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Harmonizing Human-AI Synergy in Smart Cities: Exploring Emotion Understanding and Technology Anxiety in an Asian Context

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Abstract

Artificial Superintelligence (ASI) envisions AI surpassing human cognitive abilities, mimicking and developing its own thinking skills. However, this raises ethical and control issues, emphasizing the need for robust regulations in AI development. The prime objective of the study is to align aligning human intelligence with artificial superintelligence in smart cities. Particularly, the study has examined the mediating role of emotion-understanding ability, and the technology anxiety between AI and shared decision-making. This study investigates the relationship between emotional intelligence and decision-making in the Khon Kaen Smart City, Thailand. Data was collected from various financial institutions, including community and commercial banks, and managers working in the city. The largest and most developed province served as the primary focus of the study, and area cluster sampling was employed to obtain a representative sample of the province's varied population. A total of 297 out of the 700 questionnaires that were given to the seven different groups for the survey were filled out. Shared Decision-Making (SDM) and Emotion-Understanding Ability (EUA) were found to have a strong correlation in the study, which highlights the importance of emotional intelligence in decision-making due to the strong correlation between the two. This comprehension is especially helpful when artificial intelligence is used to improve decision-making processes. This highlights the significance of human factors, such as comprehension and emotion, in the process of developing effective decision-making frameworks.

Keywords: AI, Smart cities, Technology anxiety.

INTRODUCTION

Contrastingly, human intelligence brings a different set of attributes to the table. It's not just about logical reasoning but also involves emotional intelligence, ethics, and creativity. In the context of smart cities, while AI can efficiently manage and process data, human intelligence is crucial for understanding the broader implications of these decisions, particularly in terms of ethical considerations and social impact (Ahmad Ahmad et al.,2022). Human intelligence's ability to empathize, understand complex social dynamics, and make ethically aligned decisions is something AI has yet to achieve. This aspect becomes particularly significant in areas where public perception and attitudes play a key role in the success of implemented technologies and policies. The role of AI in modern development and governance is becoming more apparent. As a result, data creation and processing have been transformed (Dwivedi et al., 2021). Emerging "smart cities" rely heavily on artificial intelligence (AI) and information and communication technology (ICT) to improve quality of life and promote sustainable development (Ahad et al., 2020). AI in this context uses large datasets, the Internet of

Things, and other methods of systematic data collection to make better decisions. This strategy is based on logic and careful planning rather than gut feelings or trial and error. By connecting disparate data sources such as sensors, cameras, and social media, smart cities enable rapid and effective decision-making (Johannessen et al., 2019). However, the use of AI in these procedures raises concerns about data privacy and security, emphasizing the importance of protecting against cyberattacks and other intrusions (Hlávka, 2020).

The concept of Artificial Superintelligence (ASI) presents a future where AI might surpass human cognitive abilities (Narain et al.,2019). ASI envisages an AI that not only mimics but also develops its own thinking skills, which could lead to breakthroughs beyond current human comprehension. However, the idea of ASI also brings forth substantial ethical and control issues. The prospect of an intelligence that exceeds human understanding and control reiterates the need for robust ethical frameworks and regulations in AI development (Stahl,2021). The future lies in finding a balance between AI and human intelligence, especially in fields like smart cities and governance. AI's data-driven efficiency must be complemented with human ethical considerations, creativity, and emotional intelligence. Developing AI in a way that respects and incorporates human values, and addresses fears and apprehensions related to technology, is crucial (Budhwar et al.,2023).

Technology anxiety, a significant factor in the acceptance and use of AI and self-service technologies, must be addressed by ensuring that AI systems are transparent, secure, and user-friendly. The synergy between AI's analytical prowess and human intelligence's empathetic and ethical reasoning could pave the way for more holistic and sustainable development in smart cities and beyond (Sheikh,2020). The integration of artificial intelligence (AI) into various sectors has emerged as a pivotal force in shaping modern society, offering transformative potential in diverse realms such as smart city development, governance, innovative disciplines, and even in enhancing human capabilities (Dwivedi et al.,2021). This burgeoning influence of AI marks a significant shift in how technology is interwoven into the fabric of daily life, highlighting its critical role in contemporary times (Allioui & Mourdi, 2023). The discussion surrounding the transformative power of AI has garnered significant attention, becoming a focal point in both practical applications and scholarly research (Dwivedi et al.,2021).

