AI-Driven Competitive Advantage: The Role of Personality Traits and Organizational Culture in Key Account Management

Abstract

Purpose – The importance of key account management (KAM) as a management technique in B2B markets has grown in recent years. The success of KAM programmes is highly dependent on the efforts of individual employees, specifically key account managers. Research on KAM at an individual level is important but lacking in the academic domain. This study fills this gap by developing and evaluating a model of key account manager personality traits and how they impact the adoption of AI technologies. The study also depicts the effect of the adoption of AI technologies on competitive advantage and firm performance.

Design/methodology/approach – The study examines how the adoption of AI technologies impacts firms' competitive advantage and performance. The study used competitive advantage as a mediator and organizational culture as a moderator. A mixed-method analysis was used to conduct the study. In the first phase, an exploratory study was conducted using interviews with 26 key account managers from the automobile industry and thematic analysis to establish nine constructs. In the second phase, which is a confirmatory study, 496 respondents finally responded to the questionnaire.

Findings – All constructs are used for confirmatory analysis and validate the data. Our research shows that key account managers' adoption of AI technologies is influenced significantly by personality traits. Extraversion, agreeableness, conscientiousness, neuroticism, and openness have substantial links to adopting AI technologies, which impacts firms' competitive advantage and performance. Organizational culture significantly moderates the association between agreeableness and the adoption of AI technologies.

Practical implications – The findings of this research allow organizations to optimize team composition, customize training programs based on individual traits, and incorporate personality assessments into recruitment processes for streamlined technology adoption and improved competitiveness. Overall, these actions aim to enhance AI integration, driving competitive advantage and client satisfaction.

Originality/value – This study stands out as one of the limited inquiries examining how the Big Five personality traits of key account managers influence the integration of AI technologies and its resulting impact on company performance. Therefore, this research makes notable contributions to the realms of organizational psychology and technology adoption studies.

Keywords: Big 5 Personality Traits; KAM; Competitive Advantage; Firm Performance

1. Introduction

Although, presently AI is being used with number of business-to-consumer (B2C) interfaces and has received considerable attention from the market research community (Dwivedi *et al.*, 2023; Liu, 2020; Upadhyay *et al.*, 2022), the application of AI in B2B market has only recently captured the attention of researchers (Božič and Dimovski, 2019; Herhausen *et al.*, 2020, 2022; Kumar *et al.*, 2019). While factors were identified based on the qualitative study acknowledged the significance and advantages of adopting AI in B2B context and have reported that adoption is influenced by organizational readiness and culture (AlSheibani *et al.*, 2020; Cao *et al.*, 2021; Latinovic and Chatterjee, 2022; Rahman *et al.*, 2023), availability of resources (Cao *et al.*, 2021), perceived ease of use, perceived usefulness and price value (Chatterjee *et al.*, 2021;

Dubey *et al.*, 2020), performance and effort expectancy (Cao *et al.*, 2021), and managerial support and attitude (AlSheibani *et al.*, 2020; Cao *et al.*, 2021; Dubey *et al.*, 2020; Latinovic and Chatterjee, 2022). While acknowledging the role of managerial support and attitude, the earlier research has ignored the role of personality. Previous research in psychology suggests that personality is a reflection towards understanding why and how one thinks, feels and behaves in a specific way under different circumstances and situations (Kenrick and Funder, 1988; Moskowitz, 1994) and that it acts as a lens through which one views his/her surroundings comprising people, objects and events in them (Moskowitz, 1994). Therefore, when faced with AI an individual's orientation towards different cues/stimuli in the environment (such as novelty, complexity, functionality, etc.) is likely to affect his/her attitudes toward AI. The present research attempts to plug this gap and intends to examine the role of personality in influencing AI adoption.

In B2B environment, firms manage a variety of customers with differing business prospects and opportunities (Sandesh *et al.*, 2023). The success in B2B market depends upon creating and nurturing deep-rooted relationships by addressing specific customer demands through value creation. This technique of managing high-profile customers based on relationships that are nurtured through value-creation (Guesalaga *et al.*, 2018; Murphy and Coughlan, 2018; Ulaga, 2003) leading to customer satisfaction and loyalty (Tzempelikos and Gounaris, 2013, 2015; Woodall, 2003) has gained considerable traction and high acceptance in B2B business (Božič and Dimovski, 2019; Herhausen *et al.*, 2020, 2022; Kumar *et al.*, 2019). Accordingly, key account management (KAM) has emanated as a reliable relationship management tool that has helped B2B business in cultivating and deepening long-term customer focussed business relationships (Badawi *et al.*, 2022; Ivens and Pardo, 2007; Pardo *et al.*, 2014) by facilitating value creation (Pardo *et al.*, 2006; Salojärvi and Saarenketo, 2013; Sengupta *et al.*, 2000; Sharma, 2006; Sheth and Parvatiyar, 1995).

Addressing the complex customer needs through value-creation in B2B business follows a long transaction cycle involving gathering information from the suppliers, customers, and downstream value chain (Salojärvi and Saarenketo, 2013). Further, transactions of many firms have shifted to electronic mode, leading to generation of vast structured (such as sales data, customer information, etc.) and unstructured (such as pictures, videos, etc.) data characterised by high volume, velocity, and variety (Paschen *et al.*, 2019) which needs to be analysed on a real-time basis for accuracy and meaningfulness of the results (Sandesh *et al.*, 2023). Artificial intelligence can assist in uncovering, organizing, analysing, capturing in-depth knowledge about the customers, and identifying hidden patterns from this vast dataset thereby helping the organizations in formulating effective strategies to close the deals quickly (Martínez-López and Casillas, 2013; Moradi and Dass, 2022; Singh *et al.*, 2019; Syam and Sharma, 2018) and shorten the transaction cycle as compared to their competitors. Therefore, adoption of AI technologies is likely to offer a distinct competitive advantage to the firms and help them in improving their performance (Hossain *et al.*, 2020; Rahman *et al.*, 2023).

Technology Organization Environment (TOE) framework is one of the models that forms theoretical backbone of the current research. According to TOE framework, technology adoption depends upon the nature of technology (functionality, complexity, and compatibility with the existing systems), organization (top management support, organizational culture such as innovative or customer-centric, size, etc.) and the environment (government regulations, competition, etc.) (Neumann *et al.*, 2024). The organization component of the TOE framework represents the context in which the technology is being used (Awa, Baridam, *et al.*, 2015; Mohtaramzadeh *et al.*, 2018; Neumann *et al.*, 2024). Organizational culture, often referred to as shared assumptions, values, and beliefs within the organizational members (Liu *et al.*, 2010) represents one such significant context. It has been argued that different organizational cultures often have different underlying values, assumptions, and beliefs that directly or indirectly influences technology adoption in firms (Mohtaramzadeh *et al.*, 2018). Further, it has been argued that organizational culture influences individual willingness to accept and/or use technology (Dasgupta and Gupta, 2019; Melitski *et al.*, 2010). As such, it can be concluded that organizational culture may strengthen or weaken the influence of antecedent variables on technology adoption as well as its use. The present study therefore discusses organizational culture as a moderating variable.

Innovation is driving the global market as well as workplace by curating solutions to the challenges that the organizations face. However, reluctance on the part of business to adopt these new technological innovations may result in considerable costs in the form of loss of competitive advantage and revenue loss (Makkonen *et al.*, 2016). Although, organizational, market, and economic factors have been frequently used to examine technology adoption, psychological factors can also act as significant barriers or facilitators to corporate or institutional technology adoption (Knobloch and Mercure, 2016; Makkonen *et al.*, 2016). These are, however, studied to a lesser extent (Roberts *et al.*, 2021). The term 'psychological' relates to gamut of factors relating to the mind and behaviour (Kenrick and Funder, 1988; Moskowitz, 1994). Factoring in psychological aspect brings into focus the role of individual decision makers who take a call whether a technology is to be introduced (or not). In B2B context this individual is a central figure who takes decision on behalf of the organization (Roberts *et al.*, 2021). These 'gatekeepers' make the pivotal decisions to appraise, trial, or adopt technologies for deployment in their organizations and are often located at key positions with power to make a significant impact upon the success or failure of adoption (Roberts *et al.*, 2021). Understanding how psychological factors influence adoption of innovative technologies is crucial to support the successful introduction of new systems and products (Roberts *et al.*, 2021), that can address the challenges that an organization is facing and provide distinct competitive edge over its competitors.

This study is as such aimed at investigating the relationship between Big-five personality traits and firm performance as well as competitive advantage with adoption of Artificial Intelligence (AI) as a mediator in the context of KAM. Organizational culture is considered as a moderating variable. The research seeks to address the following questions:

RQ1: *How the Big five personality traits of key account managers are affecting the adoption of AI technologies which simultaneously impact the competitive advantage and firm performance*?

RQ2: *How the organizational culture (moderator) is affecting the relationship between big-five personality traits and AI adoption, as also the relationship between AI adoption and competitive advantage alongwith firm performance*?

Against this background the present study attempts to investigate the relationship between Big-five personality traits and firm performance as well as competitive advantage with adoption of Artificial Intelligence (AI) as a mediator in the context of KAM. Organizational culture is considered as a moderating variable.

2. Literature review

Organizations are investing a significant portion of their budget on high-profile solutions to cater to their most strategic and valuable customers (Nätti *et al.*, 2006; Salojärvi and Sainio, 2010; Sandesh *et al.*, 2023). These solutions focus on human capabilities and knowledge-intensive business exchanges (i.e. KAM) Scholars from varied disciplines acknowledge that businesses are no longer viewed from an industrial perspective but are seen from knowledge perspective (Grant, 1996; Paschen *et al.*, 2019; Spender and Grant, 1996). An in-depth understanding of the customer value expectations and the ability to mobilize this knowledge in the organization are the key factors for the performance of KAM (Kleinaltenkamp *et al.*, 2022; Kumar *et al.*, 2019; Sandesh *et al.*, 2023). This is particularly evident with respect to data, information, and knowledge, which help the organizations to extract comparative competitive advantages and drive innovation (Campbell, 2003; Hakanen, 2014). In case of KAM, AI can help translate (big) data into information and knowledge required for creating effective marketing and sales strategies and tactics. The practitioners thus expect that AI will assist in personalization, customization, innovation and enhanced marketing effectiveness and efficiencies (Moradi and Dass, 2022; Paschen *et al.*, 2019).

