level:

- Secondary
- Some college or further education
- Bachelor's Degree
- Master's Degree
- PhD

8. Please choose your job category:

- Officer Senior
- Executive
- Middle Management (Manager/Supervisor)
- Senior Management (HOD, GM, etc.)
- Strategic level (CIO, CEO, etc.)

9. Please indicate your experience using Data Science/AI powered technologies:

- <1 year
- 1 – 3 years
- 4 – 5 years
- 5 -9 year
- Above 10 years

10. Please choose the category that best fits your role:

- End Users/administrator
- Serving as a Data Science and AI technology specialist.
- Making or influencing decisions around Data Science and AI technology.
- Managing or overseeing Data Science and AI technology implementation.
- Developing Data Science and AI technology strategies.
- Responsible for Data Science and AI technology spending or approval of AI investments.

11. Please choose your Industry:

- Agriculture, forestry, and fishing
- Mining and quarrying
- Manufacturing
- Construction
- Wholesale and retail trade; repair of motor vehicles and motorcycles
- Accommodation and food service activities
- Electricity, gas, steam, and air conditioning supply
- Transport and storage of Information and communication
- Financial and insurance activities
- Real estate activities Professional, scientific, and technical activities Administrative and support service activities
- Public administration and defence; compulsory social security
- Education
- Human health and social work activities
- Arts, entertainment and recreation, other service activities
- Activities of households as employers and services-producing activities of households for own use

12. Firm size (Number of employees):

- ☐ 1-9
- ☐ 10 – 49
- ☐ 50 – 249
- ☐ 250 – 999
- ☐ 1000+
- ☐ Unknown

13. Age of Company:

- ☐ <1 year
- ☐ 1 – 9 years
- ☐ 10 – 24 years
- ☐ 25 – 49 years
- ☐ 50+ years
- ☐ Unknown

14. Please select the origin of the Data Science and AI technology currently being used (can be more than one).

- ☐ Built-in (DIY solution, made inhouse)
- ☐ Subscription based (Off shelf solutions, support included)
- ☐ Licensing (support is paid)
- ☐ Bespoke solutions (Custom made, one-time purchase)
- ☐ Freemium (Offer limited functionality, with an option to upgrade)
- ☐ Hybrid solutions

15. Please select the implementation stage of the Data Science and AI project(s)

- ☐ Planning to adopt (Within next 3 years)
- ☐ Development phase / Piloting (Pre-implementation) Introduction / Launch phase (Stage 1)
- ☐ Successful implementation / Growth stage (Stage 2)
- ☐ Productively implemented / Performing up to expectation (Stage 3)
- ☐ Implemented but declining / minimal or no impact (Stage 4)
- ☐ Re-engineering / Upgrading. (Stage 4b)
- ☐ Failed Implementation / Terminated due to misfit

31. Please select the most important considerations when purchasing or subscribing to Data Science and AI technology from a vendor (Select up to 5 factors):

- ☐ Price / Cost of the product
- ☐ Quality of support services / Responsiveness
- ☐ Reliability of the technology / Product performance
- ☐ Customised solution / Flexibility of Offer
- ☐ Vendor technical capabilities / competency
- ☐ Product fit / Return on Investment
- ☐ Vendor reputation / Trust
- ☐ Data Security / Legal Compliance
- ☐ Product updates / Vendor ability to innovate
- ☐ Flexible payment options / Subscriptions

32. Please indicate your annual (or estimated) spending on Data Science and AI technologies solutions in pounds (£)

Minimum per annum:
Maximum per annum:

Appendix 2.1.2

Construct	Indicators	Questions	Skewness	Kurtosis	Model contributing to construct
Organisation Performance Expectancy	PE1	I find Data Science, AI and ML technologies useful at work.	-0.263	-0.098	Venkatesh et al. (2003); Jain et al., (2022); Cao et al, (2021)
	PE2	Using Data Science, AI and ML technologies enhance my efficiency at work.	-0.375	-0.112	
	PE3	Using Data Science and AI technologies help me to accomplish tasks more quickly	-0.740	0.944	
Effort Expectancy	EE1	Learning to use Data Science, AI and ML technologies would be easy for me.	-0.483	0.233	Andrews et al., (2021); Chatterjee and Bhattacharjee, (2020); Jain et al., (2022)
	EE2	I find Data Science, AI and ML technologies easy to use.	-0.089	-0.189	
	EE3	My Interaction with Data Science, AI and ML technologies is clear and understandable.	-0.215	-0.250	
Norms and Social Infuencers	SI1	In General, the organisation has supported the use of Data Science, AI and ML technologies .	-0.186	-0.290	Andrews et al., (2021); Chatterjee and Bhattacharjee, (2020); Jain et al., (2022)
	SI2	People who are important to me think I should use Data Science, AI and ML technologies .	-0.229	-0.235	
	SI3	I will discuss Data Science and AI technologies with my peers.	-0.559	0.858	
Organisation Facilitating condition	FC1	I have the knowledge necessary to use Data Science, AI and ML technologies .	-0.439	-0.260	Chatterjee and Bhattacharjee, (2020); Jain et al., (2022); Cao et al, (2021)
	FC2	I can get technical support when I have difficulties using Data Science, AI and ML technologies.	-0.525	-0.074	
	FC3	Data Science, AI and ML technologies are compatible with other technology I use at work.	-0.187	-0.066	
Price Value	PV1	Data Science, AI and ML technologies are reasonably priced.	-0.393	0.722	Venkatesh, (2012); Alhwaiti, (2023)
	PV2	Data Science, AI and ML technologies would be good value for money.	-0.414	0.823	
Corporate Learning Culture	LC1	The company I work for values continuous learning and the development of its employees	-0.814	0.954	Mikalef and Gupta, (2021); Venkatesh (2022); Marsick and Watkins (2003)
	LC2	My peers and senior management team support the learning and experimentation of these new technologies.	-0.558	1.071	
	LC3	My organisation fosters an environment where employees feel comfortable asking questions and seeking help using Data Science, AI and ML technologies.	-0.471	0.093	
Algorithm Skeptism	AS1	I am concerned about the trustworthiness of predictions from these technologies due to their "black box" nature.	-0.217	-0.519	Mohr et al., (1998); Van der Veer et al', (2013); Jain et al., (2022); Venkatesh (2022); Patil et al, (2020)
	AS2	I am uncomfortable about using Data Science, AI and ML technologies due to the lack of transparency	-0.195	-0.581	
	AS3	I am hesistant about using Data Science, AI and ML technologies at work as it can produce biased and unfair results	-0.311	-0.768	
	AS4	I am uneasy about relying on Data Science, AI and ML to make important decisions.	-0.417	-0.613	
Security risk	SR1	Using Data Science, AI, and ML technologies at work increases the risk of data breaches and unauthorised access to sensitive information.	-0.118	-0.604	Chatterjee and Bhattacharjee, (2020); Tai and Ku, (2013); Chao, (2019)
	SR2	I am concerned about the risk of privacy disclosure and frauds when using Data Science, AI, and ML technologies	-0.188	-0.499	
	SR3	I would not feel secure processing information on Data Science and AI-powered tools due to potential cyber attacked.	-0.129	-0.618	
Financial risk	FR1	I am uneasy about using Data Science, AI and ML technologies because my company can lose business from incorrect operations	0.181	-0.742	Chatterjee and Bhattacharjee, (2020); Tai and Ku, (2013); Lin et al, (2022) Twum el al., (2022)
	FR2	I am concerned about using Data Science, AI and ML technologies at work due to uncertainty on financial returns.	0.373	-0.711	
	FR3	I am hesistant about using Data Science, AI and ML technology due to the financial risk associated to it.	0.227	-1.165	
Organisation Personnel's Innovativeness	PI1	I like to experiment using Data Science, AI and ML technologies at work.	-0.474	-0.141	Abu-Shanab and Pearson, (2009); Patil et al, (2020); Slade et al., (2015).
	PI2	Among my peers, I am usually among the first to try new ways of implementing Data Science, AI and ML initiatives.	-0.243	-0.340	
	PI3	If I hear about new techniques for Data Science, AI and ML technologies, I look for ways to experiment with it	-0.581	0.487	
	PI3	In general, I am not hesitant to try out new Data Science, AI and ML technologies.	-0.753	0.733	
Confidence & Self-efficacy	SE1	I can adapt Data Science, AI and ML initiatives when manuals and/or handbooks are available.	-0.886	1.703	Chao, (2019); Abu-Shanab and Pearson, (2009)
	SE2	I could adopt Data Science, AI and ML technologies if someone guides me to use it.	-0.899	3.408	
	SE3	I will adopt Data Science, AI and ML initiatives if I am train well to achieve the highest performance at work.	-0.961	3.276	
	SE4	I feel confident using Data Science, AI and ML technologies for business needs	-1.017	2.192	
Attitude	ATT1	Using Data Science, AI and ML technologies is a good idea.	-0.255	0.274	Andrews et al., (2021); Chatterjee and Bhattacharjee, (2020); Cao et al, (2021)
	ATT2	I like the idea of using Data Science, AI and ML technologies at work	-0.856	2.314	
	ATT3	Using Data Science, AI and ML technologies is beneficial to my business needs.	-0.634	1.754	
Behaviour Intention	BI1	I plan to continue to use Data Science, AI and ML technologies frequently.	-0.578	1.251	Andrews et al., (2021); Cao et al, (2021); Chatterjee et al., (2021)
	BI2	I would use Data Science, AI and ML technologies for my business needs.	-0.714	1.071	
	BI3	I plan to use Data Science, AI and ML technologies in the upcoming months.	-0.831	1.055	
Use behaviour	UB1	I often use Data Science, AI and ML technologies at work.	-0.493	0.090	Venkatesh, (2012); Zhang, (2020). Patil et al, (2020)
	UB2	I am satisfied with my decision to use Data Science, AI and ML technologies.	-0.363	1.290	
	UB3	I regularly use Data Science, AI and ML technologies to achieve my goal	-0.629	0.408	

Appendix 2.6.1

Porter Value Chain

Support Activities

Procurement
- EmergeIQ source it hardware and software for data storage, processing, and analysis through Microsoft Azure, Google and Amazon Aws (Rahman, 2022)

Technology
- EmergeIQ develop new data analytics techniques and tools to improve the quality and speed of analysis (Vryonides, 2022)

Human Resources Management
- The HR managers state that EmergeIQ have a team of highly trained and qualified data scientists, engineers, and other staff members to support primary activities (Patel, 2022)

Firm Infrastructure
- Designing, constructing, and maintaining the IT infrastructure
- Management and support functions such as finance, accounting, legal, and administration.

Primary Activities

Inbound Logistics

Procurement, storage, and distribution of data from various sources such as IBM and Microsoft Azure (EmergeIQ, 2022)

Operations

According to the company CDO, EmergeIQ operates in the development, testing, and deployment of data analytics algorithms, libraries and models (Vryonides, 2022)

Outbound Logistics

EmergeIQ (2023) delivers the results of the data analysis to the customers through 5 solutions.

- FUNDSaiQ
- MUSICiQ
- INVENTORYiQ
- WELLNESSiq
- LEGALiQ

- MARKETSiQ
- INSUREiQ
- PROMOiQ
- FIBREiQ

Marketing and Sales

EmergeIQ is creating awareness about the company's data analytics services mainly through Word of Mouth and Conferences attendance (Rahman, 2022)

Services

According to EmergeIQ, CTO, Consultation and Bespoke Solutions to clients and providing after-sale support and maintenance services to ensure customer satisfaction. (Rahman, 2022)

Margins

Appendix 2.6.2

SWOT Analysis

Strength

Advanced-Data Analytics Capabilities:
EmergeIQ have access to cutting-edge data analytics tools and techniques, which can help their clients gain deeper insights into their data and make more informed decisions (Vryonides, 2022).

Scalability:
EmergeIQ can quickly scale its services to meet the changing needs of its clients, allowing them to grow and adapt as needed (Rahman, 2022; Pohl et al., 2018) supporting **tech origin investigation**

Cost-Effective:
Using outsourced solutions can be more cost-effective than building an in-house data analytics team. This is especially true for small and medium-sized businesses that may need more resources to hire a full-time data scientist (Vryonides, 2022)

Expertise:
DSaaS providers such as EmergeIQ employ data scientists who are experts in their field. They can provide valuable insights and recommendations that can help businesses achieve their goals (Patel, 2022; Clark Schaefer Hackett, 2023; Violino, 2018) supporting **demographic moderators**

Weakness

Customer adoption challenges:
There is a lack of understanding of the linkages between developers and clients, as clients often struggle with defining their requirements (Rahman, 2022; Vryonides, 2022; Bley et al., 2022)

Client perception:
The complexity of the industry terminologies make the solution challenging to understand from an end-user perspective (Vryonides, 2022)

Security Concerns:
The company may handle sensitive data on behalf of its clients, which can be a significant security concern. A breach could result in a loss of trust and reputational damage (Dzone, n.d.)