One of the key areas where AI has made an indelible impact is in the generation and utilization of data in both government and private sectors. The advent of AI has opened new avenues for exploring and understanding our world in innovative ways. The rapid advancement of big data technologies, coupled with their increased accessibility, has breathed new life into AI applications. This revitalization of AI capabilities has led to more informed and strategically sound decision-making processes (Lee et al.,2021). In the context of smart cities, AI's role is particularly noteworthy. Smart Decision Making (SDM) in smart cities leverages AI for its systematic techniques in data collection, eschewing traditional methods that rely on experience, intuition, or trial and error. Instead, AI employs logical decision-making methods that are rooted in a thorough analysis of extensive data sets (Herrera-Viedma et al.,2020; Bibri & Krogstie,2021; De Guimarães et al.,2020).

The concept of "smart cities" has been interpreted in a variety of ways by numerous scholars, reflecting its complex and multi-dimensional nature. However, a common thread in these definitions is the emphasis on enhancing the quality of life and achieving sustainable development through the integration of Artificial Intelligence (AI) and Information and Communication Technology (ICT). Palomares et al. (2021) have described a smart city from a technological standpoint as a networked entity powered by the Internet of Things (IoT), using big data to manage city resources efficiently and intelligently. This definition underscores the importance of technological interconnectivity in the urban environment.

Expanding on this, Li et al. (2022) have explored Smart Decision Making (SDM) in smart cities, particularly through the lens of big data. They propose a three-layered framework for understanding smart cities: instrumentation, interconnection, and intelligence. This model illustrates how smart cities, at their implementation phase, rely on AI and IoT for data collection using various tools like sensors, meters, cameras, and social media platforms. This data collection is vital for quick feedback and informed decision-making. The data obtained from these sources is then synthesized, forming the basis for a comprehensive understanding that informs city planning and policy decisions (Bibri,2021).

However, with the increased dependency on AI and IoT systems in smart cities comes the heightened risk of security breaches, such as unauthorized access and misuse of user data. Tawalbeh et al. (2020) have highlighted that one of the primary challenges in IoT is ensuring robust security measures to protect sensitive information. The success of smart city initiatives heavily depends on public perception and attitude towards these technologies. Here, the concept of technology anxiety becomes pertinent. This term refers to the apprehensions and fears that individuals might have regarding the adoption and use of new technological systems (Almaiah et al.,2022).

The extent to which individuals are inclined to utilize and adopt AI-driven services and tools is greatly influenced by their degree of technological anxiety. Wu et al. (2021) assert that behavioral intentions are significantly influenced by anxiety within the framework of social cognitive theory. Within the realm of smart cities, it is imperative to acknowledge that mitigating individuals' apprehensions towards technological advancements is crucial in order to optimize the advantages presented by artificial intelligence (AI) and the Internet of Things (IoT). Enhanced adoption and improved utilization of self-service technologies in urban environments can be achieved through a comprehensive comprehension and proactive addressing of these considerations.

In summary, advancements in artificial intelligence (AI) and the Internet of Things (IoT) play a crucial role in the development and expansion of intelligent urban environments, commonly referred to as smart cities. According to Lee (2020), the utilization of these technologies has the potential to significantly improve resource management and policymaking, thereby offering promising prospects for enhancing urban living conditions. Undoubtedly, the significance of technological expertise is noteworthy; however, it is equally imperative to acknowledge the significance of security concerns and the psychological ramifications that technology imposes on individuals. In order to ensure the successful implementation of smart urban living, city planners and technologists must not only focus on the technological aspects, but also consider the social acceptance and benefits of such initiatives. This can be achieved by acknowledging and mitigating concerns related to technology anxiety.