Key Account Managers (KAMs) often need a certain combination of characteristics in order to thrive in their respective positions (Hakanen, 2014; Lai and Yang, 2017; Ellis and Iwasaki, 2018). Elevated degrees of extraversion and agreeableness are often seen as advantageous characteristics due to their facilitation of proficient communication, establishment of rapport, and settlement of conflicts with significant clientele (Hakanen, 2014; Lai and Yang, 2017). Conscientiousness is a crucial trait that guarantees meticulousness and dependability in the management of intricate financial records. Moreover, possessing a modest degree of openness to experience might help KAMs in effectively adjusting to evolving client demands and market dynamics (Guenzi and Storbacka, 2015; Tzempelikos and Gounaris, 2015). In addition, it is necessary to possess emotional stability or exhibit low levels of neuroticism in order to effectively navigate the stress and strain associated with overseeing crucial client relationships (Guenzi and Storbacka, 2015; Tzempelikos and Gounaris, 2015; Speakman and Ryals, 2012). When KAMs exhibit these characteristics, there is a higher probability of cultivating customer loyalty, driving revenue development, and favourably influencing the overall performance of the company via the assurance of client happiness and the establishment of long-term relationships (Hakanen, 2014; Lai and Yang, 2017; Pereira *et al.*, 2019). Hence, organizations that acknowledge the importance of these personality qualities in their KAMs are more likely to attain long-term success in their respective markets.

In business-to-business (B2B) markets, the significance of key account management has been recognized as an important research area (Leischnig *et al.*, 2018; Mahlamäki *et al.*, 2019). While extensive literature exists for organizational level themes like, key account management (KAM) teams (Hakanen, 2014; Lai and Yang, 2017), KAM implementation (Guenzi and Storbacka, 2015; Tzempelikos and Gounaris, 2015), relationship management (Ivens *et al.*, 2016; Ivens and Pardo, 2007; Ryals and Davies, 2013; Salojärvi *et al.*, 2010) and related conceptual models (Guenzi *et al.*, 2007; Homburg *et al.*, 2002; Jones *et al.*, 2005), relatively limited research exists on the role of individual level factors that may impact KAM.

Research on individual level factors has primarily focussed on topics such as behaviours and skills (Davies and Ryals, 2013; Guenzi *et al.*, 2007), and limited research examines psychological factors such as personality (Mahlamäki *et al.*, 2019). Like other professionals, key account managers have different personalities that can impact their performance and eventually firm performance. While the role of personality has gained prominence in the area of industrial marketing (Anaza and Nowlin, 2017; Johnson and Sohi, 2017; McCarthy Byrne *et al.*, 2011; Sok *et al.*, 2016; Tuncdogan *et al.*, 2015) this is largely neglected in KAM and limited studies focus on the relationship between personality and individual performance (Mahlamäki *et al.*, 2019). Further, while studies investigate the role of personality on firm's performance (O'Reilly *et al.*, 2014; Oh *et al.*, 2015; Shalender and Yadav, 2019), a review of literature indicates lack of any study that explores the relationship in the context of KAM. This research gap warrants the need for studies on role of personality in KAM.

People have the tendency to display differing levels of favour or disfavour towards AI (Gaudiello *et al.*, 2016; Shank *et al.*, 2019; Waytz *et al.*, 2010). These orientations regarding favour and disfavour are based on one's cognitive, affective, and behavioural evaluations of the entity. These evaluations in turn determine how one feels and thinks about it and what he/she intends to do with it (Eagly and Chaiken, 2007). Previous studies indicate that one's attitudes towards technology are significant predictors of its acceptance and usage (Marangunić and Granić, 2015) and as such it is important to examine how individuals differ in these attitudes. In the present study we are attempting to understand how personality influences AI adoption of AI.

Psychological research indicates that personality presents an effective framework towards understanding why and how one thinks, feels and behaves in a particular manner under different circumstances and situations (Kenrick and Funder, 1988; Moskowitz, 1994) and that it acts as a lens through which one views his/her surroundings comprising people, objects and events in them (Moskowitz, 1994). Therefore, when faced with AI an individual's orientation towards different cues/stimuli in the environment (such as novelty, complexity, functionality etc.) is likely to affect his/her attitudes toward AI. Personality traits are primary determinants of attitudes as they represent variations in sensitivity to different stimuli (Gray, 1973). Since, AI is a novel stimuli that has social, emotional, and functional aspects (Gaudiello *et al.*, 2016; Shank *et al.*, 2019; Waytz *et al.*, 2010) therefore personality traits are likely to determine the extent to which individuals will exhibit certain attitudes toward it. Some of the previous studies have indicated that people's personality features have considerable influence on their attitudes toward autonomous technology (Stein *et al.*, 2019) and interaction with robots (Santamaria and Nathan-Roberts, 2017).

Artificial intelligence has been defined as "a system's ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through fexible adaptation" (Kaplan and Haenlein, 2019, p. 15). Besides other businesses, B2B business has not escaped from the fundamental changes accompanying the advent of AI. The traditional business is facing challenges due to rapidly changing customer preferences, a longer sales process that is influenced by multiple actors, and fluidity in the markets (Chen *et al.*, 2022). It is anticipated that AI may influence B2B business through personalization, customization, acting as a power source to negotiate competitive advantage (Keegan *et al.*, 2022) and enhanced marketing effectiveness and efficiency (Keegan *et al.*, 2024; Paschen *et al.*, 2019; Wei and Pardo, 2022). While, organizational, market, and economic factors have been frequently used to examine technology adoption, psychological factors can also act as significant barriers or facilitators to corporate or institutional technology adoption (Knobloch and Mercure, 2016; Makkonen *et al.*, 2016). Previous research has indicated that technology's *a priori* acceptability and intention to use is influenced by attitudes (Albarracin *et al.*, 2005; Bhat *et al.*, 2022; Parasuraman *et al.*, 1993).

This paper aims to bridge this gap and intends to investigate how personality traits influence AI adoption. In doing so our article contributes to the literature on AI and personality traits while addressing the call for more scholarly work in this area. The study adopts a mixed method approach. The first phase of the study involved exploratory analysis to explore the various themes from the interviews. The second phase focussed on empirical analysis to buttress these relationships. The resource based view of the firm and conceptualization of personality in line with big-five personality traits form the theorectical background of the study. The remaining sections of the paper are organized as introduction to theoretical background, qualitative analysis to explore the relationship between variables, followed by review of literature, data analysis, discussion, theoretical and practical implications, and conclusion.

3. Theoretical background

While factors were identified based on the qualitative study, the theoretical background of the study was based on Big-five personality model, Technology, Organization, Environment (TOE) model, and Resource Based View (RBV) of the firm. Using big-five personality model we examine the influence of five personality traits – namely extraversion, agreeableness, neuroticism, openness to change, and conscientiousness on attitudes towards AI adoption. Researchers in the area of human-computer interaction have frequently used big-five traits (Santamaria and Nathan-Roberts, 2017). Personality traits are primary determinants of attitudes as they represent variations in sensitivity to different stimuli (Gray, 1973). Since, AI is a novel stimuli that has social, emotional, and functional aspects (Gaudiello *et al.*, 2016; Shank *et al.*, 2019; Waytz *et al.*, 2010) therefore personality traits are likely to determine the extent to which individuals will exhibit certain attitudes toward it.

TOE based model stresses that adoption of new technology is influenced by nature of the technology itself, including its functionality, complexity, compatibility with existing systems, and ease of use. Organization refers to the internal context in which the technology is used including culture (top management support), change management, innovative culture, organizational size, financial and human resources. Environment refers to competitive pressure, government regulations, and industry requirements (Neumann *et al.*, 2024)

In general, it is acknowledged that technology adoption explanation at the individual and organizational level requires two different set of theories. While behavioural theories such as technology acceptance model (TAM), theory of planned behaviour (TPB) and unified theory of acceptance and use of technology (UTAUT) have been frequently used to explain technology adoption at the individual level, theories, and models like diffusion of innovation (DOI) and technology-organization-environment (TOE) framework have been employed at the organizational level. Although, this segregation of theories appears to be reasonable and logical, however, the process of investigating the organization is ultimately performed based on gathering opinion of the individuals. Also, there are no established criteria regarding how to fairly obtain the organizational characteristics when organization is the target of investigation. These organizational characteristics may include readiness to adopt technology, perceived advantages, competitive edge etc. In the absence of proven methodology to fairly identify these organizational characteristics, the researchers frequently choose to survey decisionmakers who have the authority to approve final purchase (Kuan and Chau, 2001; Oliveira and Martins, 2010). Further, these decision-makers may have different assessments of these organizational characteristics, underscoring the role of individual perceptions. Therefore, it can be said that the adoption of technology in the organizational context depends upon the perception of key decision makers towards it.

As the key account managers play a pivotal role in the handling of high-volume customers of the firm, they play a significant role in decision making (Georges and Eggert, 2003; Pardo *et al.*, 2020). Infact it has been suggested that decision making process suffers if key account managers lack decision making authority (Larson and Gobeli, 1988). The orientation of these decisions may be influenced by their perceptions towards firm level characteristics. Previous studies under different contexts have indicated that personality has a significant influence on perception (Caligiuri, 2000; Judge and Zapata, 2015; Saksvik and Hetland, 2011). The present research borrows the conceptualization of organization from the TOE based model and combines it with Big-5 personality trait model in order to achieve its overall objective of investigating the role of Big-5 personality traits on technology adoption in the organizational context.

The resource-based view (RBV) conceptualizes the firm as a bundle of resources and these resources account for the growth or decline of the firm (Penrose, 1959). Resources may include technical know-how, assets, capabilities, processes, culture, and attributes that are possessed by the firm and these help the firm to formulate and implement competitive strategies (Barney, 1991). RBV relies on two basic assertions, that of resource heterogeneity, and resource immobility. If a resource possessed by a firm is also possessed by other firms, this resource cannot contribute to competitive advantage. Heterogeneity is an essential condition for enjoying at least temporary competitive advantage. Resource immobility is the required condition for enjoying long-term competitive advantage, since competitors would face cost disadvantages in obtaining, developing, and using it compared to the firm that already possess it (Rivard *et al.*, 2006). Since, adoption of AI is likely to equip the firm with a heterogenous and immobile resource it may provide distinct competitive advantage to the firm and boost its performance. Also, as organizational culture constitutes a distinct resource for the organization it may influence the adoption of AI and hence moderate the relationship between five personality traits and AI adoption as well as between AI adoption and competitive advantage.