Limited Customization:
DSaaS providers typically offer a standardised set of services, which may only be suitable for some clients. This can limit their ability to meet the specific needs of some businesses (Rahman, 2022).

Dependence on Technology:
EmergeIQ relies heavily on technology to deliver its services. Any disruptions or outages could cause significant problems for their clients.

Opportunity

Emerging Markets:
DSaaS providers could expand their services into emerging or niche markets with a growing demand for data analytics services. The increasing demand for flexible and remote work practices creates a need for innovative digital tools, which DSaaS providers can develop and offer to businesses and individuals. (Gartner, 2023) supporting **tech origin investigation**

Increasing Demand:
As businesses become more data-driven, the demand for data analytics services will likely increase. This presents a significant opportunity for DSaaS providers (Intechnica, 2023; BCG, 2020) Supporting **use frequency investigation**

Partnerships:
EmergeIQ can partner with other technology companies to offer a broader range of services. For example, they can swap their services with cloud computing platforms (EmergeIQ, 2022)

Treat

Economic Downturns:
Economic turmoil can cause businesses to divest from data analytics services, which could impact the revenue of EmergeIQ (Guardians, 2022; ft.com, 2022)

Competition:
The data analytics market is becoming increasingly crowded, which means there is much competition. EmergeIQ will need to differentiate itself to stay ahead of the competition (Rahman, 2022) supporting **supplier attributes**

Regulatory Changes:
Changes to data protection laws or regulations could impact how DSaaS providers operate and potentially limit their ability to provide certain services (ICO, 2018).

Algorith Sceptcism:
AI is a relatively novel technology and there is a lack of trust due to concern other accuracy, fairness, and transparency (Venkatesh, 2022)

Appendix 2.6.3

Porter 5 forces

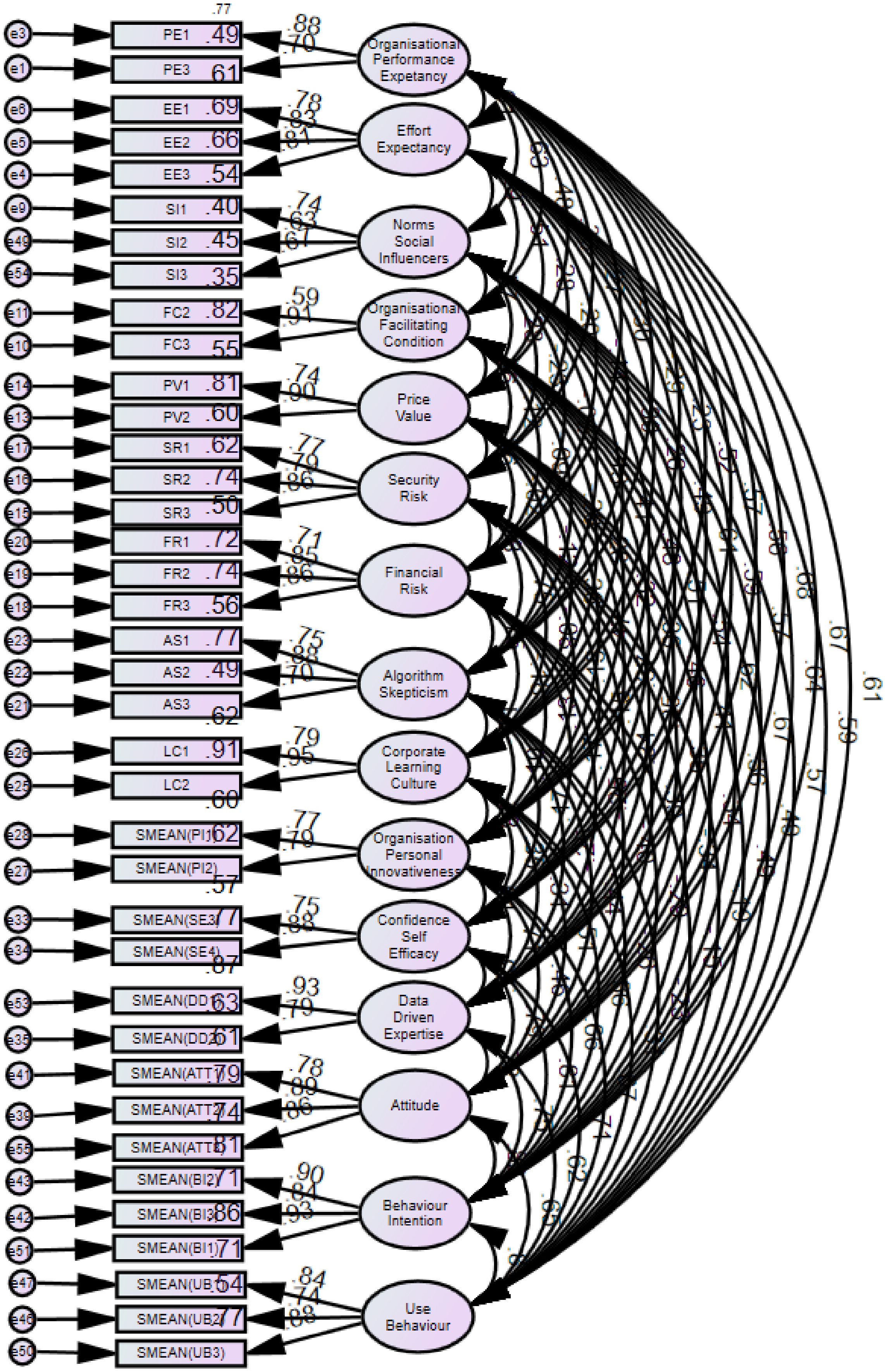
Rivalry Among Existing Competitor	Threat of New Entrant	Bargaining power of Suppliers	Threat of Substitute Product	Bargaining power of Buyers
Relatively High	Relatively High	Relatively low	Medium	Relatively High
The intensity of competitive rivalry in the DSaaS industry is relatively high, as a few prominent players dominate the market (Amplify. Peak.ai and Jiva.ai), and the industry is multiplying (Rahman, 2022). Additionally, the low barriers to entry may lead to new competitors entering the market, increasing competition. Customers have access to a range of similar services from multiple providers (Rahman, 2022).	With the rise of B2B platforms such as IBM, Google AutoML, OpenAI, Microsoft Azure and AI Builder, Monkey learn, and Amazon autoML, investments in data storage, processing, and analytics technology are becoming more and more affordable, making it easy for new players to enter the market (Vryonides, 2022)	B2B platforms such as IBM, Google AutoML, OpenAI, Microsoft Azure and AI Builder, Monkey learn, and Amazon autoML make it easy for Dsaas providers such as EmergeIQ to bargain and switch providers as API and EAI solutions make integration relatively easy.	The threat of substitutes in the industry is relatively low as only some can provide the same sophisticated data analytics services. However, some companies can switch to in-house data analytics capabilities, especially if they have a large IT department (Vryonides, 2022)	The market for AI is expected to grow from $57.6 B to $15 trillion by 2030 (Forbes, 2019). Current clients include: • Theirperfectgift.co.uk • BambuuBrush • Humanitas • Lamberth Scientific Services • Vista • GroovSense Additionally, switching costs are relatively low, making it easy for customers to switch to another provider if they are not satisfied with the service. There is also a low level of adoption by businesses (Rahman, 2022; Vryonides, 2022)

Appendix 2.6.4

PESTEL Analysis

	Political	Economical	Social	Technological	Environmental	Legal
Opportunity	**Trade agreement** - The Brexit deal created uncertainty, but it's a way towards new possibilities and opportunities. (Guardian, 2020) The **Recovery Loan Scheme** supports access to finance for small and medium-sized UK businesses, so they can grow and invest (Gov.uk, 2022), supporting **Price value and Firm size as moderator**	The **government's financial support** to struggling businesses due to the recent economic conditions (gov.uk, 2022). A hand-up for start-ups: 33,000 **new loans for small businesses** as £900 million government scheme widened (gov.uk, 2022), supporting **Price value and budjet investigation**	The **growing demand for flexible and remote work** practices creates a need for innovative digital tools, which DSaaS providers can develop and offer to businesses and individuals. (Gartner, 2023), supporting **Performance Expectancy**	The **increasing adoption of cloud computing** and other digital technologies creates new opportunities for DSaaS providers to develop innovative solutions, streamline operations and reduce costs. (Intechnica, 2023) supporting **adoption likelihood**	The growing interest in sustainable and eco-friendly business practices **creates opportunities** for DSaaS providers to offer services that reduce carbon footprint and promote sustainable practices.(BCG, 2020)	The **UK is one of the safest and easiest places to do business** in the world. One of the highest-ranking countries in the World Bank's Ease of Doing Business index (data. worldbank.org, 2019) The **lowest average corporation tax** rate in the G20 group of major economies (gov.uk, 2022)
Threat	**Kwarteng mini-Budget** had a 'material' impact on the UK economy (ft.com, 2022) **Trade agreement - The Brexit** deal created an environment of uncertainty in the business community (Guardian, 2022) supporting **budjet investigation**	**British shoppers are likely to spend £4.4bn** less on non-essentials during the Christmas period (Guardian, 2022) UK **borrowing costs hit highest levels** since September market chaos (Guardian, 2022) **Rising costs –** Recent events have increased the cost of doing business and affected the bottom line of many companies. Cost-push inflation (ft.com, 2022) **Company insolvencies hit a 13-year high in England** and Wales (Guardians, 2022) supporting **tech origins investigation**	UK's society may be **influenced by various factors such as demographics,** culture, values, attitudes, lifestyles and trends. These factors may affect how people perceive and use data science services supporting **demographic moderators** Labour unrest - **workers demand wage increases.** Industrial action ups pressure on supply chains. E.g Uk railways affected deliveries of construction materials. (Independent, 2022)	The **growing cyber threats and data breaches** that pose risks to data security and privacy (Dzone, n.d.) supporting **Security risk** The rapid development and innovation of data science tools and techniques, such as artificial intelligence, machine learning, big data analytics, and cloud computing, creates both opportunities and challenges for DSaas providers. (Intechnica, 2023)	The **increasing awareness and concern about environmental** issues such as climate change, pollution, resource depletion, etc. This may influence the preferences and expectations of DSaas clients regarding sustainability and social responsibility. DSaas providers may need to adopt green practices such as reducing energy consumption, carbon footprint, waste generation etc. (BCG, 2020), supporting **Norms and Socio Influencers**	Changes in data protection and privacy **regulations (UK GDPR**) can affect the way DSaaS providers collect, store and use customer data, (ICO, 2018) supporting **Algorithm skepticism**

Appendix 3.5



PE1
PE3
EE1
EE2
EE3
SI1
SI2
SI3
FC2
FC3
PV1
PV2
SR1
SR2
SR3
FR1
FR2
FR3
AS1
AS2
AS3
LC1
LC2
SMEAN(PI1)
SMEAN(PI2)
SMEAN(SE3)
SMEAN(SE4)
SMEAN(DD1)
SMEAN(DD2)
SMEAN(ATT1)
SMEAN(ATT2)
SMEAN(ATT3)
SMEAN(BI2)
SMEAN(BI3)
SMEAN(BI1)
SMEAN(UB1)
SMEAN(UB2)
SMEAN(UB3)
Organisational Performance Expetancy
Effort Expectancy
Norms Social Influencers
Organisational Facilitating Condition
Price Value
Security Risk
Financial Risk
Algorithm Skepticism
Corporate Learning Culture
Organisation Personal Innovativeness
Confidence Self Efficacy
Data Driven Expertise
Attitude
Behaviour Intention
Use Behaviour

Appendix 3.6

College of Business, Arts and Social Sciences Research Ethics Committee
Brunel University London
Kingston Lane
Uxbridge
UB8 3PH
United Kingdom

www.brunel.ac.uk

24 January 2023

LETTER OF APPROVAL

APPROVAL HAS BEEN GRANTED FOR THIS STUDY TO BE CARRIED OUT BETWEEN 27/01/2023 AND 10/02/2023

Applicant (s): Mr Gerald Teddy David Diolle

Project Title: Identifying the factors influencing the adoption of data science and AI/ML technologies.