THEORETICAL BACKGROUND AND HYPOTHESES

According to Dwivedi et al. (2021), the utilization of artificial intelligence (AI) in government agencies and local governments is currently at an early stage of development. The incorporation of artificial intelligence (AI) in these domains encounters a diverse range of obstacles, encompassing legal, political, and policy impediments (Nitzberg & Zysman, 2022). In recent times, there has been a notable surge in scholarly investigations (Benbya et al., 2020) centered on the utilization of artificial intelligence (AI) within governmental organizations. The aforementioned studies shed light on the potential of artificial intelligence (AI) to enhance governance across various domains. However, they also acknowledge the constraints posed by institutional, technological, and policy impediments.

The utilization of artificial intelligence (AI) in decision-making processes within the public sector holds significant promise for enhancing the well-being of citizens and advancing the development of smart cities. There is a growing recognition that the implementation of AI-driven governance has the potential to facilitate collaborative efforts among cities in the development of intelligent services, which would pose significant challenges if pursued individually by each city (van Noordt & Tangi, 2023). In the realm of smart city governance, the utilization of artificial intelligence (AI) proves to be highly advantageous in bolstering urban safety administration. This is achieved through the collection of data from various sources, including sensors, as highlighted by Deng et al. (2021). According to Chamola et al. (2020), the utilization of artificial intelligence (AI) in South Korea played a significant role in the distribution of information to the general population amidst the outbreak of the coronavirus disease.

This implementation not only enhanced individuals' comprehension of the prevailing circumstances but also bolstered their adherence to safety protocols mandated by the government. However, it is crucial not to underestimate the significance of human intelligence in this context. Although artificial intelligence (AI) facilitates data collection and analysis, the interpretation of this data in an ethical, culturally sensitive, and contextually appropriate manner relies heavily on human intelligence. The presence of human decision-makers is crucial due to the limitations of AI in comprehending the intricate nature and consequences of data generated by humans. In contrast to the data-centric focus of artificial intelligence (AI), human intelligence encompasses additional dimensions such as ethical considerations, the ability to generate innovative problem-solving approaches, and the capacity for empathizing with the emotions of others (Formosa et al., 2022).

Smart cities heavily depend on artificial intelligence (AI), which has become an essential element due to the expansion of the information technology (IT) sector (Zamponi & Barbierato, 2022). The utilization of artificial intelligence (AI) technologies is progressively being employed to enhance the standard of living in urban settings, a matter of significant significance given the ongoing global population expansion and rapid urbanization. Gade (2019) identifies several areas of focus in the realm of smart technology, including the improvement of intelligent information management, the development of smart transportation systems, and the advancement of smart healthcare delivery. There is a growing trend among decision-makers in smart cities to incorporate artificial intelligence (AI) techniques in order to establish administrative structures that are more adaptable and efficient. AI's role in smart cities extends to intelligent information processing and data analysis, significantly enhancing the efficiency of data cleaning, collection, and storage. This improvement in data management allows for deeper insights to be extracted from the gathered information, which is crucial for automated learning and the decision-making process (Sarker,2021). AI's ability to handle complex mathematical modeling of various issues further augments its utility in urban management.