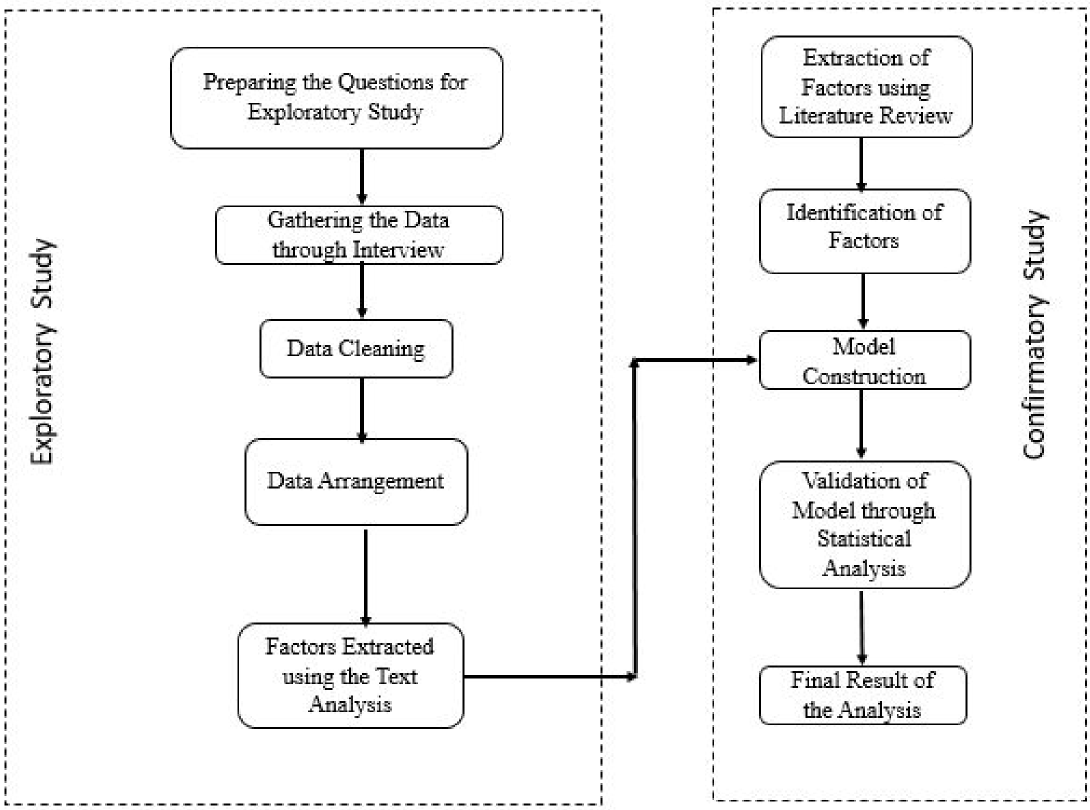
4. Research Design

The research used a mixed methods strategy, including both qualitative and quantitative approaches, in order to mitigate the potential constraints associated with relying only on a single methodological approach (Venkatesh et al., 2013). Qualitative research techniques, such as interviews and observations, provide comprehensive and detailed understandings of the experiences, perceptions, and behaviours of people or groups (Fossey et al., 2002). These approaches enable researchers to delve into the complexities of a given subject matter. In contrast, quantitative methodologies such as surveys provide a higher level of statistical rigour and generalizability, allowing researchers to make more extensive inferences and discern patterns and trends (Finnegan et al., 2016). Through the integration of both the methodologies, mixed-method research offers a more comprehensive and rigorous comprehension of research inquiries, hence augmenting the credibility and dependability of outcomes (Castro et al., 2010).

Utilizing a mixed methods approach is crucial for the study as it delves into the intricate dynamics between human (personality traits) and organizational (culture) factors, in conjunction with technological advancements (AI), within key account management. This design enables researchers to measure the impact of AI and human elements on success, while also capturing the intricate experiences and decision-making processes that shape the implementation of AI and its interaction with company culture and individual personalities. By considering multiple perspectives, a deeper insight can be gained into the optimal utilization of AI in the unique social environment of key account management.

During the qualitative phase of the exploratory investigation, data analysis was conducted using interview technique. Specifically, theme analysis was performed following text summarization using Atlas.ti 9. The objective was to discover and analyse significant components. The aforementioned parameters were used for the purpose of identifying theoretical lexicons, which were then subjected to validation in the confirmatory research. The framework under consideration was developed utilising theoretical lexicons, and afterwards subjected to validation via a cross-sectional confirmatory research. The confirmatory investigation was conducted using a cross-sectional design, employing a structured questionnaire. The data analysis was conducted with structural equation modelling (SEM) which provided the final output of the study. Figure 1 illustrates the steps used to conduct the study.

Fig. 1. Steps Used to Conduct the Study



5. Exploratory Study (First Phase)

The first phase of the study employed an inductive research approach and utilized semi-structured interviews to develop the research model. The data for the qualitative study was collected from National Capital Region (NCR) of India from the managers working with

Original Equipment Manufacturers (OEMs) of automobile industry. All the interviews were conducted by the researchers in English. Around 58 managers we have approached and a total of 26 of them were agree to provide their responses. On an average each interview lasted for around 40 minutes. The interviews were conducted in three separate stages. Using an intervention approach, the interviews began with general inquiries and gradually transitioned to more focused ones (Brinkmann, 2013). Attached in Annexure 1 are the comprehensive questions that were used as a reference guide during these interviews. The main interview commenced with interviewers asking the respondents to recall the most critical incidents affecting the firm's performance and its competitive edge over the others. Many of the respondents suggested that their organization was able to perform better and beat the competition due to timely adoption of newer technologies, like AI based technologies.

All the interviews were recorded and transcribed verbatim. A systematic analysis was conducted by applying open coding to excerpts from the qualitative findings. Through careful analysis of the data, patterns were discovered by comparing and contrasting the information. The authors thoroughly analyzed the open coding results and carefully examined the data patterns. They then moved on to selective coding in order to identify and categorize the various themes or dimensions. This was accomplished by thoroughly cross-referencing the data with relevant literature.

The transcripts were coded using thematic analysis (Medisauskaite *et al.*, 2023; Fereday and Muir-Cochrane, 2006). While, thematic analysis prevents separating codes from their context. However, the process of clubbing the text into themes may lead to their disconnection from the overall narrative. Therefore, every transcript was reread by including the codes to holistically understand how each of the constructs was felt by each of the respondents, which has been shown in Annexure 2. The thematic analysis resulted in the emergence of nine themes, from which five personality trait constructs were identified: Extraversion, Agreeableness, Conscientiousness, Neuroticism, and Openness. Other than this, four more constructs, namely firm performance, competitive advantage, adoption of AI technologies, and organizational culture, have also been extracted from the qualitative responses.

The variables in the study were identified and extracted using a systematic process of thematic analysis applied to the semi-structured interview transcripts (Refer to Annexure). Initially, open coding was used to identify patterns in the data, which helped to reveal key themes and constructs from the responses provided by the managers. We cross-referenced these patterns with existing literature to ensure they aligned with the theoretical framework and were valid. Through thematic analysis, a set of five personality traits were identified including extraversion, agreeableness, conscientiousness, neuroticism, and openness. These traits were found to be significant in understanding managerial behaviors and their impact on organizational outcomes. In addition, we identified several key factors that consistently emerged as critical to the success of firms. These factors include firm performance, competitive advantage, AI technology adoption, and organizational culture. This approach guarantees that the extracted variables are relevant to the context and based on empirical evidence, effectively capturing the intricate dynamics within the automotive OEM sector.

6. Confirmatory Study (Phase 2): Literature Review and Hypotheses Development

The TOE framework (Tornatzky and Fleischer, 1990) indicates that technology adoption is influenced by technology development (Kauffman and Walden, 2001); organizational conditions (Chatterjee *et al.*, 2002); and industry environment (Kowtha and Choon, 2001). The technological factors that can influence adoption include pool of internal and external technologies and their perceived usefulness, technology complexity and learning curve, etc. (Awa *et al.*, 2015; Awa *et al.*, 2015). The organizational factors include top management support, organizational culture, organizational structure, human capital (Jeyaraj *et al.*, 2006; Sabherwal *et al.*, 2006). Environment includes facilitators and inhibitors that are external to the organization like competitive pressure, government policies, technology support infrastructure etc. (Jeyaraj *et al.*, 2006). Previous studies have indicated that organizational and environmental factors are strong predictors of technology adoption as compared to technology related factors (Chittipaka *et al.*, 2022; Henriksen, 2006).

As the primary aim of this study was to examine the role of personality of key account managers in the adoption of AI and evaluate its impact on the overall performance of the firm. Since, TOE is the only framework that examines the role of organizational factors in technology adoption, this study borrowed the concept of organization as explained in the TOE framework to investigate the role of personality and moderating impact of organizational culture on technology adoption in firms. The organizational context in accordance with the TOE framework includes enterprise scope, managerial beliefs and support, organizational culture and complexity of organizational structure characterised by degree of centralization, formalization, and vertical differentiation, formal and informal linking structure among employees, intra-organizational communication, the human capital quality, size and size related issues, and specialization (Awa *et al.*, 2017; Low *et al.*, 2011; Melville and Ramirez, 2008; Salwani *et al.*, 2009; Xu and Lu, 2022).

6.1. Extraversion and AI adoption

The organization component of TOE model focuses on the internal structure, processes, and size of the organization. An organizational structure and culture that is characterised by friendly, family-like atmosphere may provide a fertile ground for people high on extraversion(Gardner *et al.*, 2012). Previous research has indicated that person-organization fit facilitates adoption of technology (Xu and Lu, 2022). As such extraverted employees in affiliated with an organization that exhibits a clan like structure may facilitate AI adoption. Extraverted people are characterised as fun loving, active, affectionate and talkative (Costa and McCrae, 2006). The assumption that AI may replace people in some repetitive jobs suggests that introvert people may favour the adoption of AI (Schepman and Rodway, 2023). On the other hand a contrasting view suggests that people who are extroverted may have a positive attitude towards adoption of AI as this gives them an opportunity to engage socially and gain attention (Ashton *et al.*, 2002; Schepman and Rodway, 2023). Previous studies have indicated that individuals with high extraversion felt less anxious while communicating through computer-mediated communication technology In the context of the present study, it is hypothesised that extroverted key account managers may have a more positive outlook towards adoption of AI.