Reference: 40106-LR-Jan/2023- 43415-3

Dear Mr Gerald Teddy David Diolle

The Research Ethics Committee has considered the above application recently submitted by you.

The Chair, acting under delegated authority has agreed that there is no objection on ethical grounds to the proposed study. Approval is given on the understanding that the conditions of approval set out below are followed:

- PIS and A14 – You should only collect demographic data that you intend to use for your study. If you are using this data for comparisons in your results, then add these details to your PIS. If you are not, then please change your demographic questionnaire to only collect data that you will actually be using.
- Data Collection Instruments - Please ensure the PIS and Consent form are available to view before the participant can take part in the survey.
- **The agreed protocol must be followed. Any changes to the protocol will require prior approval from the Committee by way of an application for an amendment.**
- **Please ensure that you monitor and adhere to all up-to-date local and national Government health advice for the duration of your project.**

Please note that:

- Research Participant Information Sheets and (where relevant) flyers, posters, and consent forms should include a clear statement that research ethics approval has been obtained from the relevant Research Ethics Committee.
- The Research Participant Information Sheets should include a clear statement that queries should be directed, in the first instance, to the Supervisor (where relevant), or the researcher. Complaints, on the other hand, should be directed, in the first instance, to the Chair of the relevant Research Ethics Committee.
- Approval to proceed with the study is granted subject to any conditions that may appear above.
- The Research Ethics Committee reserves the right to sample and review documentation, including raw data, relevant to the study.
- If your project has been approved to run for a duration longer than 12 months, you will be required to submit an annual progress report to the Research Ethics Committee. You will be contacted about submission of this report before it becomes due.
- You may not undertake any research activity if you are not a registered student of Brunel University or if you cease to become registered, including abeyance or temporary withdrawal. As a deregistered student you would not be insured to undertake research activity. Research activity includes the recruitment of participants, undertaking consent procedures and collection of data. Breach of this requirement constitutes research misconduct and is a disciplinary offence.

Professor David Gallear

Chair of the College of Business, Arts and Social Sciences Research Ethics Committee

Brunel University London

Appendix 4.2.1

Item	Category	Frequency	Percentage
Age	18 to less than 25	17	12.1%
	25 to less than 35	43	30.7%
	35 to less than 45	45	32.1%
	45 to less than 55	25	17.9%
	more than 55	10	7.1%
Gender	Male	82	58.6%
	Female	53	37.9%
	Non-Binary/third gender	1	0.7%
	Prefer not to say	4	2.9%
Academic	Secondary	2	1.4%
	Some College or further education	13	9.3%
	Bachelor's Degree	49	35.0%
	Master's Degree	61	43.6%
	PhD	15	10.7%
Job	Officer	33	23.6%
	Senior Executive	19	13.6%
	Middle Management (Manager/Supervisor)	58	41.4%
	Senior Management (HOD, GM, etc)	20	14.3%
	Strategic Level (CIO, CEO, etc)	10	7.1%
Experience using DMAT	Less than 1 year	43	30.7%
	1 year to less than 4 years	50	35.7%
	4 years to less than 5 years	20	14.3%
	5 years to less than 9 years	16	11.4%
	Above 10 years	11	7.9%
Role with DMAT	End Users/administrator	68	48.6%
	Serving as a Data Science and AI technology specialist.	17	12.1%
	Making or influencing decisions around Data Science and AI technology.	29	20.7%
	Managing or overseeing Data Science and AI technology implementation.	14	10.0%
	Developing Data Science and AI technology strategies.	8	5.7%
	Responsible for Data Science and AI technology spending or approval of AI investments.	4	2.9%
Firm Size	1 to less than 10 employees	21	15.0%
	11 to less than 50 employees	17	12.1%
	50 to less than 250 employees	23	16.4%
	250 to less than 1000 employees	15	10.7%
	more than 1000 employees	54	38.6%
Firm Age	Less than 1 year	6	4.3%
	1 year to less than 10 years	35	25.0%
	10 years to less than 25 years	27	19.3%
	25 years to less than 50 years	23	16.4%
	Above 50 years	40	28.6%
	Unknown	9	6.4%

N=140

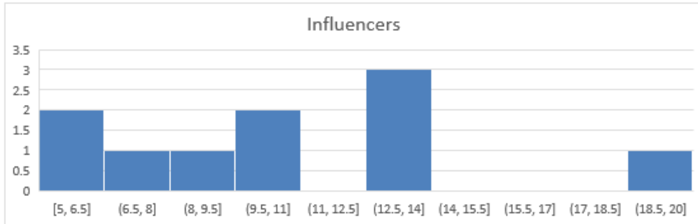
Appendix 4.2.2

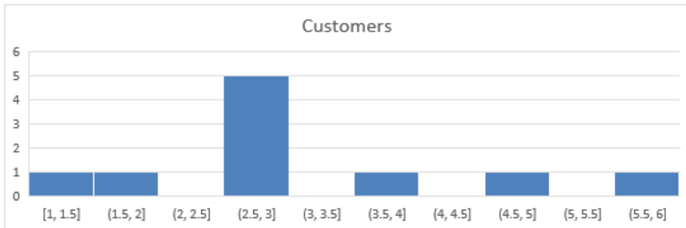
Category	Frequency	Percentage
Accommodation and food service activities	4	2.86%
Activities of households as employers and services-producing activities of households for own use	1	0.71%
Agriculture, forestry, and fishing	1	0.71%
Arts, entertainment and recreation, other service activities	15	10.71%
Construction	5	3.57%
Education	12	8.57%
Electricity, gas, steam, and air conditioning supply	1	0.71%
Financial and insurance activities	37	26.43%
Human health and social work activities	17	12.14%
Manufacturing	5	3.57%
Mining and quarrying	1	0.71%
Public administration and defence; compulsory social security	5	3.57%
Real estate activities Professional, scientific, and technical activities Administrative and support service activities	23	16.43%
Transport and storage of Information and communication	6	4.29%
Wholesale and retail trade; repair of motor vehicles and motorcycles	7	5.00%

N=140

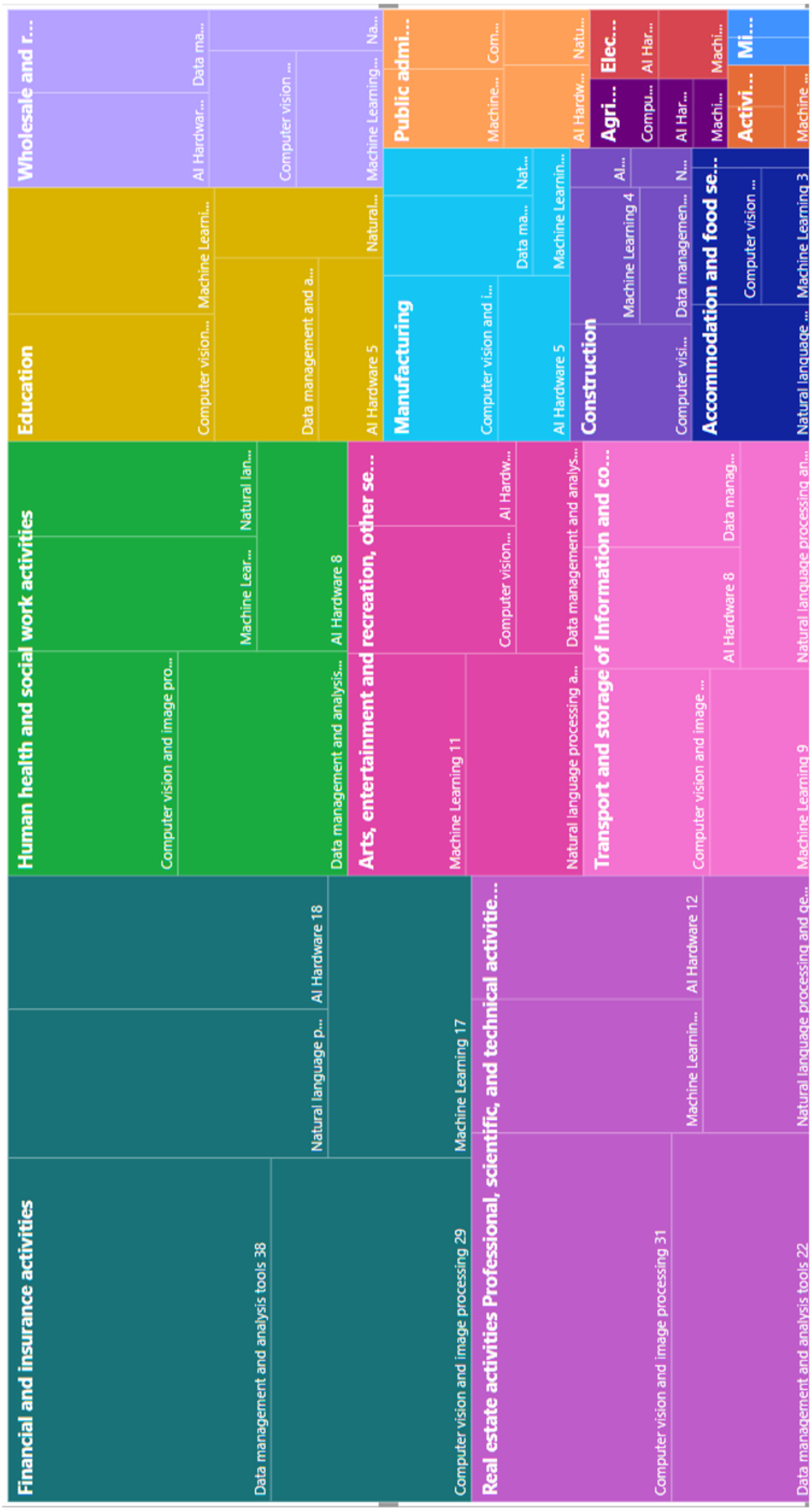
Appendix 4.2.3

	Reliability of the technology / Product performance	Price / Cost of the product	Data Security / Legal Compliance	Product fit / Return on Investment	Vendor reputation / Trust	Quality of support services / Responsiveness	Flexible payment options / Subscriptions	Product updates / Vendor ability to innovate.	Customised solution / Flexibility of Offer	Vendor technical capabilities / competency	Number of Respondent
End Users/administrator	27	34	28	21	16	20	16	17	10	12	60
Serving as a Data Science and AI technology specialist.	12	8	7	7	6	6	4	5	3	3	16
Making or influencing decisions around Data Science and AI technology.	10	7	8	10	8	5	8	2	10	4	21
Managing or overseeing Data Science and AI technology implementation.	10	7	6	4	3	2	1	3	1	1	12
Developing Data Science and AI technology strategies.	4	4	2	1	2		1	1	2	1	7
Responsible for Data Science and AI technology spending or approval of AI investments.	2	1	1	2	1	2	3		1	2	4
Clients	39	42	35	28	22	26	20	22	13	15	76
Influencers	20	14	14	14	11	7	9	5	11	5	33
Customers	6	5	3	3	3	2	4	1	3	3	11
Clients	9	10	8	6	4	5	3	4	1	1	76
Influencers	10	6	6	6	4	2	3	1	4	1	33
Customers	10	8	4	4	4	2	6	1	4	4	11