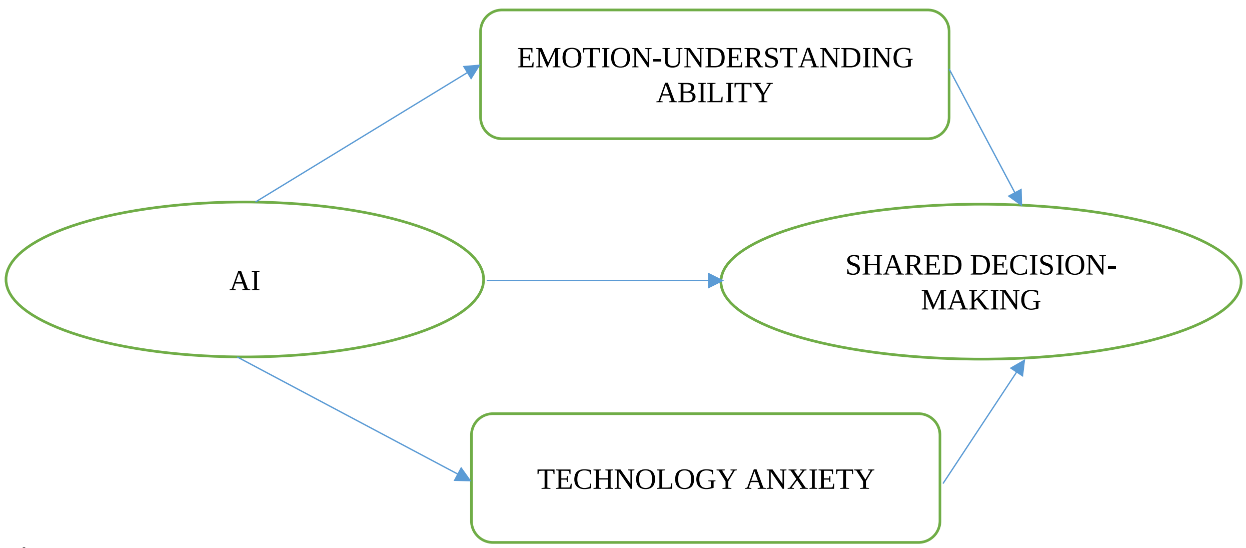

Figure 1.
Domains

The utilization of artificial intelligence (AI) to facilitate decision-making has been widely acknowledged across diverse domains, encompassing business enterprises, governmental institutions, and even entire smart urban environments. The utilization of artificial intelligence (AI) has demonstrated its efficacy in the reconfiguration of business models and ecosystems, thereby enabling more efficient decision-making processes (Burström et al.,2021). To what extent can state-of-the-art artificial intelligence (AI) systems accurately predict high-impact events? The weather serves as a valuable tool for analysts and decision-makers, enabling them to enhance their ability to examine extensive data sets in pursuit of valuable insights (Dimara et al.,2021). A multitude of both public and private entities across the globe disseminate open datasets via online platforms, which, despite their potential, remain insufficiently leveraged for the purposes of data analysis and informed decision-making.

According to Zhu (2020), the true significance of big data lies not solely in its vast quantity, but rather in its ability to facilitate the advancement of artificial intelligence systems such as machine learning. These systems possess the capability to analyse intricate and extensive datasets that surpass our most extravagant expectations. The acquisition of knowledge and understanding derived from such advancements would be of immense value in the process of decision-making. The user's text does not contain any specific information to be rewritten in an academic manner. The process of constructing a smart city encompasses integrated sensing devices, data collection, and infrastructure monitoring, all of which are aimed at enhancing decision-making (Olaniyi et al.,2023). The improvement of decision-making processes in smart cities has been extensively discussed in previous studies. The advancement of the contemporary notion of "smart" is facilitated by the acquisition of real-time data and its analysis to obtain a deeper understanding of the ways in which cities undergo changes, adapt, and respond to various environments (Sánchez-Corcuera et al.,2019). The advent of AI technologies has facilitated the transformation of cities into smart entities, owing to the integration of digital concepts. In pursuit of this objective, we formulated the hypothesis (H1) that the utilisation of artificial intelligence (AI) trained on extensive datasets would enhance the effectiveness of shared decision-making (SDM) in smart cities.