H1. Extraversion is significantly positively related to AI adoption.

6.2. Agreeableness and AI adoption

As stated earlier, an organizational structure and culture that fosters friendly and family like environment characterised by high level of trust and cooperation within members may be an ideal fit for individuals high on agreeableness. Such an organization person fit may provide a conducive environment for people high on agreeableness to promote AI adoption in their organizations (Xu *et al.*, 2022; Xu and Lu, 2022).

Individuals possessing high degree of agreeableness are characterised as straightforward, trusting, forgiving, helpful and soft hearted. While people at the lower end of the scale are uncooperative, rude, vengeful, irritable and rude (Costa and McCrae, 2006). Studies conducted earlier have reported that people who are socially compliant, trusting, and respectful, traits relating to agreeableness, have a positive approach towards technology adoption (Kortum and Oswald, 2018; Lane and Manner, 2011; Shropshire *et al.*, 2015). It could thus be argued that key account managers having agreeable personality are likely to have a positive attitude towards adoption of AI.

H2. Agreeableness is significantly positively related to AI adoption.

6.3. Conscientiousness and AI adoption

The hierarchical organization structure that is characterised by efficiency, stability, and reliable performance (Cameron and Quinn, 2011). Previous research has found positive relationship between conscientiousness and attraction to detail and outcome-oriented culture (Judge and Cable, 1997). It is therefore expected that conscientious employees will perceive a good fit between this culture and their personality. Past research suggests person-organization fit aids technology adoption (Xu *et al.*, 2022; Xu and Lu, 2022).

People with high score on conscientiousness are characterised by traits such as strong willed, purposeful, systematic, and determined (Costa and McCrae, 2006; Mahlamäki *et al.*, 2019). Earlier research has indicated a positive relationship between conscientiousness and range of technology evaluations (Schepman and Rodway, 2023; Shropshire *et al.*, 2015). Since, AI can lead to increase in productivity it is therefore hypothesised that key account managers having high conscientiousness should have a positive orientation towards AI adoption.

H3. Conscientiousness is significantly positively related to AI adoption.

6.4. Neuroticism and AI adoption

Neuroticism refers to the extent to which people are nervous, emotional, and insecure (Gardner *et al.*, 2012). As such neurotic persons are prone to respond to stressful situations a negative manner. Earlier findings suggest that such persons are likely to favour a hierarchical structure that is characterised by stability, structure, and predictability (Berings *et al.*, 2004). It is therefore believed that neurotic individuals who experience appropriate fit with their organization may aid in adoption of AI (Xu *et al.*, 2022; Xu and Lu, 2022).

In the context of the present study, it is believed that the emotional stability provided to employees high on neuroticism may facilitate adoption of AI. Earlier studies have indicated a positive relationship between emotional stability and attitude towards innovative technologies that are potentially risky (Qu *et al.*, 2021) as well as more generic technologies (Barnett *et al.*, 2015). It is therefore hypothesised that key account managers high on neuroticism may approach AI adoption positively under appropriate organizational conditions.

H4. Neuroticism is significantly positively related to AI adoption.

6.5. Openness and AI adoption

Since, organizational structure based on adhocracy values innovation, flexibility, creativity, and entrepreneurship, it is expected that employees those who score high on openness will see a fit between their quest for creativity and novel experiences with this culture. The same has been postulated in earlier studies as well (Judge and Cable, 1997). People scoring high on openness are creative, original, imaginative, creative and unconventional, while people scoring low are conventional, unimaginative and down to earth (Costa and McCrae, 2006; Mahlamäki *et al.*, 2019). Since, openness to experience is associated with inclination towards new sensations and ideas and engagement in intellectual activities (Mahlamäki *et al.*, 2019), it is reasonable to believe that technology as innovative as AI might be viewed positively by open-minded key account managers. The following hypothesis is therefore proposed.

H5. Openness is significantly positively related to AI adoption.

6.6. Adoption of AI technologies

In the present study it is proposed that AI acts as a mediator between big five personality traits and competitive advantage as well as firm performance. Preceding paragraphs have suggested possible relationship between AI adoption and big five personality traits. AI has been defined as *'theories and techniques used to create machines capable of simulating intelligence.AI is a general term that involves the use of a computer to model intelligent behaviour with minimal human intervention*' (Haenlein & Kaplan, 2019, pp 6). Earlier studies have reported that organizations have been implementing AI technological initiatives with the purpose of either disrupting or adapting their ecosystem, concomitantly optimizing and developing their strategic and competitive advantage (Mishra *et al.*, 2022; Wamba-Taguimdje *et al.*, 2020). It has been reported that AI is able to fully express its potential by virtue of its capability to optimize existing processes, detect, predict and interact with humans thereby improving on performance at both the organizational and process level (Wamba-Taguimdje *et al.*, 2020). It is therefore hypothesised that:

H6. AI adoption has a significant positive impact upon competitive advantage of the firm.

H7. AI adoption has a significant positive impact upon firm performance.

6.7. Competitive advantage as a mediator and firm performance as dependent variable

Competitive advantage results when an organization is able to execute value accruing strategy that cannot be concurrently implemented by other competing firms (Kiyabo and Isaga, 2020). Resource based view indicates that a firm's competitive edge and superior performance results from organization specific resources that are difficult to copy or imitate, valuable, rare, and non-substitutable (Kiyabo and Isaga, 2020). It is further reported that resources include assets, capabilities, organizational processes, information and knowledge (Kiyabo and Isaga, 2020). It can therefore be considered that adoption of AI gives distinct competitive advantage to the firm which ultimately translates into firm's overall performance.

H8. Competitive advantage has a significant positive impact upon firm performance.

H9. Competitive advantage has a mediating influence on adoption of AI technologies & firm performance.

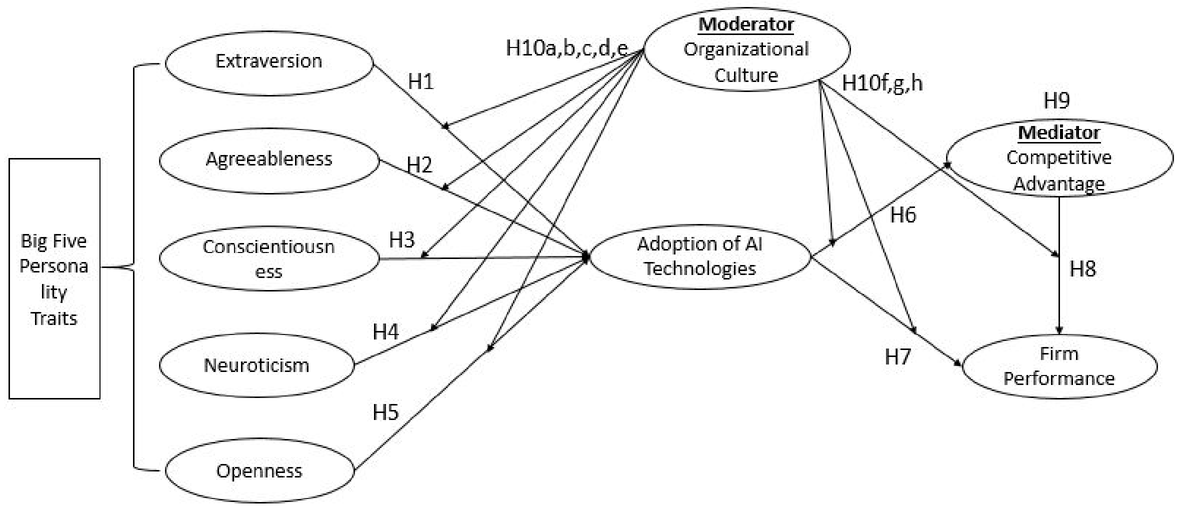
6.8. Organizational culture as a moderator

The organization component of TOE framework represents, besides, the internal processes, structure, and size, the organizational culture as well.(Awa and Ojiabo, 2016; Tornatzky and Fleischer, 1990; Xu and Lu, 2022). It has been argued that organizational culture influences individual willingness to accept and/or use technology (Dasgupta and Gupta, 2019; Melitski *et al.*, 2010) and it may strengthen or weaken the influence of antecedent variables on technology adoption as well as its use. In the context of the present study, it is assumed that organizational culture acts as a moderator between big five personality traits and AI adoption. It is further proposed that organizational culture moderates the relationship between AI adoption and competitive advantage as well as firm's performance. However, the attention has to be redirected towards the personality's direct role in AI adoption which can be best substantiated with the human resource element of the TOE framework (Occhipinti et al., 2023). With a focus on human resources, the defining framework could also formulate how the dispositions of individuals, such as extraversion, openness, or conscientiousness, drive attitudes and decisions concerning AI adoption (Riedl., 2022). It is important to recognize that the adoption of items at the organisational level, in the analysis, has to be moderated by key people within the organisation, such as decision makers and key account managers (El-Kassar & Singh, 2019). When including the human resource view into the TOE model one may provide comprehensive picture of the ways in which personality traits determine the AI adoption behavior without ignoring the organizational factor (Kumar & Shankar, 2024). More significantly, the integration of the human resource aspect in TOE provides a better viewpoint on the role of the organizational context and the role of an individual in the organizational context who uses AI technology (Chatterjee etal., 2021). Organizational culture has been described as a collection of shared values, beliefs and assumptions that are present in organizational practices and that help the members of the organization to understand organizational functioning (Liu *et al.*, 2010). It has also been reported that organizational culture affects how an organizational responds to external environment and makes strategic choices (Liu *et al.*, 2010). It is indicated that organizational culture may influence a manager's ability to process information, rationalize and ability to exercise discretion over their decision making (Berthon *et al.*, 2001). The following hypotheses are proposed:

H10a,b,c,d,e. Organizational culture moderates the relationship between big five personality traits and AI adoption.
H10f. Organizational culture moderates the relationship between AI adoption and competitive advantage.
H10g. Organizational culture moderates the relationship between AI adoption and firm performance.
H10h. Organizational culture moderates the relationship between and competitive advantage and firm performance.

The research model is shown below in Fig 2.

Fig. 2. Research Model



6.9. Methods for confirmatory study (Phase 2)

The automobile industry was chosen as the main focus of this study because of the widespread use of AI throughout its value chain. This includes areas such as manufacturing, design, supply chain management, etc. The industry is going through a significant shift due to the rapid progress in technology and increased competition. The market for AI in automotive applications is expected to experience significant growth in the coming years. Considering the growing acknowledgment of AI's crucial role in various aspects of the automotive industry, such as predictive maintenance, and emergency assistance, it was deemed appropriate to conduct this investigation in this context.