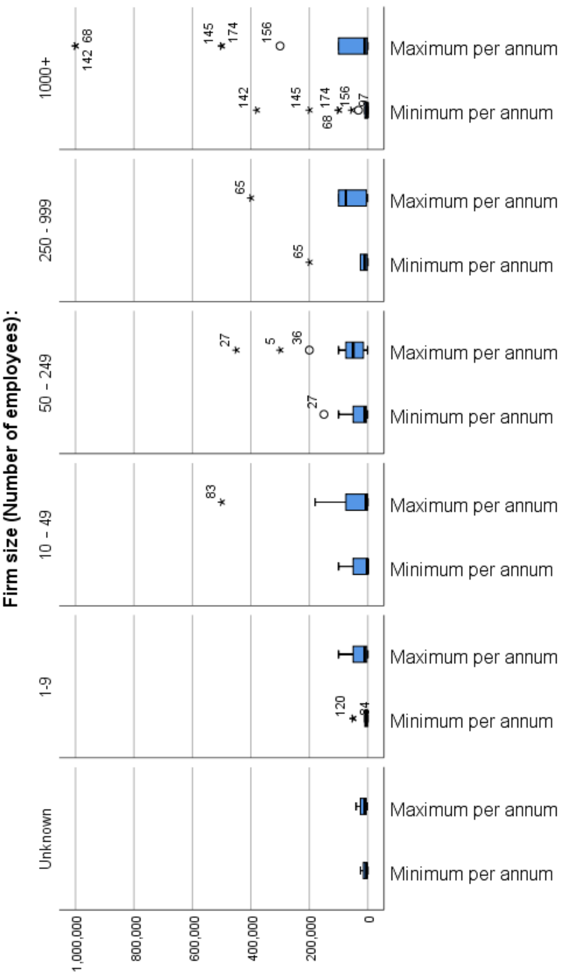


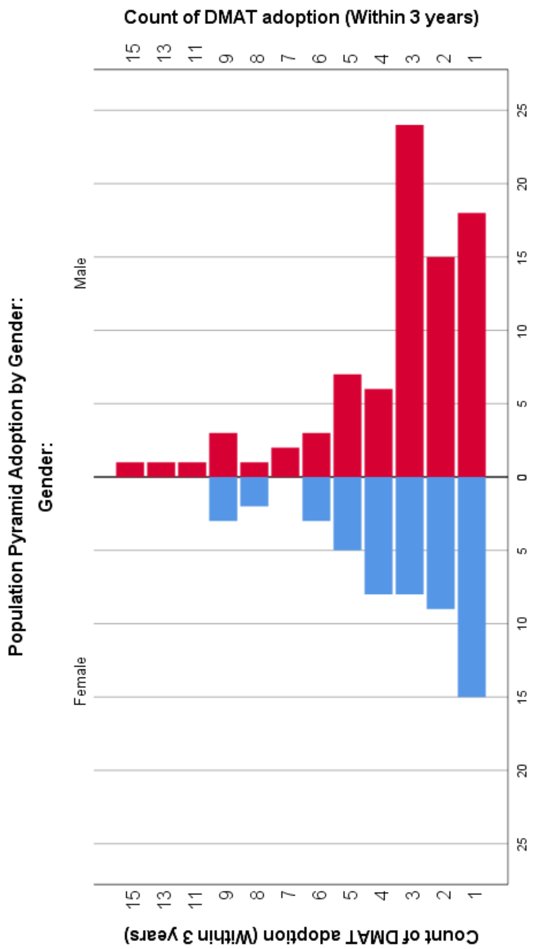


Appendix 4.2.4



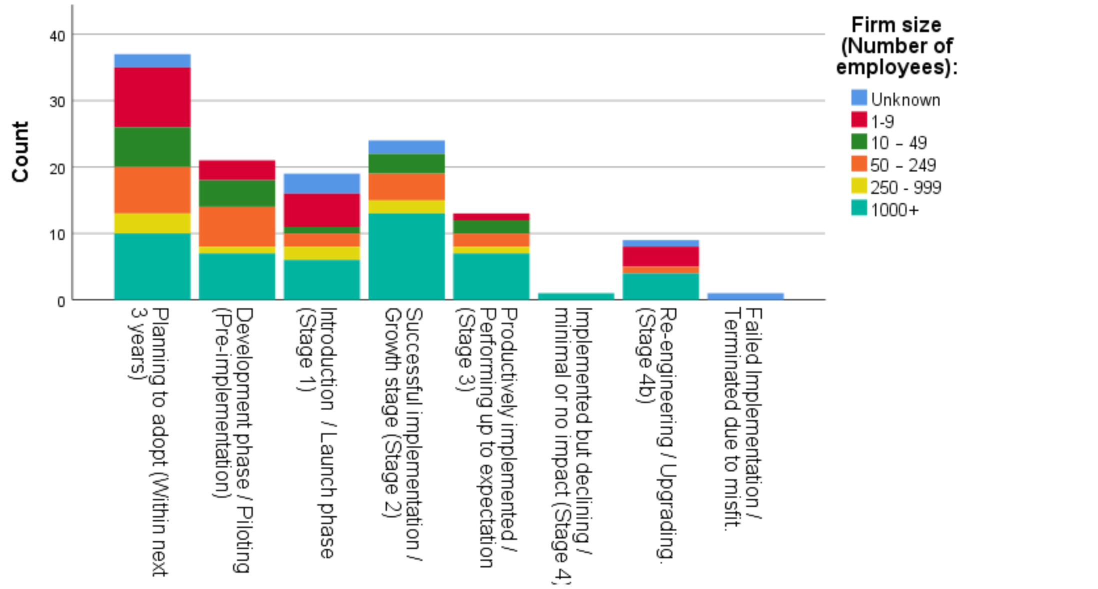
Appendix 4.2.5



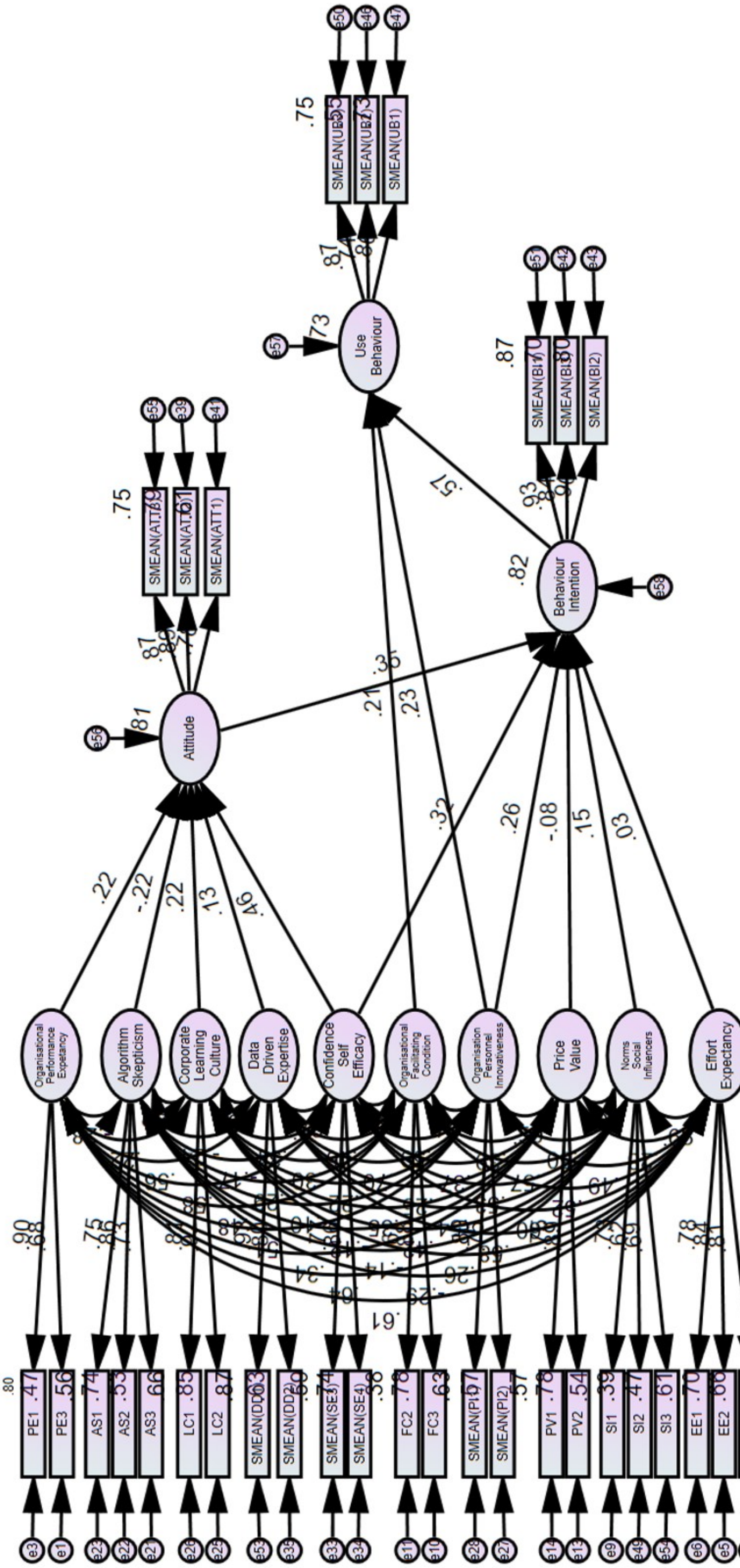


Appendix 4.2.6

Stacked Bar Count of Please select the implementation stage of the Data Science and AI project(s) by Firm size (Number of employees):

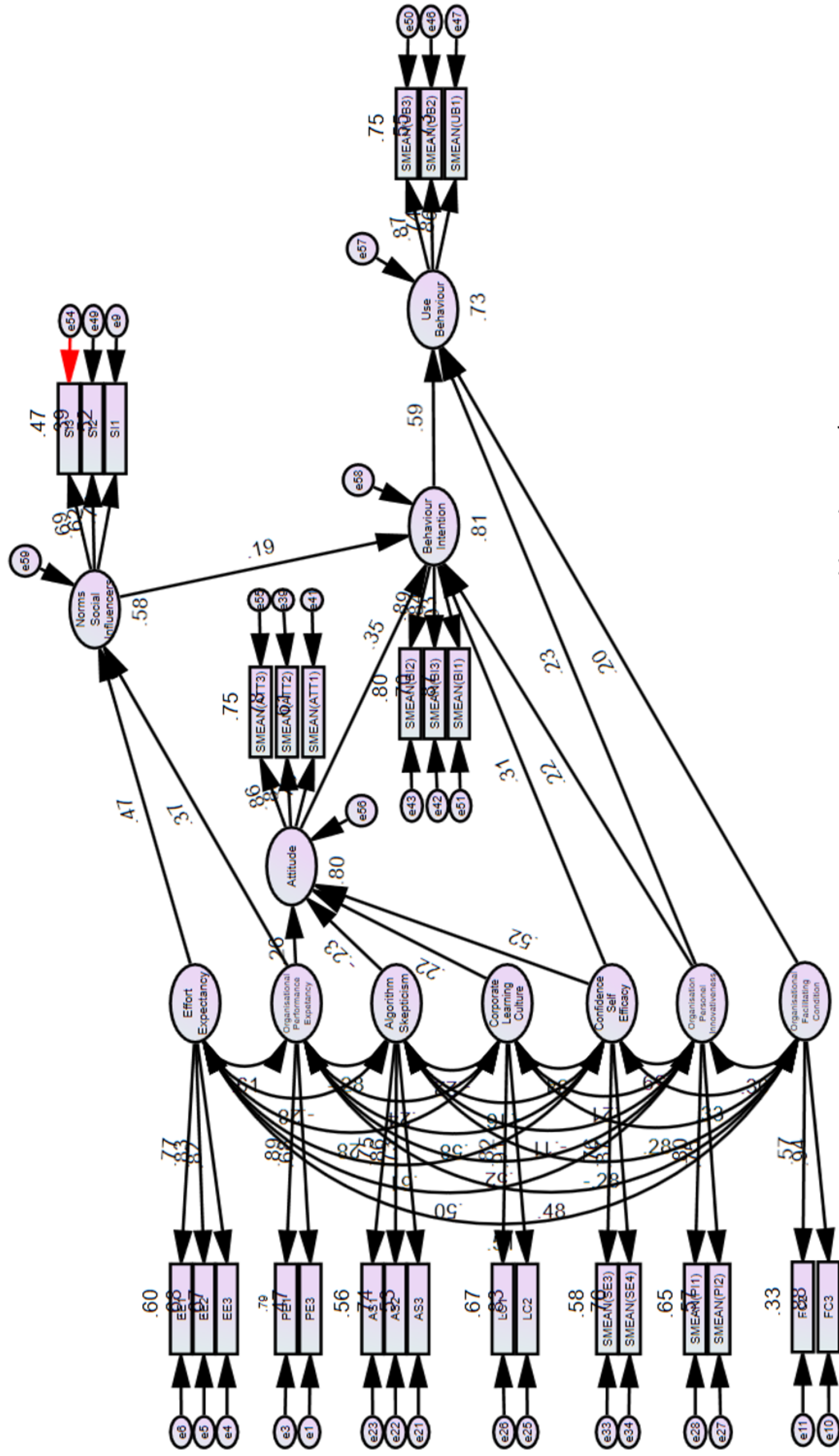


Appendix 4.5



Model Fit Indices: CMIN/DF: 1.303 IFI: 0.950, CFI: 0.948, PCFI: 0.774, RMSEA: 0.049

Appendix 4.6



Model Fit Indices: CMIN/DF: 1.175 IFI: 0.973, CFI: 0.972, PCFI: 0.813, RMSEA: 0.038