Furthermore, extant literature has underscored the significance of artificial intelligence (AI) in the processing and interpretation of large-scale datasets, with the aim of augmenting decision-making capabilities within the context of smart urban environments (Yigitcanlare t al.,2020). The advancement of the contemporary notion of "smart" is facilitated by the acquisition of up-to-date data and its analysis to obtain a deeper understanding of the ways in which cities undergo changes, adapt, and respond to various environments. The advent of AI technologies has facilitated the transformation of cities into smart entities, owing to the integration of digital concepts. In order to achieve this objective, we formulated the hypothesis (H1) that the utilisation of artificial intelligence (AI) trained on extensive datasets would enhance the effectiveness of shared decision-making (SDM) in smart cities. Based on the above evidence and reasoning, we hypothesized that

H1: AI has significant impact shared decision-making.

Concerns regarding artificial intelligence (AI) have grown in tandem with the rapid pace of its advancement (Dwivedi et al.,2021). From this perspective, several studies have demonstrated that artificial intelligence (AI) technologies have outperformed human capabilities in various domains. For instance, AI exhibits significantly superior performance in the game of Go compared to humans, and it has achieved victory against 99.8% of human players in StarCraft. Anxiety has been further intensified by a multitude of studies and expert assessments. According to a forecast by the McKinsey Global Institute, it has been projected that A1 will result in the elimination of approximately 400 to 800 million jobs on a global scale by the year 2030 (Gielen,2021). There is a growing global concern regarding the potential impact of artificial intelligence on various aspects of individuals' lives, including their careers, education, and personal well-being. This concern is supported by the insights and empirical evidence provided by numerous experts and substantial data. There is speculation among certain individuals that the advent of AI may potentially lead to a series of social issues, specifically in the form of technology anxiety within smart cities [39]. Based on the above evidence and reasoning, we hypothesized that

H2: AI has significant impact technology anxiety.

A smart city employs information system-centric methodologies by intelligently utilising information and communication technology (ICT) within an interactive infrastructure to provide its citizens with innovative and enhanced amenities, thereby impacting the overall quality of life of the population (Alloulbi et al.,2022). The integration of technological advancements has facilitated individuals in effectively managing their personal and professional commitments. Nevertheless, within various present-day contexts, there is a growing concern among individuals regarding the potential emergence of superintelligent technologies (Totschnig,2019). The ability to effectively utilise new technologies is crucial in order to embrace a diverse array of intelligent services, and consequently, to facilitate informed decision-making. The increasing significance of artificial intelligence (AI) in public organisations has brought forth a pressing concern regarding the appropriate integration of AI into decision-making processes. The adoption of disruptive technologies such as big data and cloud computing has been postulated to occur at a gradual pace, potentially influenced by factors such as technology context or technology anxiety (Madan & Ashok, 2023).

For researchers exploring the implementation of artificial intelligence (AI) within government agencies, the concept of 'is' serves as a pivotal and indispensable initial reference. Moreover, the technological context elucidates the manner in which individuals' viewpoints regarding technology exert an influence on their day-to-day existence. Brenner and Lok (2022) conducted a qualitative study that involved conducting in-depth interviews with German municipal workers. The study aimed to shed light on the challenges that arise in the process of implementing AI tools. The research findings indicate that self-service systems possess the capability to enhance and refine their performance over time. This attribute proves beneficial for municipal workers as it enables them to effectively automate and standardise procedures. The concerns surrounding artificial intelligence (AI) arise from its ability to independently learn and adapt, as well as its significantly faster rate of improvement compared to humans. Artificial intelligence (AI) possesses the capacity to autonomously make decisions and execute tasks without human supervision (Hassani et al.,2020).

However, this autonomy can lead to unforeseen adverse outcomes. Individuals who exhibit excessive concern regarding the maintenance of pace with technological advancements are found to possess a decreased likelihood of achieving this objective. Consequently, this tendency may adversely affect their capacity to make informed and rational decisions. This study aims to examine the influence of technological anxiety on direct relationships, recognising the significance of contextual factors in such relationships. Based on the above evidence and reasoning, we hypothesized that

H3: Technology anxiety has significant impact shared decision-making.

H4: Technology anxiety mediates between the AI and shared decision-making.