This study examined companies operating in India, with a particular interest in various governmental initiatives. These initiatives highlight the country's enthusiasm for adopting Industry 4.0. Although prepared, the extensive implementation of AI in India, like in other countries, is still in its early stages. Therefore, it is crucial to identify the obstacles to AI adoption and understand how it affects the competitive landscape of Indian companies. Representative associations of the automotive manufacturing sector, such as the Auto Components Manufacturers Association of India (ACMA) and the Society of Indian Automobile Manufacturers (SIAM), were selected to aid in the selection of our sample. Using their extensive databases, we discovered automobile manufacturers in different regions of India.

A total of twenty-six medium and large-sized firms were chosen to be part of the study, with a particular focus on those listed on the National Stock Exchange. These companies have significant abilities to adopt new technologies. Our study includes key account managers as participants, within the automotive industry. We reached out to KAMs who hold positions that involve the use of AI applications in these companies, inviting them to take part in our study. Our research relies on insights from experts who are actively involved in implementing AI-based solutions in different areas of the automotive industry. These individuals have valuable knowledge and experience in different areas like manufacturing, design, supply chain management, etc.

A structured questionnaire was utilised to conduct an online survey in order to collect data from key account managers (KAM). The study utilised a descriptive research design and applied a purposive sample strategy to collect the responses of the participants. The questionnaire underwent adaptation and customization to ensure its alignment with the specific context of the KAMs intention to adopt AI technologies and how it is affecting the competitive advantage

& firm performance. This process involved incorporating known scales from the existing literature. The data collection approach utilised a purposive sample strategy in order to determine the eligibility of participants. In this regard, a set of questions was administered to possible respondents. The questionnaire was initially disseminated to a sample of 42 who are KAMs, academicians and top managers of other firms for the purpose of evaluating the validity and suitability of the questions. This procedure enabled the alteration of certain inquiries to effectively tackle issues pertaining to language and ambiguity.

We distributed the online survey link through the email, WhatsApp, LinkedIn, and Facebook pages of KAMs working in the chosen companies in order to collect data. In addition, we asked recipients to kindly share the questionnaire with at least 15 contacts who would find it relevant. These studies emphasize the improved response rates achieved through virtual platforms like WhatsApp, Facebook, LinkedIn, and email, thanks to the personalized connection between researchers and respondents. By using social networking sites as a sampling framework, researchers can obtain a large and diverse sample size, which improves the representativeness of the sample. The survey instrument was created utilising the Google Forms platform, which was configured to only accept responses from individuals who met the pre-set inclusion criteria. The authors have used their own sources also from where they have received the responses for the questions and also got some refernces from them. Hence, with purposive sampling we have used the snowball sampling also. The data collection was conducted between May 2022 and March 2023. The initial screening questions were employed to ascertain whether the respondents were KAMs of automobile companies and were utilising AI concurrently during their work. The screening questions are provided below: a) Are you working as a key account manager in any of the automobile company?, and b) Is your company using the AI technologies?

If the answer for both the screening questions is 'yes', then only the respondents can see the final questionnaire unless they will be automatically leave the survey. Of over 2,500 people who were contacted, 496 participants provided their consent to be the respondents in the study by fulfilling the necessary documentation and submitting their responses. A total of 496 responses were collected, as the Google Form used in this study did not permit the submission of incomplete responses. Our sample included individuals who demonstrate variation in gender, economic level, and household size. Table 1 presents a thorough representation of the demographic analysis.

There was no significant difference found between early and late respondents in terms of their demographic profiles or study constructs, suggesting that there is no non-response bias present. According to the study conducted by Shanker et al., (2020), the findings revealed that there were no notable variations between participants who took the survey early and those who took it late in terms of their demographic characteristics or the variables being studied.

Table 1. Demographic Details

Demographic Measures	Items	Count	Percent
Gender	Male	342	69%
	Female	154	31%
Age	Less than 35 years	227	46%
	35 - 44 years	42	8%
	45 - 54 years	22	4%
	55 years and more	205	41%
Experience	7-10 years	323	65%
	11-15 years	132	27%
	More than 15 years	41	8%

6.10. Data Analysis and Findings for Confirmatory Study (Phase 2)

Table 2 presents the correlations between different constructs with significance levels. The current study utilised a two-step technique for data analysis. The study commenced with the implementation of a confirmatory factor analysis (CFA) in order to evaluate the construct validity and internal consistency reliability of the measurement scales. The research utilised the Structural Equation Modelling (SEM) methodology to analyse the conceptual framework, employing both SPSS 26 and Amos 26 software. In the second step, the moderation test was conducted using the PROCESS Macro 4.0 tool. The initial evaluation of the data included an assessment of missing values, revealing the absence of any such values. Furthermore, an evaluation was conducted to determine the normality of the data, revealing that it conforms to the permissible range of 1 to 7 (+ and -) for both skewness and kurtosis (Field, 2013).

Table 2. Correlations Table

Correlations										
		EXT	ORC	AGR	COS	OPE	NEU	FMP	CMA	AAT
EXT	Pearson Correlation	1	0.121**	0.101*	0.415**	0.327**	0.386**	0.066	0.109*	0.426**
	Sig. (2-tailed)		0.007	0.025	<0.001	<0.001	<0.001	0.140	0.016	<0.001
	N	496	496	496	496	496	496	496	496	496
ORC	Pearson Correlation	0.121**	1	0.170**	0.254**	0.274**	0.104*	0.078	0.108*	0.098*
	Sig. (2-tailed)	0.007		<0.001	<0.001	<0.001	0.020	0.081	0.016	0.028
	N	496	496	496	496	496	496	496	496	496
AGR	Pearson Correlation	0.101*	0.170**	1	0.067	0.093*	0.145**	0.144**	0.103*	0.230**
	Sig. (2-tailed)	0.025	<0.001		0.139	0.038	0.001	0.001	0.021	<0.001
	N	496	496	496	496	496	496	496	496	496
COS	Pearson Correlation	0.415**	0.254**	0.067	1	0.589**	0.423**	0.023	0.136**	0.466**
	Sig. (2-tailed)	<0.001	<0.001	0.139		<0.001	<0.001	0.614	0.002	<0.001
	N	496	496	496	496	496	496	496	496	496
OPE	Pearson Correlation	0.327**	0.274**	0.093*	0.589**	1	0.397**	0.018	0.132**	0.444**
	Sig. (2-tailed)	<0.001	<0.001	.038	<0.001		<0.001	0.690	0.003	<0.001
	N	496	496	496	496	496	496	496	496	496
NEU	Pearson Correlation	0.386**	0.104*	0.145**	0.423**	0.397**	1	0.033	0.110*	0.457**
	Sig. (2-tailed)	<0.001	0.020	0.001	<0.001	<0.001		0.463	0.014	<0.001
	N	496	496	496	496	496	496	496	496	496
FMP	Pearson Correlation	0.066	0.078	0.144**	0.023	0.018	0.033	1	0.377**	0.307**
	Sig. (2-tailed)	0.140	0.081	0.001	0.614	0.690	0.463		<0.001	<0.001
	N	496	496	496	496	496	496	496	496	496

CMA	Pearson Correlation	0.109*	0.108*	0.103*	0.136**	0.132**	0.110*	0.377**	1	0.307**
	Sig. (2-tailed)	0.016	0.016	0.021	0.002	0.003	0.014	<0.001		<0.001
	N	496	496	496	496	496	496	496	496	496
AAT	Pearson Correlation	0.426**	0.098*	0.230**	0.466**	0.444**	0.457**	0.307**	0.307**	1
	Sig. (2-tailed)	<0.001	.028	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	
	N	496	496	496	496	496	496	496	496	496
**. Correlation is significant at the 0.01 level (2-tailed).										
*. Correlation is significant at the 0.05 level (2-tailed).										

The values recorded for the study constructs fell within the acceptable range of +3 to -3. The assessment of multi-collinearity in the dataset involved the calculation of variance inflation factors. These factors were found to be below the threshold of 3, indicating a satisfactory level of multi-collinearity. The researchers employed the Harman one-factor test to conduct an exploratory factor analysis in order to examine the presence of common method bias (CMB). The study's findings suggest that there is a lack of evidence supporting the presence of common technique bias. The findings indicate that less than 50% of the variance can be ascribed to a singular component. A marker variable is added in this study, which was not anticipated to have any correlation with the main variables under investigation. Upon analyzing the data, it was discovered that this marker variable had minimal correlation with the other variables used in the study. The low correlation observed in the study indicates that there was no common method bias (CMB) that could have influenced the findings (Shankar et al., 2020). Following the administration of the CMB test, the Confirmatory Factor Analysis (CFA) was utilised to authenticate the model's validity, as depicted in Table 3. In Annexure 3, we have shown the items for the analysis.

Table 3. Key Constructs, Sources & Factor Loadings

Factor	**Source**	**Items code**	**Factor Laodings**
Extraversion (EXT)	(Costa and McCrae, 2006)	EXT3	0.828
		EXT2	0.717
		EXT1	0.802
Agreeableness (AGR)		AGR3	0.826
		AGR2	0.848
		AGR1	0.888
Conscientiousness (COS)	(Costa and McCrae, 2006; Mahlamäki *et al*., 2019)	COS4	0.958
		COS3	0.906
		COS2	0.913
		COS1	0.850
Neuroticism (NEU)		NEU3	0.737
		NEU2	0.898
		NEU1	0.833
Openness (OPE)		OPE3	0.892
		OPE2	0.892
		OPE1	0.864
Adoption of AI Technologies (AAT)	(Gunasekaran *et al*., 2017)	AAT3	0.875

		AAT2	0.904
		AAT1	0.937
Competitive Advantage (CMA)	(Vorhies and Morgan, 2005)	CMA3	0.661
		CMA2	0.809
		CMA1	0.825
Firm Performance (FMP)	(Gunasekaran *et al*., 2017)	FMP3	0.731
		FMP2	0.702
		FMP1	0.841
Organizational Culture (ORC)	(Huey Yiing and Zaman Bin Ahmad, 2009)	ORC3	0.871
		ORC2	0.868
		ORC1	0.832

The composite reliability (CR) of each construct demonstrated internal consistency, as indicated by values more than 0.7 (see Table 3). The constructs have exhibited convergent validity, as indicated by Average Variance Extracted (AVE) values surpassing 0.5. Based on the findings of Fornell and Larcker (1981), it is apparent that the latent variables explain at least 50% of the variability found in the indicators associated with them. The assessment of the model's discriminant validity involved the utilization of several criteria, such as Fornell-Larcker's criterion, the condition that the Average Variance Extracted (AVE) should exceed the Maximum Shared Variance (MSV), and the implementation of the Heterotrait-Monotrait-Method (HTMT). The coefficients pertaining to the other constructs, as indicated in table 4, demonstrate values that are comparatively lower than the squared average variance extracted (AVE), but the AVE values above the maximum shared variance (MSV). Hence, the constructs presented in this study will be evaluatedongoing researches have for their discriminant validity, and afterwards, the model will undergo testing.