Appendix 4.9

DEMOGRAPHICS

Control Variable: Gender		Model 1 Male (N=72)		Model 2 Female (N=46)			
Hypothesis	Path	β	p-values	β	p-values	Z-Score	Results
H1b	**OPE → ATT**	0.288	0.033	0.159	0.555	-0.429	Not supported
H1ab	**OPE → NSI**	0.212	0.252	0.588	0.007	1.319	Not supported
H2ab	**EE → NSI**	0.523	***	0.044	0.843	-1.817*	Supported
H3b	**NSI → BI**	-0.027	0.853	0.542	0.002	2.522**	Supported
H4b	**OFC → UB**	0.129	0.111	0.101	0.225	-0.239	Not supported
H6b	**CLC → ATT**	0.096	0.314	0.332	0.055	1.197	Not supported
H7b	**AS → ATT**	-0.340	***	-0.115	0.349	1.424	Not supported
H8b	**OPI → BI**	0.760	***	-0.018	0.887	-3.191***	Supported
H9b	**CSE → ATT**	0.600	***	0.573	0.031	-0.094	Not supported
H10b	**ATT → BI**	0.276	0.174	0.408	0.014	0.501	Not supported
H11b	**BI → UB**	0.445	***	0.277	0.011	-1.043	Not supported

*** Sig < 0.001, ** Sig < 0.05, * Sig < 0.10

Control Variable: Age		18 to 35 (N=52)		35 and above (N=73)			
Hypothesis	Path	β	p-values	β	p-values	Z-Score	Results
H1c	**OPE → ATT**	0.358	***	0.163	0.133	-1.358	Not Supported
H1ac	**OPE → NSI**	0.413	0.002	0.274	0.025	-0.766	Not Supported
H2ac	**EE → NSI**	0.353	***	0.459	***	0.643	Not Supported
H3c	**NSI → BI**	0.187	0.031	0.762	***	2.585***	Supported
H4c	**OFC → UB**	0.135	0.01	0.201	0.021	0.642	Not Supported
H6c	**CLC → ATT**	0.160	0.002	0.360	***	1.867*	Supported
H7c	**AS → ATT**	-0.226	***	-0.120	0.197	0.99	Not Supported
H8c	**OPI → BI**	0.250	0.001	0.125	0.281	-0.898	Not Supported
H9c	**CSE → ATT**	0.411	***	0.832	***	2.65***	Supported
H10c	**ATT → BI**	0.530	***	-0.396	0.156	-3.073***	Supported
H11c	**BI → UB**	0.475	***	0.266	0.001	-1.884*	Supported

*** Sig < 0.001, ** Sig < 0.05, * Sig < 0.10

Control Variable: Academic		Secondary to Bachelor (N=56)		Master and above (N=69)			
Hypothesis	Path	β	p-values	β	p-values	Z-Score	Results
H1d	**OPE → ATT**	0.082	0.623	0.529	***	2.059**	Supported
H1ad	**OPE → NSI**	0.040	0.865	0.556	0.001	1.772*	Supported
H2ad	**EE → NSI**	0.679	0.006	0.277	0.039	-1.43	Not Supported
H3d	**NSI → BI**	-0.009	0.96	0.379	0.024	1.594	Not Supported
H4d	**OFC → UB**	0.335	0.038	0.051	0.224	-1.701*	Supported
H6d	**CLC → ATT**	0.235	0.011	0.134	0.184	-0.742	Not Supported
H7d	**AS → ATT**	-0.237	0.013	-0.219	0.033	0.125	Not Supported
H8d	**OPI → BI**	0.385	0.009	0.338	0.016	-0.235	Not Supported
H9d	**CSE → ATT**	0.644	***	0.162	0.122	-2.943***	Supported
H10d	**ATT → BI**	0.187	0.405	0.414	0.015	0.807	Not Supported
H11d	**BI → UB**	0.484	***	0.393	0.001	-0.553	Not Supported

*** Sig < 0.001, ** Sig < 0.05, * Sig < 0.10

Control Variable: Job		Officer (N=41)		Middle manager and Above (N=84)			
Hypothesis	Path	β	p-values	β	p-values	Z-Score	Results
H1e	**OPE → ATT**	0.672	0.004	0.192	0.107	-1.83*	Supported
H1ae	**OPE → NSI**	0.417	0.063	0.445	***	0.108	Not Supported
H2ae	**EE → NSI**	-0.071	0.245	0.459	***	3.493***	Supported
H3e	**NSI → BI**	-3.716	0.084	0.165	0.155	1.8*	Supported
H4e	**OFC → UB**	-0.001	0.872	0.273	0.004	2.887***	Supported
H6e	**CLC → ATT**	0.218	0.101	0.129	0.02	-0.617	Not Supported
H7e	**AS → ATT**	-0.176	0.327	-0.255	***	-0.412	Not Supported
H8e	**OPI → BI**	0.372	0.154	0.289	0.001	-0.299	Not Supported
H9e	**CSE → ATT**	0.083	0.378	0.677	***	3.908***	Supported
H10e	**ATT → BI**	2.055	0.007	0.362	0.004	-2.21**	Supported
H11e	**BI → UB**	0.332	0.008	0.421	***	0.56	Not Supported

*** Sig < 0.001, ** Sig < 0.05, * Sig < 0.10

Control Variable: Experience		Less than 1 year (N=36)		1 to 3 years (N=46)			
Hypothesis	Path	β	p-values	β	p-values	Z-Score	Results
H1f	**OPE → ATT**	0.295	0.008	0.411	0.032	0.522	Not Supported
H1af	**OPE → NSI**	0.356	0.045	0.326	0.103	-0.116	Not Supported
H2af	**EE → NSI**	0.401	0.015	0.472	0.006	0.3	Not Supported
H3f	**NSI → BI**	0.212	0.085	0.347	0.103	0.549	Not Supported
H4f	**OFC → UB**	0.078	0.22	0.403	0.006	2.03**	Supported
H6f	**CLC → ATT**	0.195	0.055	0.158	0.045	-0.285	Not Supported
H7f	**AS → ATT**	-0.160	0.072	-0.218	0.047	-0.409	Not Supported
H8f	**OPI → BI**	0.266	0.042	0.829	0.04	1.329	Not Supported
H9f	**CSE → ATT**	0.482	***	0.373	0.003	-0.672	Not Supported
H10f	**ATT → BI**	0.610	***	0.372	0.028	-0.98	Not Supported
H11f	**BI → UB**	0.417	***	0.095	0.51	-1.871*	Supported

*** Sig < 0.001, ** Sig < 0.05, * Sig < 0.10

Control Variable: Role		Customers (N=79)		Influencers and Clients (N=46)			
Hypothesis	Path	β	p-values	β	p-values	Z-Score	Results
H1g	**OPE → ATT**	0.262	0.021	0.616	0.029	1.167	Not Supported
H1ag	**OPE → NSI**	0.239	0.072	12.107	0.625	0.479	Not Supported
H2ag	**EE → NSI**	0.482	0.002	-4.805	0.658	-0.487	Not Supported
H3g	**NSI → BI**	0.228	0.086	-0.347	0.107	-2.271**	Supported
H4g	**OFC → UB**	0.079	0.261	0.291	0.003	1.761*	Supported
H6g	**CLC → ATT**	0.280	0.013	0.136	0.03	-1.114	Not Supported
H7g	**AS → ATT**	-0.278	0.008	-0.145	0.029	1.069	Not Supported
H8g	**OPI → BI**	0.308	0.045	0.271	0.017	-0.197	Not Supported
H9g	**CSE → ATT**	0.521	***	0.334	0.004	-1.158	Not Supported
H10g	**ATT → BI**	0.430	0.006	1.115	0.001	1.805*	Supported
H11g	**BI → UB**	0.336	0.002	0.408	***	0.449	Not Supported

*** Sig < 0.001, ** Sig < 0.05, * Sig < 0.10

FIRMOGRAPHICS

Control Variable: Firm Size		1 to 249 (N=59)		250 and above (N=57)			
Hypothesis	Path	β	p-values	β	p-values	Z-Score	Results
H1h	**OPE → ATT**	0.406	0.012	0.363	0.100	-0.16	Not Supported
H1ah	**OPE → NSI**	0.597	0.005	0.092	0.631	-1.758*	Supported
H2ah	**EE → NSI**	0.328	0.014	0.607	0.003	1.149	Not Supported
H3h	**NSI → BI**	0.293	0.114	0.089	0.538	-0.867	Not Supported
H4h	**OFC → UB**	0.160	0.211	0.117	0.067	-0.298	Not Supported
H6h	**CLC → ATT**	0.094	0.156	0.234	0.046	1.042	Not Supported
H7h	**AS → ATT**	-0.213	0.02	-0.184	0.143	0.189	Not Supported
H8h	**OPI → BI**	0.069	0.538	0.477	0.034	1.63	Not Supported
H9h	**CSE → ATT**	0.511	***	0.281	0.195	-0.944	Not Supported
H10h	**ATT → BI**	0.506	0.007	0.544	0.024	0.126	Not Supported
H11h	**BI → UB**	0.436	***	0.33	0.002	-0.645	Not Supported

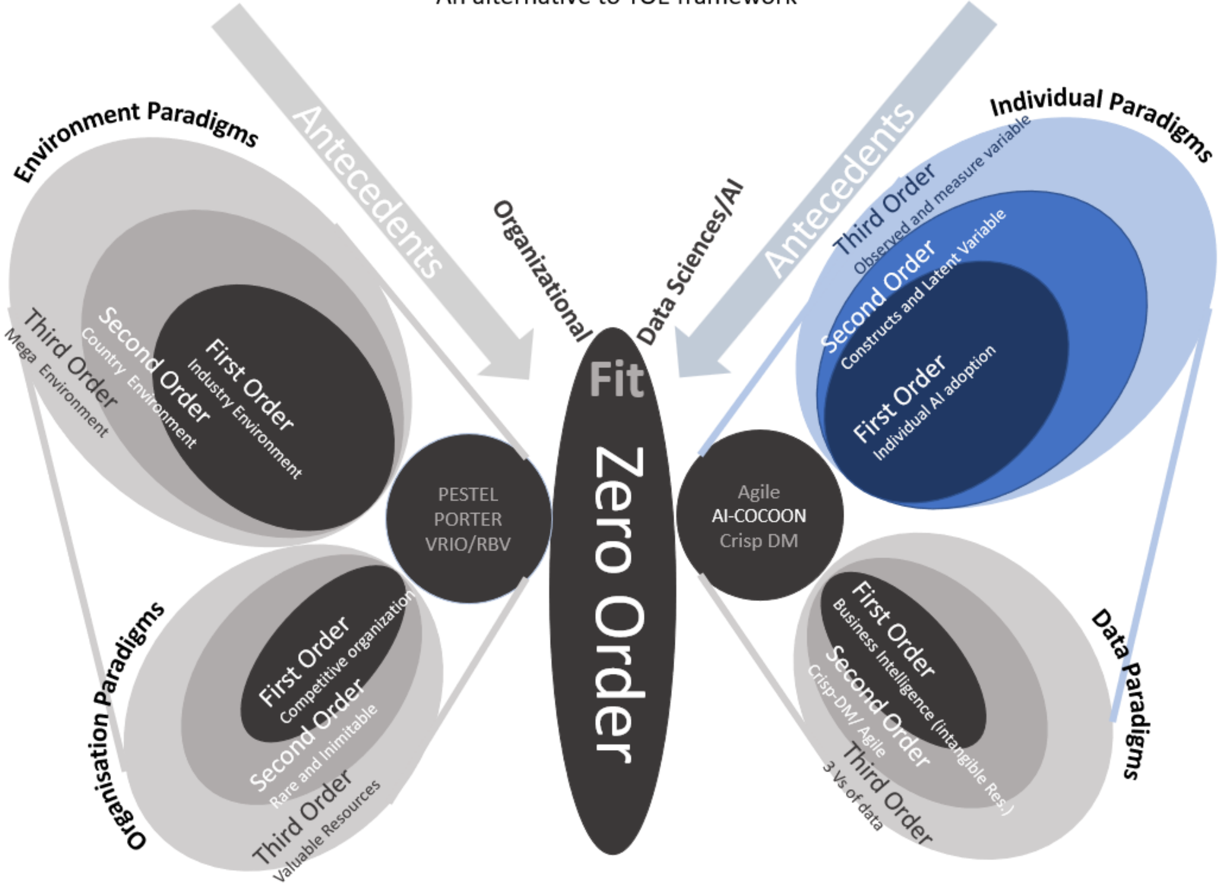
*** Sig < 0.001, ** Sig < 0.05, * Sig < 0.10

Control Variable: Firm age		Less than 25 years (N=60)		25 years and above (N=57)			
Hypothesis	Path	β	p-values	β	p-values	Z-Score	Results
H1i	**OPE → ATT**	0.326	0.041	0.318	0.062	-0.034	Not Supported
H1ai	**OPE → NSI**	0.416	0.006	0.222	0.254	-0.787	Not Supported
H2ai	**EE → NSI**	0.338	0.005	0.493	0.013	0.674	Not Supported
H3i	**NSI → BI**	0.433	0.024	-0.123	0.496	-2.107**	Supported
H4i	**OFC → UB**	0.059	0.426	0.132	0.049	0.727	Not Supported
H6i	**CLC → ATT**	0.084	0.194	0.145	0.073	0.59	Not Supported
H7i	**AS → ATT**	-0.192	0.023	-0.292	0.057	-0.573	Not Supported
H8i	**OPI → BI**	0.072	0.535	0.45	0.028	1.606	Not Supported
H9i	**CSE → ATT**	0.525	***	0.346	0.067	-0.794	Not Supported
H10i	**ATT → BI**	0.472	0.005	0.18	0.569	-0.818	Not Supported
H11i	**BI → UB**	0.68	***	0.214	0.011	-2.923***	Supported

*** Sig < 0.001, ** Sig < 0.05, * Sig < 0.10

Appendix 6.2

An alternative to TOE framework



The Butterfly canvas, to leverage AI/Organization fit Diolle (2023)

A multi-dimensional canvas that introduces the components of AI/Organisation fit in "Dimensions" and "Orders" to establish the linkages in-between the forces that impact organisations' ability to achieve AI/Organisation fit. Those elements are represented in a butterfly to denote the leveraging potential of those forces/resources if adequately synergised.