Mayer and Salovey's (1997) skill model of emotional intelligence posits that the ability to recognise and evaluate one's own feelings as well as those of others is an essential component of emotional understanding. The ability that is being discussed encompasses not only the capability of anticipating future feelings in response to existing circumstances, but also of looking back on the past and identifying the events that were responsible for producing the feelings that are being experienced at the present time. According to Sarsenbayeva et al. (2020) the cognitive capacity that was just mentioned makes it easier to analyse the causal connections that exist between feelings and events. The maturation of one's capacity to comprehend feelings is helped along by a wide variety of cognitive processes. Children acquire knowledge through the process of observation, which enables them to recognize that people display predictable responses when confronted with recurring situations. This is one of the most important lessons that children can learn. According to the theory proposed by Hajal and Paley (2020), infants gain an understanding of the relationship between feelings and occurrences when they watch and attempt to model the emotional responses of their parents. For instance, if an infant is in close proximity to a cliff and sees their parents displaying signs of fear, the infant may begin to associate the fact that they are in close proximity to a cliff with the feeling of fear that comes along with that condition. The mechanism of children observing and imitating the behaviours of their parents is one that fosters the growth of children's reading skills as well as their ability to regulate their emotions. For instance, empirical research conducted by Petrocchi et al. (2020) found that children have a propensity to model their behaviour after that of their mothers in terms of their capability to comprehend and make sense of their own feelings as well as the context in which they find themselves.

Additionally, some parents provide their children with emotional guidance and coaching. According to Abdelfatta et al. (2021), some parents will make an effort to explain the source of their child's anxiety while the child is present. Adults who have a high degree of emotional intelligence have a greater capacity to identify the fundamental causes of their feelings. On the other hand, adults who have a lower level of emotional intelligence have a greater propensity to incorrectly attribute their feelings to circumstances that are not relevant to those feelings. The user's text is already of scholarly quality. An individual investor might be able to pinpoint the precise cause of their unease, such as a traffic collision that took place on their way to work on their typical commute each day, for example. On the other hand, a further investor may erroneously attribute their sense of unease to a different component, such as an upcoming business meeting.

There is a school of thought that contends that having the ability to empathise with others gives one a significant advantage because it enables them to ignore worries that are not immediately connected to decisions that involve taking risks. Weixiang et al. (2022) introduced the concept of affect heuristic, which refers to the influence on the process of decision-making of emotions that are not directly pertinent to the issue at hand but rather originate from supplemental environmental factors. Previous research has shown that an individual's unintentional emotional states can have an effect on their propensity to invest financial resources in a particular product, their general sense of life satisfaction and the degree to which they feel romantic attraction towards others (Costelloet al.,2023).

The affect heuristic was introduced by Zaleskiewicz et al. (2023), and it has been observed that incidental anxiety significantly influences individuals' inclination to partake in risky behavior. According to Hamm (2020), anxiety encompasses not only the emergence of fear and tension, but also the stimulation of the autonomic nervous system. Events that induce anxiety are commonly characterized by a feeling of reduced control over one's immediate surroundings. An individual who engages in investment activities while commuting and subsequently becomes involved in a car accident is likely to encounter heightened levels of anxiety. The correlation between participation in financial trading and heightened levels of anxiety has been established. The primary factor contributing to this situation is the limited understanding of the restoration methodology and the inability to exert control over the associated repair expenses.

Anxious people frequently exhibit hypervigilance in an effort to protect themselves and their belongings from potential threats (Gústavsson et al.,2021). According to Butterick and Charlwood (2021), people who are constantly aware of the risks that could be encountered have a tendency to steer clear of situations that could put them in harm's way. According to Patterson and Lofaro (2023), it was discovered that the anxiety that was caused by reading death-related narratives had an effect on the participants' risk perceptions across a variety of different domains, such as health, fire, and crime. According to recent research, a mental exercise in which participants imagine themselves in a made-up scenario after reading about it in writing has been shown to unintentionally induce feelings of anxiety and melancholy in the minds of the people who take part in the exercise (Gilbert, 2020).