Table 4. Validity Analysis

	CR	**AVE**	**MSV**	**MR(H)**	**EXT**	**ORC**	**COS**	**AGR**	**OPE**	**NEU**	**FMP**	**CMA**	**AAT**
EXT	0.826	0.614	0.236	0.834	**0.784**								
ORC	0.892	0.734	0.096	0.894	0.149**	**0.857**							
COS	0.949	0.823	0.381	0.959	0.460***	0.257***	**0.907**						
AGR	0.890	0.730	0.066	0.894	0.118*	0.189***	0.061	**0.854**					
OPE	0.914	0.779	0.381	0.915	0.368***	0.309***	0.617***	0.095†	**0.883**				
NEU	0.864	0.681	0.237	0.884	0.434***	0.104*	0.447***	0.166**	0.429***	**0.825**			
FMP	0.803	0.578	0.211	0.819	0.070	0.083	0.018	0.177**	0.014	0.030	**0.760**		
CMA	0.811	0.591	0.211	0.828	0.134*	0.117*	0.143**	0.122*	0.147**	0.142**	0.459***	**0.769**	
AAT	0.932	0.820	0.237	0.937	0.486***	0.105*	0.487***	0.258***	0.481***	0.487***	0.349***	0.340***	**0.906**

[Note: MR(H): MaxR(H)]

Henseler et al. (2015) demonstrated that the HTMT technique shown more sensitivity in determining discriminant validity of constructs when compared to the Fornell-Larcker criterion and the assessment of cross-loadings (Table 5). To guarantee the presence of adequate discriminant validity among constructs, it is advisable to maintain HTMT (Heterotrait-Monotrait Ratio of Correlations) ratios below the established level of 0.85. The results suggest that the HTMT ratios demonstrate values that are lower than 0.85, therefore confirming the presence of discriminant validity.

Table 5. HTMT Analysis

	EXT	ORC	COS	AGR	OPE	NEU	FMP	CMA	AAT
EXT									
ORC	0.122								
COS	0.415	0.254							
AGR	0.100	0.171	0.067						
OPE	0.327	0.274	0.590	0.095					
NEU	0.386	0.104	0.423	0.144	0.397				
FMP	0.066	0.079	0.022	0.144	0.018	0.032			
CMA	0.108	0.108	0.136	0.103	0.133	0.110	0.375		
AAT	0.426	0.098	0.466	0.228	0.444	0.456	0.307	0.307	

The adequacy of fit for the study model was additionally assessed by covariance structure analysis conducted in the AMOS programme. The observed model fit metrics for the measurement model, including CMIN/DF = 1.689, IFI = 0.977, TLI = 0.972, RMSEA = 0.037, all demonstrate satisfactory values within acceptable ranges. Regarding the structural model, the model fit indices are as follows: CMIN/DF = 1.652, IFI = 0.980, TLI = 0.977, RMSEA = 0.036. The coefficient of determination (R^2) for the variables AAT, CMI and FMP is 42.3%, 11.4% and 25%, respectively.

The notion of direct influence was examined by examining the moderating effect of organizational culture using the PROCESS Macro. The present investigation posited hypotheses H1, H2, H3, H4, H5, H6, H7 and H8 which proposed a substantial correlation between the independent and dependent variables. Based on the findings shown in table 6, there is a positive and statistically significant relationship between all the variables. Therefore, the evidence supports hypothesis H1 to H8.

Table 6. Results of Hypothesis Testing

Path			**Estimate**	**S.E.**	**C.R.**	**P**	**Accept/ Reject**	**Hypothesis**
AAT	←	EXT	0.301	0.065	4.621	***	Accept	H2
AAT	←	AGR	0.261	0.061	4.248	***	Accept	H1
AAT	←	COS	0.198	0.067	2.941	0.003	Accept	H3
AAT	←	NEU	0.314	0.077	4.082	***	Accept	H4
AAT	←	OPE	0.238	0.065	3.643	***	Accept	H5
CMA	←	AAT	0.260	0.040	6.433	***	Accept	H6
FMP	←	AAT	0.167	0.041	4.062	***	Accept	H7
FMP	←	CMA	0.405	0.063	6.475	***	Accept	H8

The present research used the AMOS 28 version, to examine the mediating effect of CMA on the proposed link between AAT & FMP. The findings are shown in Table 7. The results suggest that CMA has a role in partially mediating the relationship between AAT & FMP.

Table 7. Summary of Mediation Effects (Mediator-CMA)

Hypothesis	**Hypothesized relationship**	**Direct effect**	**Indirect effect**	**Result**	**Accepted| rejected**
H9	AAT→CMA→FMP	0.167***	0.105**	Partial	Accepted

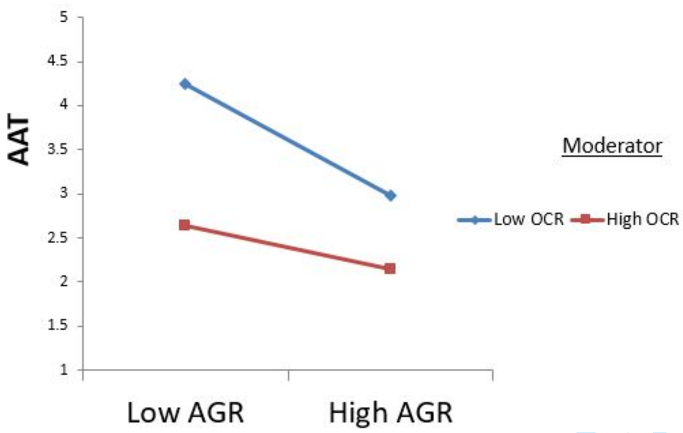
[Note: **$p < 0.01$; *$p < 0.05$; n.s.: Non-significant]

The study used the SPSS PROCESS macro, especially Model 1, to investigate the moderating influence of ORC on the hypothesised relationship between all the associations. The analysis is reported in Table 8. The findings indicate that ORC does have a moderating effect on the association between AGR & AAT (Fig. 3). However, it has been seen that ORC does not have any moderating impact on any of the other relationships.

Table 8. Results of Moderation Analysis

Moderator is ORC										
Hypothesis	**Path**			**β**	**SE**	**t**	**p**	**LLCI**	**ULCI**	**Moderation?**
H10a	AAT	←	EXT	-0.03	0.06	0.56	0.57	-0.14	0.08	No
H10b	AAT	←	AGR	0.19	0.05	4.03	0.00	0.10	0.29	Yes
H10c	AAT	←	COS	0.01	0.04	0.23	0.82	-0.07	0.09	No
H10d	AAT	←	NEU	-0.03	0.04	-0.74	0.46	-0.12	0.05	No
H10e	AAT	←	OPE	-0.13	0.06	-1.98	0.05	-0.25	0.00	No
H10f	CMA	←	AAT	0.03	0.05	0.59	0.55	-0.06	0.12	No
H10g	FMP	←	AAT	-0.01	0.04	-0.36	0.72	-0.09	0.06	No
H10h	FMP	←	CMA	-0.04	0.05	-0.83	0.40	-0.15	0.06	No

Fig 3. Moderating Influence of ORC (Graphically)



Control variables are crucial in addressing endogeneity issues as they help reduce the impact of omitted variable bias, which is a major contributor to endogeneity (Antonakis et al., 2014). It is important to consider all relevant variables when constructing a model to avoid any misleading relationships between the independent and dependent variables. Failure to do so can result in estimates that are biased and inconsistent. Through the inclusion of control variables, we are able to address any potential confounding factors, thereby focusing on the impact of the primary independent variable on the dependent variable (Hill et al., 2021). This inclusion is crucial in ensuring that the relationships observed in the model accurately represent genuine associations, without being influenced by hidden factors. Through this approach, control variables play a crucial role in capturing the causal pathways and enhancing the reliability of the model.

In addition, the use of control variables can be beneficial in minimizing measurement error and addressing issues of simultaneity, which are common sources of endogeneity. For example, when a variable has an impact on both the independent and dependent variables at the same time, it can result in feedback loops or reciprocal relationships. This can make it difficult to determine the causal direction. By incorporating control variables that consider these shared influences, we can mitigate these concerns and improve the credibility of their results. Control variables play a vital role in addressing endogeneity and enhancing the clarity and reliability of the relationships within the data. By including them, we can obtain more interpretable results. In Table 9 we have shown the control variable results which also signifies that there is no confounding effect of age, gender and experience towars AAT, CMA and FMP.