AI/DS are only components of the framework, **NOT** the core element.

Macro-Level
Hofstede's Cultural Dimensions
Porter's Diamond of National Advantage
PESTEL Analysis

Industry-Level
Industry Life Cycle
Porter's Five Forces
Value Net Model

Corporate-Level
Acquisition Integration Approaches
A.T. Kearney Strategy Chessboard
BCG Growth-Share Matrix
GE/McKinsey Matrix
McKinsey 7S Model
Strategy Diamond

Business-Level
Ansoff Matrix
Bartlett and Ghoshal's Matrix
Business Model Canvas
OLI Paradigm
Porter's Generic Strategies
Profit Tree
SWOT Analysis
Value Chain Analysis
Value Disciplines
VRIO Framework

Product-Level
AIDA Model
Marketing Funnel
Technology Adoption Life Cycle
Product Life Cycle
Price Elasticity

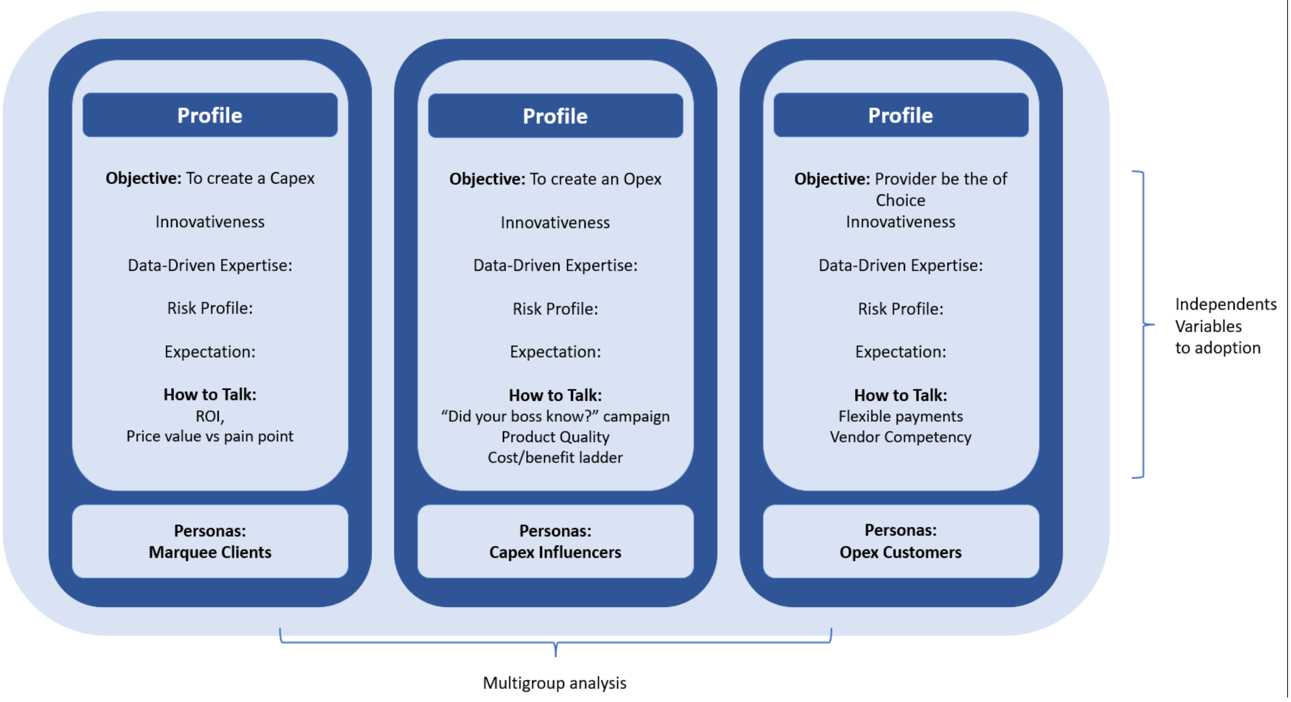
Management-Level
Blake and Mouton's Managerial Grid
Fiedler's Contingency Model of Leader-Situation Matches
Hersey and Blanchard's Leadership Styles
Kotter's 8 Steps of Change (Management) Model
Lewin's 3 Step Model of Change (Management)

DMAT Adoption
AI-Cocoon
CRISP DM/AGILE
SAM/TOE

Appendix 6.3.1.

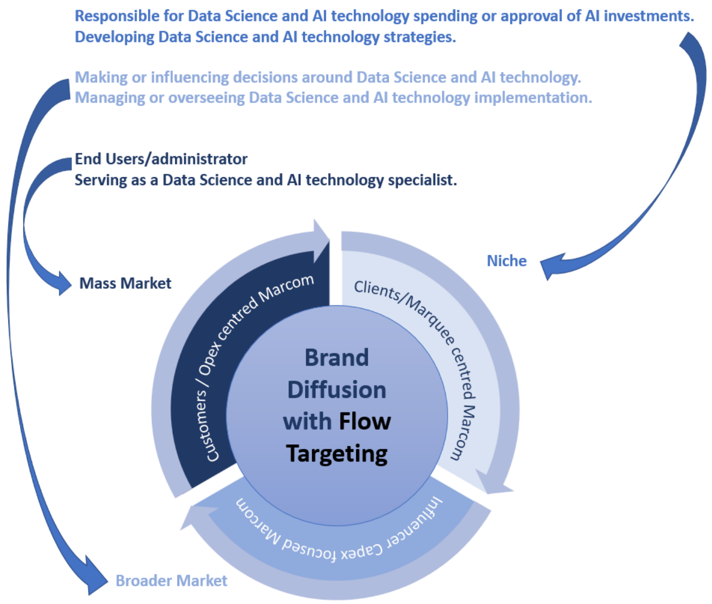
Buyer Profile/Personas

Assumptions:
To check the inference IVs and DV using Role and Job in multigroup analysis

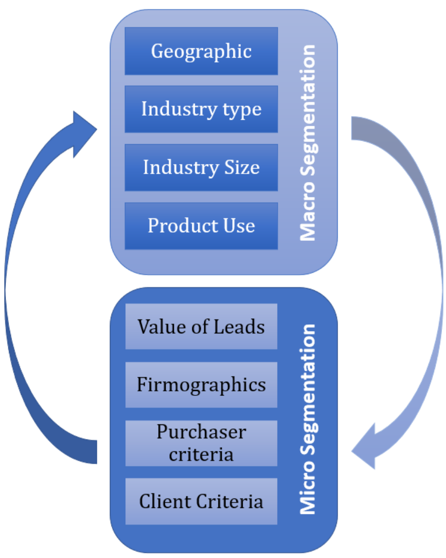


Appendix 6.3.2

B2B STP



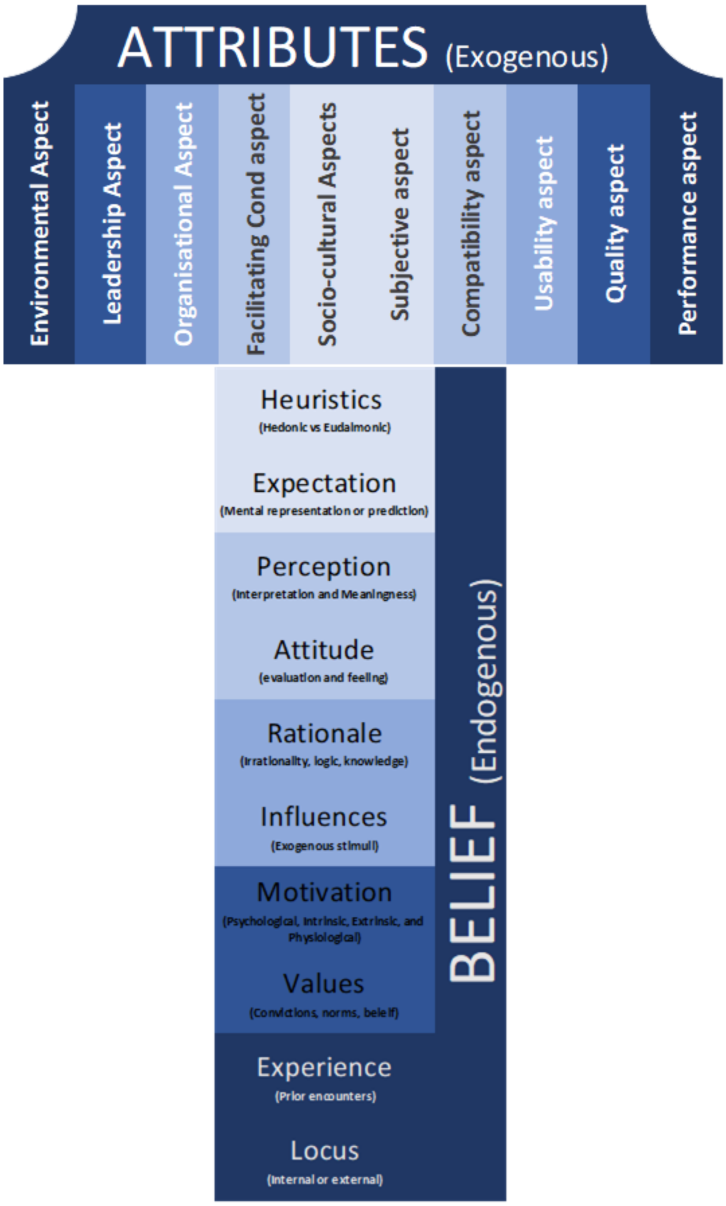
Flow Targeting, Diolle (2023)



Agile B2B Segmentation, Diolle (2022)

Assumptions:
To check the inference between Budget, Role, job, implementation stage and personal innovativeness using multigroup analysis, boxplot and histogram

Appendix 6.4



The T-Scale model (Diolle, 2023)

Appendix 7

The BEST Framework (Diolle, 2023)