Table 9. Results of Control Variables

Paths			Estimate	SE	CR	P
AAT	←	Age	0.045	0.030	1.506	0.132
AAT	←	Gender	-0.019	0.091	-0.21	0.834
AAT	←	Experience	0.120	0.066	1.806	0.071
CMA	←	Age	0.048	0.034	1.391	0.164
CMA	←	Gender	-0.001	0.105	-0.01	0.992
CMA	←	Experience	0.048	0.077	0.633	0.527
FMP	←	Age	-0.006	0.029	-0.202	0.840
FMP	←	Gender	-0.039	0.088	-0.447	0.655
FMP	←	Experience	0.011	0.064	0.179	0.858

7. Discussion

The adoption of artificial intelligence (AI) technology can be significantly influenced by many personality factors, such as extraversion, agreeableness, conscientiousness, neuroticism, and openness. These characteristics offer essential insights into the manner in which individuals and organizations engage with and perceive artificial intelligence-driven solutions across different situations. Extraversion, which is defined by traits such as friendliness and enthusiasm, has the potential to influence the adoption of AI by promoting a greater receptiveness towards AI technologies that facilitate social interactions (H1). For example, persons who exhibit extraverted traits may readily adopt chatbots or virtual assistants that feature conversational interfaces, perceiving them as both engaging and valuable for facilitating communication. Additionally, individuals' inclination towards engaging in interpersonal interactions may result in their acceptance and utilization of AI tools that facilitate cooperation and teamwork. This, in turn, would contribute to the increased integration of such technologies within their professional and social contexts. Conversely, agreeableness (H2), which is associated with characteristics such as cooperativeness and empathy, may influence the adoption of AI by fostering a propensity to utilise AI for the purpose of increasing customer service and elevating user experiences. Individuals who possess agreeable personality traits are more inclined to endorse AI practises that prioritise ethical issues and cultivate beneficial relationships. Consequently, individuals may exhibit a preference for AI solutions that prioritise the enjoyment of users and the promotion of societal harmony. The adoption of AI technology is significantly influenced by conscientiousness (H3), which is defined by traits such as organization and discipline. Conscientious persons possess a deep appreciation for the efficacy and accuracy provided by AI systems. It is probable that they will have a propensity for early adoption of AI technologies that facilitate the optimization of activities, automation of repetitive procedures, and improvement of data management. AI solutions that facilitate project management, data analysis, and task tracking are congruent with their inclination towards structured and methodical processes. On the other hand, the presence of neuroticism (H4), which is linked to emotional instability and anxiety, may instil a sense of caution in the process of adopting artificial intelligence. Individuals with elevated levels of neuroticism may demonstrate a propensity for scepticism and reluctance towards AI technologies, particularly when they regard these technologies as potential encroachments on their employment stability or personal privacy. Finally, the inclination towards openness to experience (H5), which encompasses a sense of curiosity and a readiness to delve into novel concepts, serves as a catalyst for the widespread acceptance and implementation of AI in various fields and industries. Individuals that possess an open mind-set exhibit a strong enthusiasm towards the advancements in AI and its application in several domains including art, education, entertainment, and creative pursuits. Their inclination towards embracing new experiences positions them as early users of artificial intelligence technology that push the limits and provide innovative viewpoints.

The integration of AI technology has emerged as a pivotal factor in enhancing corporate performance and gaining a competitive edge within the contemporary business environment (H6, H7, H8). AI have the capacity to revolutionise multiple facets of operations, strategy, and decision-making, resulting in heightened levels of efficiency, innovation, and competitiveness. To begin with, the incorporation of AI technology has the potential to greatly enhance the overall performance of organizations through the optimization of processes and the augmentation of operational efficiency. The implementation of AI-driven automation has the potential to decrease the amount of manual labour required, mitigate the occurrence of errors, and expedite operations that would otherwise consume a significant amount of time. This results in financial advantages and enables staff to concentrate on tasks that generate greater value. Consequently, enterprises that successfully integrate AI into their operations frequently observe enhanced productivity and more efficient allocation of resources, thereby leading to bolstered financial outcomes. Furthermore, AI enables organizations to enhance their competitive position by leveraging data-driven insights and analytics. AI systems have exceptional proficiency in the analysis of extensive datasets, enabling them to identify and extract significant patterns and trends of value. This functionality empowers enterprises to make well-informed decisions, gain deeper insights into client preferences, and recognise emerging market prospects. By utilising predictive analytics powered by artificial intelligence, organizations can maintain a competitive edge by effectively forecasting market fluctuations and promptly taking proactive measures in response. In addition, the implementation of AI technologies allows companies to improve their client experiences, thereby potentially gaining a substantial competitive edge. Customised recommendations, conversational agents for customer assistance, and product suggestions powered by AI have the potential to enhance customer happiness and foster customer loyalty. Organizations that employ AI to deliver a cohesive and personalised consumer experience have the potential to distinguish themselves in the marketplace and establish a more robust presence within their specific sectors.

The moderating function of organizational culture (H10a,b,c,d,e,f,g,h) is of considerable importance in determining the extent to which a company can effectively utilise AI to attain a competitive advantage. Within the realm of AI-Driven competitive advantage within companies, there is an interesting connection between organizational culture and agreeableness when it comes to adopting AI technologies. This connection suggests a unique synergy between individual disposition and organizational ethos. Cooperation and interpersonal harmony, when prioritized in organizational cultures, can naturally align with a focus on collaboration and innovation. Within these settings, key account managers who possess a strong inclination towards cooperation may view AI technologies as tools that enhance collaboration and foster stronger relationships, rather than perceiving them as potential risks to their own independence or job stability. Organizational cultures that prioritize collective problem-solving and experimentation create an ideal environment for the integration of AI tools. These cultures foster trust and openness to new methodologies, which in turn accelerates the adoption process, particularly among individuals who are open to new ideas.

On the other hand, the lack of moderating associations between the adoption of AI technologies and personality traits like Extraversion, Conscientiousness, Neuroticism, and Openness might indicate the complex nature of technology adoption in key account management contexts. Although these traits certainly impact individual behaviors and attitudes, their influence may not be as directly influenced by organizational culture when it comes to AI adoption. For example, extraversion may influence a person's inclination for socializing and networking. However, when it comes to adopting technology, personal preferences and perceived usefulness may play a bigger role than organizational norms. Just like a management researcher, it is worth noting that factors such as Conscientiousness and Openness can impact how individuals respond to change and innovation. However, it is important to recognize that these traits may not solely depend on organizational cultural factors. Thus, the intricate relationship between organizational culture and agreeableness highlights the complex interplay between individual personality traits and organizational dynamics in influencing the adoption of AI technologies. This understanding can guide the development of effective strategies for harnessing AI-driven competitive advantages in the field of key account management.

There may be several factors within the context of AI-driven competitive advantage that contribute to the absence of a moderating association between organizational culture and the adoption of AI technologies, competitive advantage, and firm performance by key account managers. First and foremost, it is important to note that organizational culture may not place enough emphasis on integrating and adopting AI technologies. If the organization's culture does not prioritize innovation, technological advancement, or adaptability, key account managers may not feel encouraged or empowered to explore AI-driven solutions extensively. Without proper emphasis, there is a risk of a disconnect between the organizational culture and the adoption of AI technologies. This can hinder the potential for gaining a competitive advantage and improving performance. Furthermore, in the context of organizational culture promoting innovation and technological adoption, it is worth considering the influence of key account managers' individual personality traits on their approach to AI technologies. Factors such as personal openness to new experiences, proficiency with technology, and willingness to take risks can greatly impact how key account managers perceive and utilize AI tools. If the organizational culture does not acknowledge or adapt to these individual differences, it might face challenges in fully utilizing the potential of AI-driven competitive advantage. Hence, the lack of a moderating link between organizational culture and the adoption of AI technologies, competitive advantage, and firm performance by key account managers highlights the significance of taking into account both organizational and individual factors in driving AI integration and success within a company.

8. Theoretical Implications

Examining the theoretical implications of the Big Five personality traits of key account managers in relation to the adoption of AI technologies and its subsequent influence on company performance provides significant contributions to the fields of organizational psychology and technology adoption research. To begin with, this study contributes to the existing body of knowledge by enhancing our comprehension of the significance of personality traits in the professional setting. Specifically, it elucidates the impact of traits such as extraversion, agreeableness, conscientiousness, neuroticism, and openness on individuals' attitudes and behaviours towards the adoption of technology within a business-to-business (B2B) environment. Furthermore, this study has the potential to enhance the advancement of more inclusive frameworks that incorporate personality features inside known theories of technology adoption. This research attempts to carry forward the discussion on the role of decision makers on technology adoption at the firm level (Thong, 1999). Previous studies have indicated that adoption behaviour is incomplete in absence of such factors as manager's belief, knowledge and characteristics (Riemenschneider *et al.*, 2003; Shiau *et al.*, 2009; Thong, 1999), enthusiasim and growth aimbition of the owner (Fillis *et al.*, 2004), top management support and managerial productivity (Grandon and Pearson, 2004).

Also, this study inline with previous studies have indicated that possibility of integration of individual based theory of technology adoption with organizational technology adoption theories, since in both the cases the survey unit happens to be an individual (Awa, Ojiabo, *et al.*, 2015; Awa and Ojiabo, 2016). A further research on comparison between decision-maker-centered approach to organizational technology adoption theories and direct application of individual behaviour models may through up some interesting scenarios. This may also enhance our comprehension of the intricate dynamics between individual variances and organizational procedures. Furthermore, this research can provide clarification on the moderating mechanisms that explain how personality traits influence decisions regarding the adoption of technology and, subsequently, the performance of an organization. This comprehensive comprehension can assist organizations in customising their AI implementation methods and team structures to capitalise on the personality characteristics of key account managers in B2B business, so augmenting their competitive edge in the swiftly changing technological environment.

9. Practical Implications

The findings of this research have important practical implications for organizations seeking to improve their strategies for adopting AI technology. First and foremost, it is crucial for organizations to acknowledge the impact of personality traits on the adoption of AI technology. By recognizing and harnessing the strengths of outgoing team members, organizations can create a welcoming atmosphere for AI tools that enhance social interactions, like chatbots and virtual assistants. Customizing AI solutions to match the personality traits of users can encourage higher levels of acceptance and usage. Training programs and workshops that emphasize the advantages of AI in enhancing communication and collaboration can contribute to the wider adoption of these technologies in various professional and social settings.

Second, organizations have the ability to utilise this intelligence in order to make more informed decisions pertaining to the composition of their teams. For example, organizations have the ability to selectively allocate key account managers who possess personality attributes that are congruent with the unique requirements of AI adoption endeavours. Individuals with extraverted personality traits may demonstrate exceptional performance in positions that require interaction with customers using AI tools. On the other hand, conscientious personnel may exhibit high levels of success in project management roles, where they may effectively oversee the seamless integration of AI technologies.

Third, the impact of personality traits on AI adoption is significantly influenced by the organizational culture. It is crucial for companies to foster a culture that prioritizes cooperation, innovation, and adaptability. By placing a strong emphasis on these values, organizations can establish a conducive atmosphere that encourages individuals with agreeable traits to readily embrace AI technologies, thereby improving customer service and enhancing user experiences. Promoting collective problem-solving and experimentation can help foster the adoption of AI tools, especially among individuals who are inclined towards embracing new concepts. In order to accomplish this, it is crucial for leadership to actively encourage and back cultural initiatives that are in line with these values. This will help create an organizational environment that is conducive to the integration of AI.

Fourth, organizations have the opportunity to incorporate continuous assessments and feedback mechanisms to get insights into the potential transformation of key account managers' personality qualities. It has been found that artificial intelligence technologies become increasingly integrated into their responsibilities. This information can be utilised to inform the creation of personalised growth plans and strategies aimed at optimising the synergy between individual features and the adoption of technology.

Lastly, organizations must take into account both organizational and individual factors when formulating AI adoption strategies. Recognizing the significance of cultivating an environment that encourages innovation, it is also essential to consider the unique personality traits and technological skills of key account managers. Providing tailored assistance and resources, such as specialized training sessions and technological support, can effectively address the disconnect between an organization's culture and an individual's preparedness for adopting AI. Through a comprehensive approach that considers cultural, individual, and technological factors, organizations can better leverage AI-driven competitive advantages, resulting in enhanced firm performance and long-term market dominance.

10. Limitations and Future Research Directions

The present investigation is subject to several limitations. Initially, data was gathered from key Account Managers (KAMs) employed inside the Indian automotive sector. Hence, the conclusions derived from this study lack generalizability to other industries, including healthcare, manufacturing, power generation, hospitality, etc. (Al-Muftah et al., 2018; Chatterjee et al., 2022). There exists potential for the replication of this study in several sectors and nations, which might potentially yield valuable insights. Furthermore, the research employed a cross-sectional research method (quantitative data analysis) to gather data at a single time point. The dynamic nature of the AI presents an opportunity for major insights into the automobile sector through the utilization of a longitudinal study strategy. Furthermore, we employed organizational culture as a moderating factor. Subsequent research endeavours may incorporate a range of variables, including environmental influences, legislative changes, and organizational competencies, in order to comprehensively investigate the phenomenon from diverse viewpoints. In order to get deeper insights into the phenomenon, future research endeavours may consider integrating the technology, organization, and environment framework, innovation resistance theory, task-technology fit theory, and diffusion of innovation theory inside a cohesive model. In order to enhance the scope of inquiry and facilitate a more comprehensive comprehension of the phenomena, it is recommended that next investigations incorporate a multi-method design. This approach would offer improved prospects for subsequent research endeavours and the development of novel conceptual frameworks. Additionally, the focus on key account managers may present a limitation; therefore, in future research, we could include other types of managers, such as Sales Managers, Product Managers, and Marketing Managers, to gain a more comprehensive perspective. Another limitation of the study is there are no constructs which talks about capabilities and knowledge. Further investigation can be used to examine the impact of an organization's current AI capabilities, such as their data infrastructure and technical expertise, as well as their understanding of AI's potential applications, on the adoption of AI in key account management. Understanding an organization's specific strengths and weaknesses can offer valuable insights for customizing AI adoption strategies.

11. Conclusions

In summary, the relationship between the adoption of AI technologies and business performance, as influenced by the Big Five personality traits of senior account managers, is complex and subject to several factors. Gaining insight into the intersection of personality qualities, such as extraversion, agreeableness, conscientiousness, neuroticism, and openness, and the adoption of AI provides organizations with useful knowledge for enhancing their approaches to integrating technology. Organizations can optimise the capabilities of AI technologies by carefully assigning personnel with appropriate attributes to positions and responsibilities associated with AI adoption. In addition, the customization of training and development programmes to optimise the strengths of important account managers, as determined by their personality profiles, can effectively augment their proficiency and flexibility within the dynamic and swiftly changing technological environment. In essence, acknowledging the influence of personality traits on the adoption of AI not only enhances the efficacy of technology integration but also enables organizations to gain a competitive edge and cultivate more robust client connections. The integration of personality and technology in a comprehensive manner enables organizations to flourish within a commercial climate that is heavily influenced by artificial intelligence.

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ANNEXURE -1: Interview Questions for Qualitative Analysis

Interview Guide:

Generic Questions

a) Discuss about the company and the industry in a broader sense
b) Discuss regarding the job roles and industry experience of yours as a key account manager

Initial Interview Guide

a) What is your level of understanding about artificial intelligence?
b) Can you elaborate on how AI has impacted your understanding of the processes within your organization?
c) What factors led to the shift or transformation towards AI in your business and industry?

Final Interview Guide:

a) How does different personality traits influence their perception and adoption of AI technologies in their role?
b) Which personality traits impact the approach to utilizing AI for enhancing customer relationships and services?
c) Could you elaborate on how your level of conscientiousness influences your interaction with AI tools designed to enhance business processes?
d) How does neuroticism affect your attitude towards the implementation of AI technologies in your organization?
e) How does one's openness to experience impact their level of enthusiasm for exploring and adopting new AI solutions in their work?
f) What factors have led to the adoption of AI technologies in your organization and how they have affected your role.
g) How has the implementation of AI technologies helped your business operations gain a competitive advantage?
h) How has the adoption of AI impacted the overall performance of your firm?

i) What impact does the organizational culture have on the adoption and integration of AI technologies within your company?

ANNEXURE 2: Themes Extracted from Interview Excerpts

SN	Second-order themes	First Order Codes	Interview Excerpts
1	Extraversion	Balancing excitement with tangible advantages	I am particularly receptive to AI technologies that enhance social interactions, such as chatbots and virtual assistants, as I find them engaging and useful. I love utilizing AI tools that promote collaboration and enhance communication, as they perfectly complement my warm and energetic personality. Nevertheless, there are instances where I must strike a balance between my excitement for innovative AI solutions and the need to prioritize their tangible advantages for the organization.
2	Agreeableness	Aligns with agreeable disposition.	I have a deep appreciation for AI technologies that enhance customer service and user experiences while upholding ethical practices and fostering positive relationships. I am in favor of AI initiatives that prioritize societal harmony and user satisfaction, which aligns with my agreeable disposition. I strongly believe in the widespread implementation of user-centric AI solutions throughout the company.
3	Conscientiousness	Enhance organization and discipline	I am driven to adopt AI tools that enhance organization, discipline, and accuracy in business processes. I appreciate AI systems that streamline repetitive tasks, enhance operational efficiency, and enhance data management, as they resonate with my systematic approach. I have become an enthusiastic proponent of AI technologies that enhance productivity and streamline processes.
4	Neuroticism	Cautious rather than fully embracing.	I approach the adoption of AI technologies with caution and a healthy dose of skepticism, especially when it comes to their potential effects on job security and privacy. There are times when I experience a sense of unease regarding the potential risks that come with the implementation of AI. This can sometimes lead me to approach these solutions with caution rather than fully embracing them. In order to address these concerns, I am in search of thorough information and reassurances regarding the safety and advantages of AI.
5	Openness	Exploring innovative AI solutions enthusiastically	Exploring and adopting innovative AI solutions across various domains such as art, education, and entertainment is fueled by my openness to experience and enthusiasm.

			I am enthusiastic about the potential of AI to inspire innovative and imaginative approaches within the organization. I am always driven by curiosity, constantly seeking new ways to push the boundaries of AI applications.
6	Adoption of AI Technologies	Embraced AI for enhanced efficiency.	Our organization has embraced AI technologies to enhance efficiency and enable data-driven decision-making. These technologies have greatly improved operational efficiency, minimized the need for manual labor, and offered valuable insights through the use of predictive analytics. Due to its significance, AI has become a crucial component of our strategic initiatives and daily operations.
7	Competitive Advantage	AI-driven solutions will provide the edge amongst other competitors.	AI technologies have played a crucial role in improving our competitive advantage through process optimization and fostering innovation. Being able to analyze large datasets and gain insights has enabled us to make well-informed decisions and stay ahead of market trends. Our company stands out from competitors by offering customized AI-driven solutions that have significantly enhanced customer satisfaction.
8	Firm Performance	Improved profitability and competitiveness enhance company performance	Our firm's performance has been significantly improved by the integration of AI, resulting in increased productivity and more efficient resource allocation. Automated processes and data-driven strategies have resulted in significant cost savings and improved profitability. In general, AI has allowed us to achieve improved financial outcomes and a more competitive market position.
9	Organizational Culture	Openness and collaboration drive competitiveness which creates good culture	Our organizational culture, with a strong focus on innovation and adaptability, has played a crucial role in enabling the successful integration of AI technologies. An environment that fosters support and encourages experimentation and collective problem-solving has greatly expedited the integration of AI. The culture of openness and collaboration has played a crucial role in effectively harnessing AI for gaining a competitive edge.

Annexure 3: Items and Sources for Quantitative Analysis

Factors	Source	Items	Items code
Extraversion (EXT)	(Costa and McCrae, 2006)	I believe I am an extroverted and sociable person.	EXT3
		I am gregarious and possess an assertive personality.	EXT2
		I generate considerable enthusiasm.	EXT1
Agreeableness (AGR)		I am considerate towards nearly everyone and enjoy collaborating with others.	AGR3

		I am always considerate and selfless towards others.	AGR2
		I am a tolerant person	AGR1
Conscientiousness (CON)	(Costa and McCrae, 2006; Mahlamäki *et al.*, 2019)	I will work diligently.	COS4
		I perform tasks efficiently.	COS3
		I adhere to my schedule.	COS2
		I am a trustworthy individual.	COS1
Neuroticism (NEU)		I'm not overly anxious.	NEU3
		I never become agitated	NEU2
		I am not readily frightened, and generally composed in stressful situations.	NEU1
Openness (OPE)		I am creative.	OPE3
		I am receptive to novel concepts.	OPE2
		I prefer to perform difficult tasks.	OPE1
Adoption of AI Technologies (AAT)	(Gunasekaran *et al.*, 2017)	The degree to which you believe that adopting AI technologies helps you enhance your job performance.	AAT3
		The degree to which you and your colleagues associate with the AI technologies.	AAT2
		The degree to which you believe that an organizational and technical infrastructure exists to support use of the AI technologies.	AAT1
Competitive Advantage (CMA)	(Vorhies and Morgan, 2005)	We deliver value to our customers.	CMA3
		Our market share has grown significantly relative to our customers.	CMA2
		We are able to acquire new customers.	CMA1
Firm Performance (FMP)	(Gunasekaran *et al.*, 2017)	Average return on investment	FMP3
		Average profit	FMP2
		Average profit	FMP1
Organizational Culture (ORC)	(Huey Yiing and Zaman Bin Ahmad, 2009)	We feel that mutual respect among team members are important	ORC3
		We feel that information sharing among team members are important	ORC2

		We are willingness to accept change in the organisational structure	ORC1