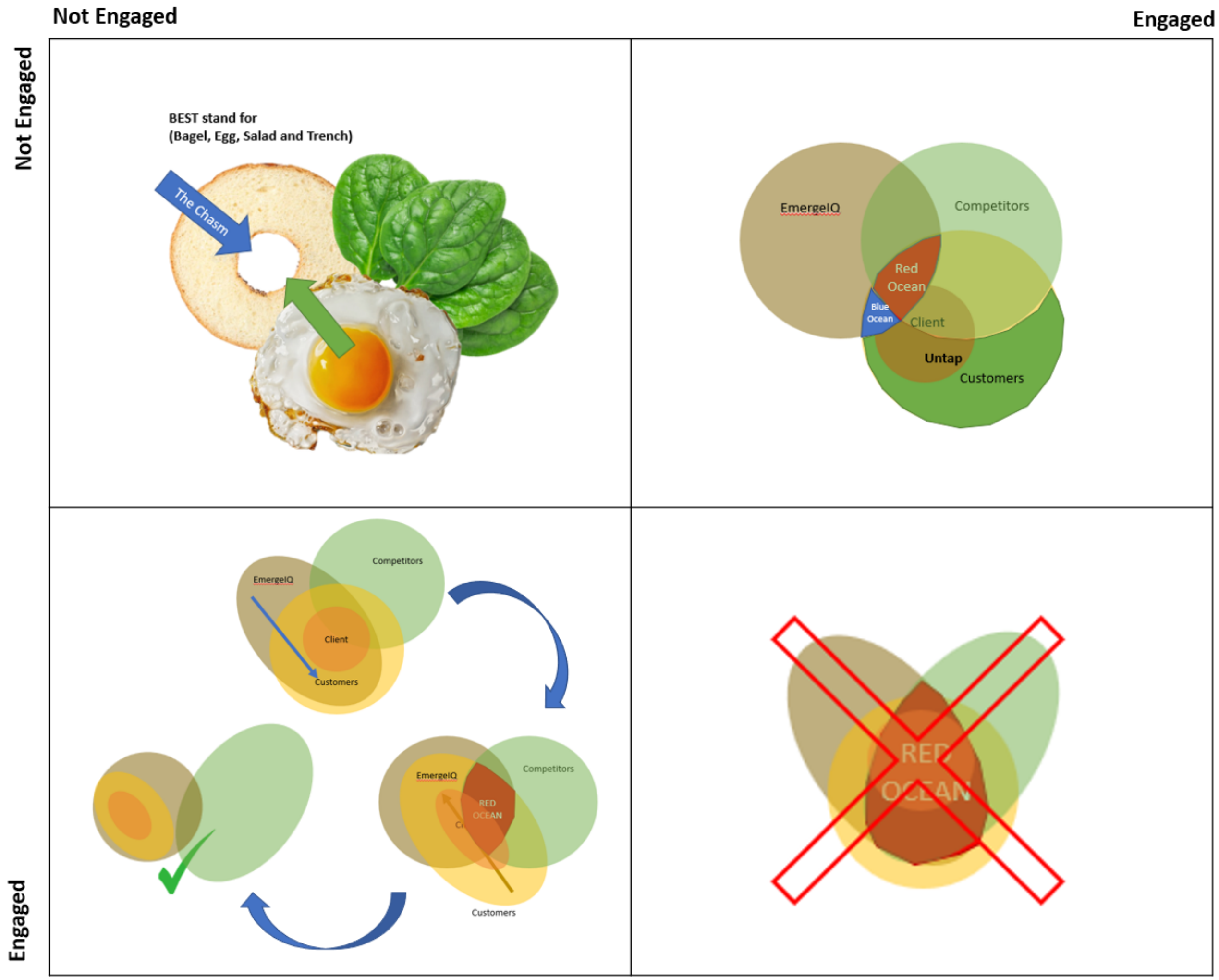
How to move a York on your bagel while avoiding the hole without spilling the Salad

Scenarios planning based on GAME THEORY principles
(with Marketing and Resource as IVs and Market Share as DV)

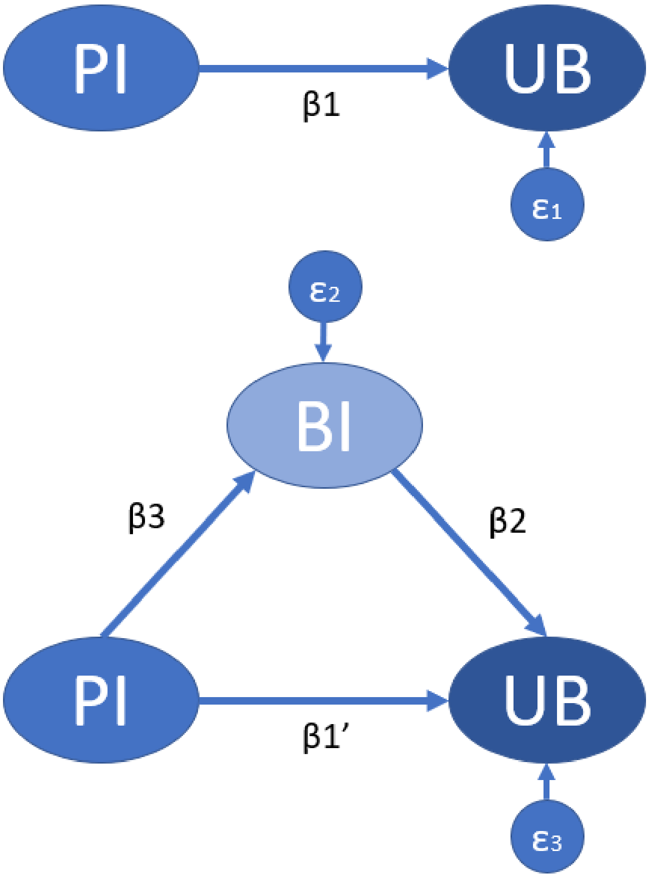
Graphical representation
EmergeIQ is not a market leader
Most sales are in a Competitive market (Red Ocean)
Client are unaware of the product offering and using mainly DS,AI and ML product from major competitor

Where "B" stand for a bagel, representing the platform model
"E" represents the egg or the client/customers you are trying to do business with
"S" is for salads, which represent the Competitor and suppliers
"T" stand for trench and represent the "Chasm"

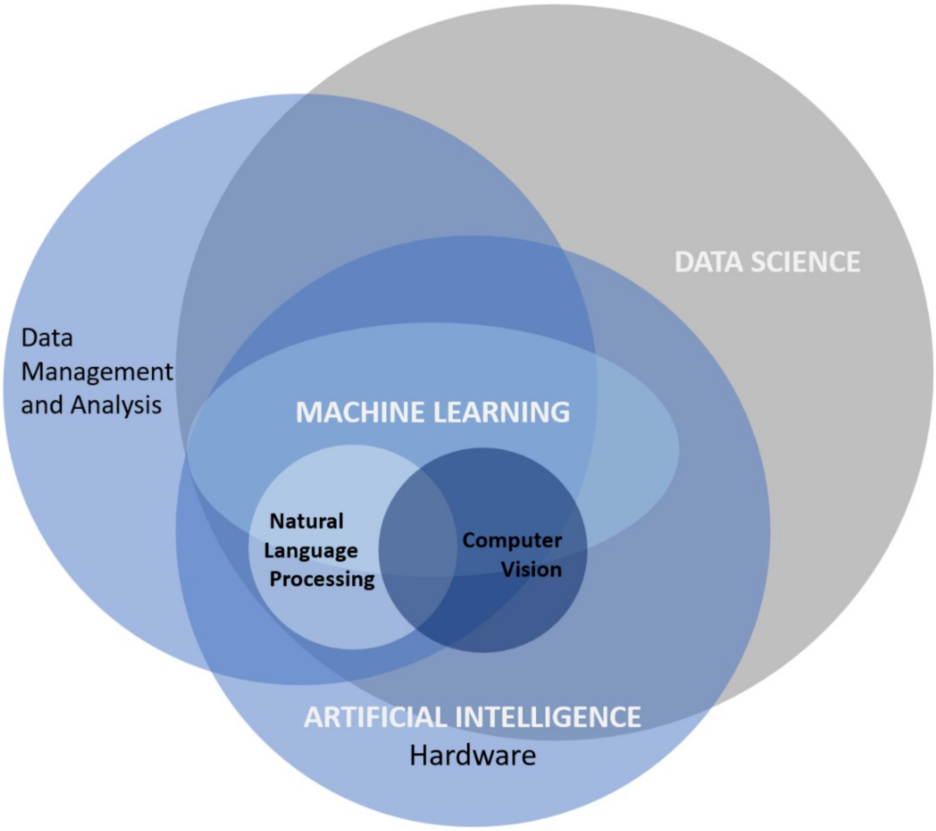
The York and the white have different consistency which represents the need for different techniques to market and approach Client (York) and Whites (Customers/Users) to optime the company **game theory.**



Appendix 8



Appendix 9



Appendix 10

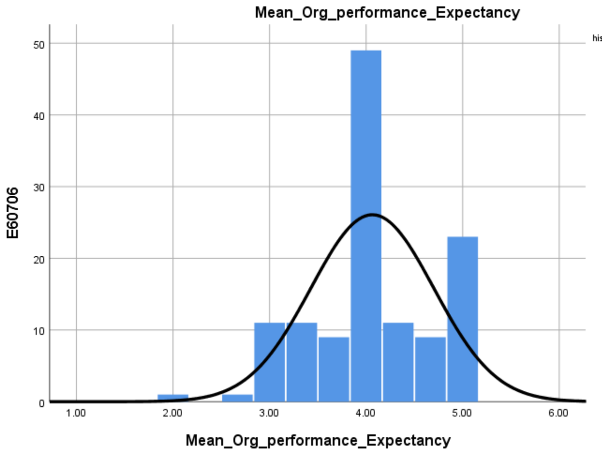
Statistics

		Use_Behaviour	Behaviour_Intention	Attitude	Data_Driven_Expertise	Self_Efficacy	Personal_Innovativeness	Learning_Culture	Algorithm_Skepticism	Financial_Risk	Security_Risk	Price_Value	Facilitating_Condition	Social_Influence	Effort_Expectancy	Performance_Expetancy
N	Valid	125	125	125	125	125	125	125	125	125	125	125	125	125	125	125
	Missing	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Mean		4.1673	4.1061	3.5949	3.2339	4.2859	3.2092	3.8644	2.1800	2.6936	3.2430	3.4470	3.4485	3.1947	3.7100	3.8770
Median		4.3241	4.2211	3.6254	3.3715	4.3993	3.3361	3.9404	2.1919	2.7736	3.2489	3.3009	3.5750	3.2164	3.7848	3.8304
Mode		3.46	3.22	2.69	2.60	3.41	2.74	2.98	2.16	2.81	3.13	2.99	2.78	2.56	2.96	2.89
Std. Deviation		.75283	.72109	.56889	.58062	.63246	.65669	.66820	.58309	.68839	.80469	.69463	.56283	.39193	.58044	.56546
Skewness		-.450	-.711	-.633	-.930	-.978	-.556	-.534	-.387	.049	-.202	-.521	-.072	.151	-.047	-.298
Std. Error of Skewness		.217	.217	.217	.217	.217	.217	.217	.217	.217	.217	.217	.217	.217	.217	.217
Kurtosis		.677	1.732	2.130	2.080	2.876	.490	1.130	.037	-.684	-.211	1.255	.071	-.210	.364	.000
Std. Error of Kurtosis		.430	.430	.430	.430	.430	.430	.430	.430	.430	.430	.430	.430	.430	.430	.430

Coefficients[a]

Model		Collinearity Statistics Tolerance	VIF
1	PE2:Using Data Science/AI powered technologies enhance my efficiency at work.	.257	3.884
	PE3: Using Data Science/AI powered technologies help me to accomplish tasks more quickly	.317	3.159
	EE1: Learning to use Data Science/AI powered technologies would be easy for me.	.283	3.529
	EE2: I find Data Science/AI powered technologies easy to use.	.285	3.511
	EE3: My Interaction with Data Science/AI powered technologies technologies is clear and understandable.	.257	3.886
	SI1: In General, the organisation has supported the use of Data Science/AI powered technologies.	.349	2.863
	SI2: People who are important to me think I should use Data Science/AI powered technologies.	.456	2.194
	SI3: I will discuss Data Science and AI technologies with my peers.	.442	2.264
	FC1: I have the knowledge necessary to use Data Science/AI powered technologies.	.328	3.049
	FC2: I can get technical support when I have difficulties using Data Science/AI powered technologies	.371	2.696
	FC3: Data Science/AI powered technologies are compatible with other technology I use at work.	.331	3.022
	SR1: Using Data Science/AI-powered technologies at work increases the risk of data breaches and unauthorised access to sensitive information.	.269	3.719
	SR2: I am concerned about the risk of privacy disclosure and frauds when using Data Science/AI powered technologies	.276	3.623
	SR3: I would not feel secure processing information on Data Science/AI powered tools due to potential cyber attacked.	.195	5.118
	FR1: I am uneasy about using Data Science/AI powered technologies because my company can lose business from incorrect operations	.328	3.045
	FR2: I am concerned about using Data Science/AI powered technologies at work due to uncertainty on financial returns.	.227	4.403

Appendix 11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4.00
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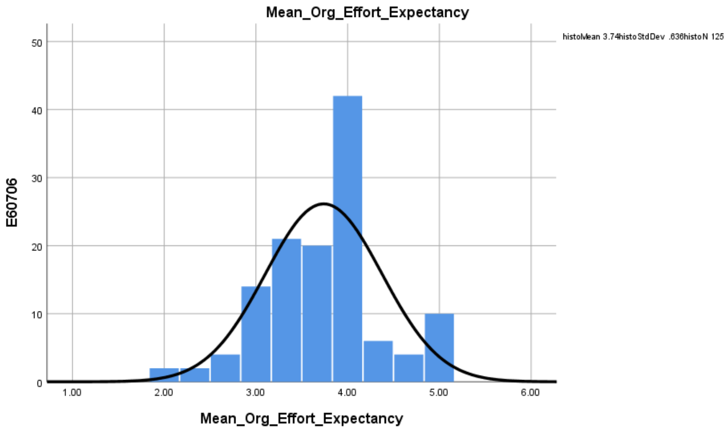
6.00
Mean_Org_performance_Expectancy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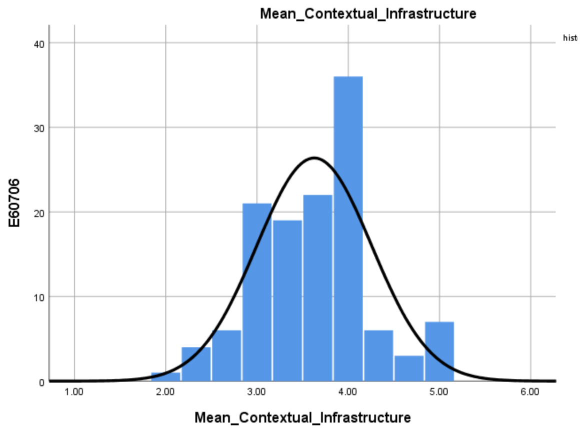
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Mean_Contextual_Infrastructure


Mean_Norms_Socio_Influences
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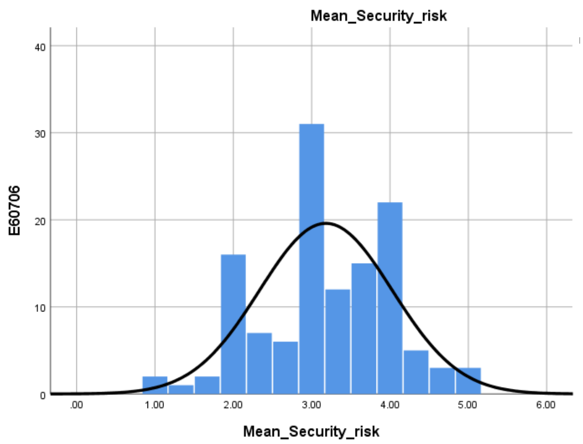
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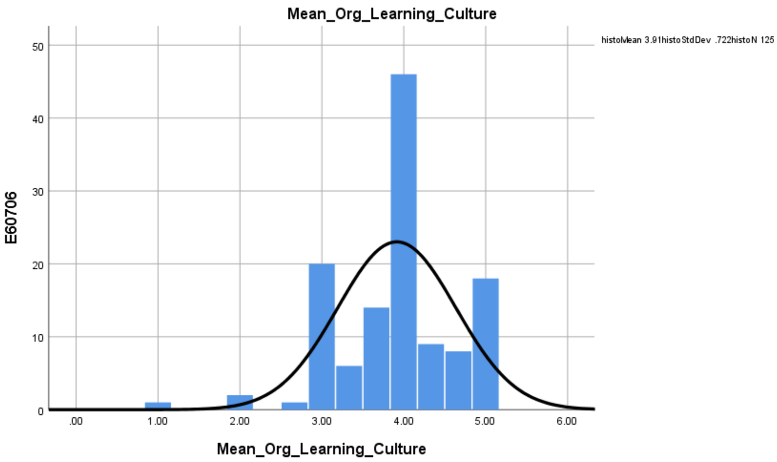
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4.00
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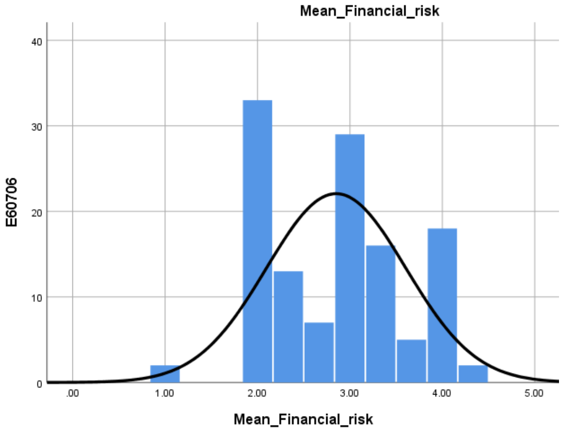
Mean_Org_Learning_Culture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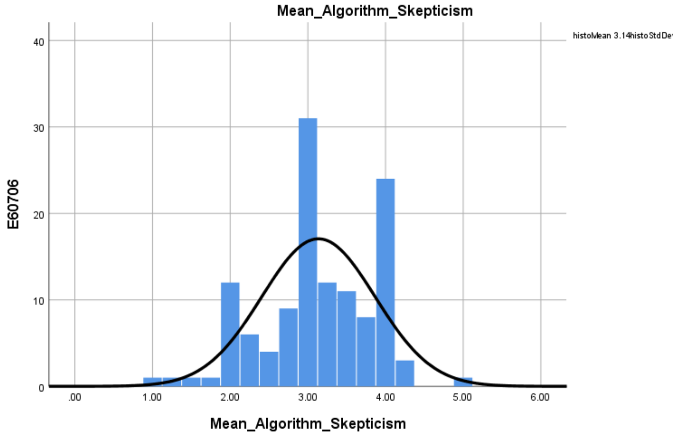
Mean_Financial_risk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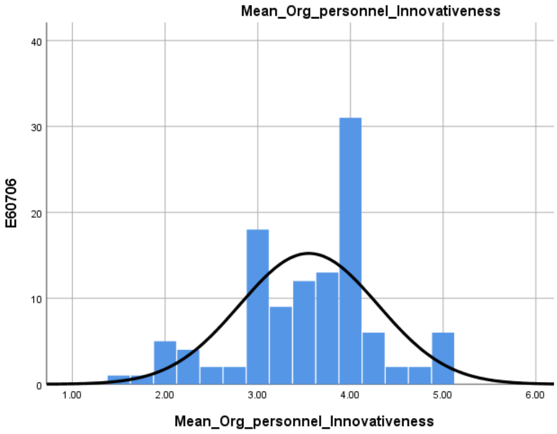
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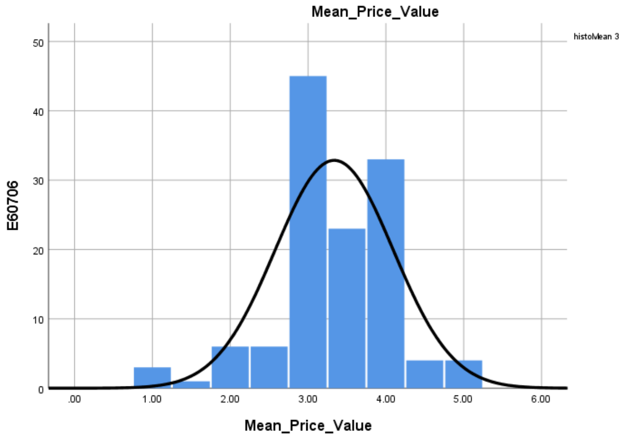
Mean_Org_personnel_Innovativeness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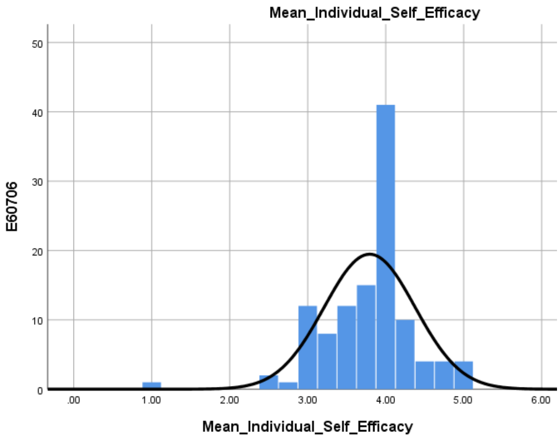
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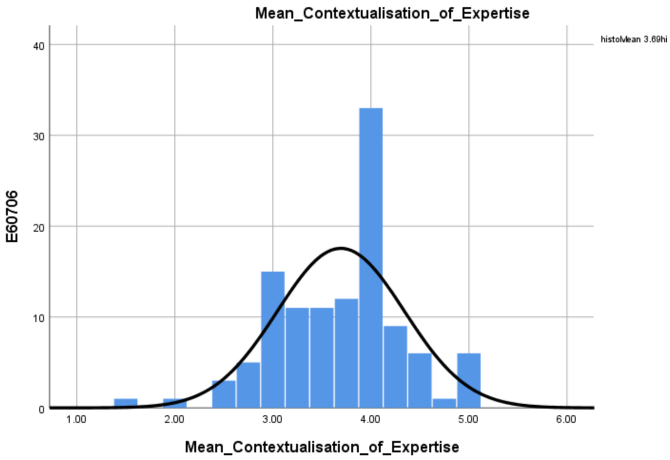
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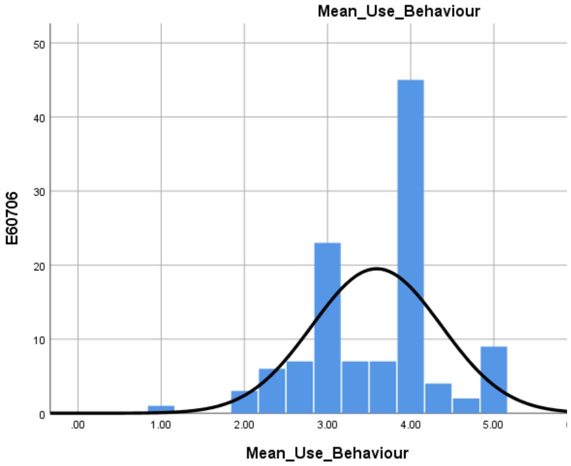
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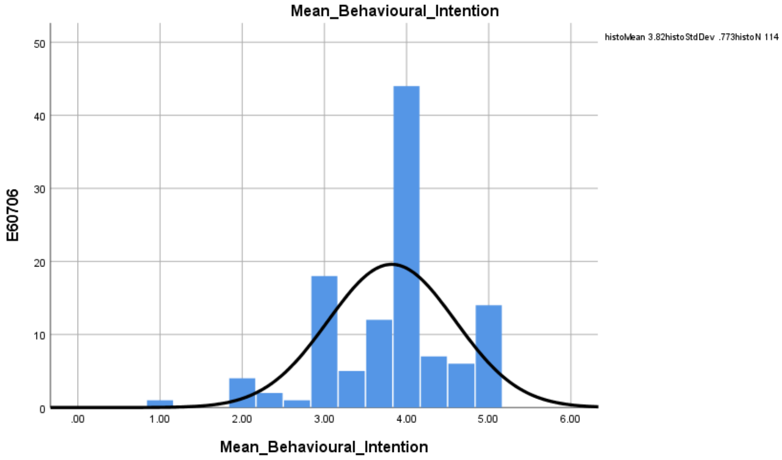
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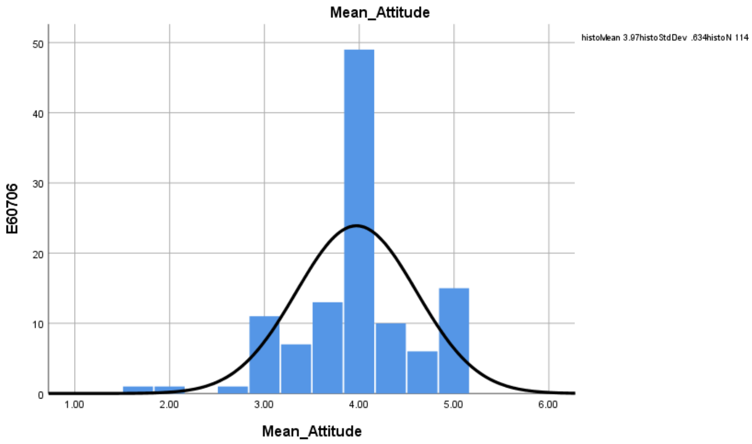
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Mean_Attitude