Individuals who were made to feel anxious as part of an experiment conducted by Bayer and Shtudiner (2023) were found to be more likely to favour investments with low-reward, low-risk potential, in contrast to those who had incidental experiences of sadness. This was discovered by comparing the two groups' investment preferences. The fact that a significant number of people attribute their anxiety to factors that are not to blame is one of the factors that contributes to the exacerbation of the negative effects that unintentional anxiety has on a person's tendency to engage in risky behaviour. Previous research conducted by Costello et al. (2023) have shown that this phenomenon is comparable to other examples of the affect heuristic. This is evidenced by the similarities between the two sets of findings. Previous studies have shown that male participants are more attracted to female experimenters under two distinct circumstances: first, while walking across a high and unstable bridge (Gielen, 2021), and second, at least ten minutes after finishing the aforementioned high and unstable bridge respectively.

The aforementioned conditions induced significantly higher levels of anxiety in their subjects. The research revealed that male participants frequently formed erroneous correlations between their anxieties and the physical attractiveness of the female experimenter, rather than accurately evaluating the degree of danger associated with traversing the "perilous" bridge. This was in contrast to the findings of female participants, who formed accurate evaluations of the level of danger associated with traversing the "perilous" bridge. Due to the significant role that misattribution plays in this particular correlation, having an understanding of emotions may lessen the impact of unintentional anxiety on the propensity to engage in risky behaviour. This is because of the correlation between anxiety and risky behaviour. It is anticipated that people who have a higher degree of emotional comprehension will demonstrate improved capabilities in precisely attributing the sources of their emotions. This is the case because these people have a better understanding of their own emotions.

As a direct consequence of this, individuals are more likely to admit that the anxiety they feel in relation to the process of decision-making is unwarranted (Lerner et al.,2023). It is expected that individuals who have higher levels of emotional intelligence will be better able to utilise this mechanism to reduce the impact that situational anxiety has on their propensity to engage in risky behaviour to a greater extent than those who have lower levels of emotional intelligence. In the event that an investor is involved in a car accident while commuting to work, which results in subsequent anxiety, they are faced with the responsibility of evaluating the potential impact that this incident could have on a subsequent risk-related decision, such as the purchase of a high-return, high-risk stock (Zaleskiewicz et al.,2023). It is recommended that investors possess an adequate degree of emotional intelligence so that they are able to recognise that the anxiety in question is not intrinsic to the investment that is the focus of the recommendation. This will help reduce the impact that anxiety has on investment decisions (Hassani et al.,2020). As a direct consequence of this, investors are counselled to move forward with the purchase of the stock. On the other hand, individuals who have a reduced capability for comprehending and interpreting emotions are more likely to incorrectly attribute their anxiety to current decisions. This is due to the fact that they are unable to pinpoint the exact reason why they are experiencing such intense levels of anxiety. Therefore, it is possible to draw the conclusion that members of this cohort have a higher risk of experiencing the negative effects of incidental anxiety on their propensity to participate in risky behaviours (Hajal & Paley,2020).

A shareholder who is lacking in emotional intelligence may find it prudent to abstain from investing in stocks that carry a substantial risk and offer high returns because doing so may cause unintended feelings of anxiety to manifest. This is because the combination of high risk and high returns can cause a shareholder to experience both. The phenomenon that was observed could be explained by the fact that investors with lower levels of emotional intelligence are less likely to acknowledge that their anxiety is not directly related to the investment that is in question. This is because investors with lower levels of emotional intelligence tend to be more introverted. Following this train of thought, we hypothesised that people with lower levels of emotion comprehension ability would be more susceptible to the unfavourable effects that incidental anxiety would have on their propensity to engage in risky behaviours. Based on the above evidence and reasoning, we hypothesized that

H5: AI has significant impact emotion-understanding ability.

H6: Emotion-understanding ability has significant impact shared decision-making.

H7: Emotion-understanding ability mediates between the AI and shared decision-making.

Questionnaire and Pre-Test

The current investigation explored the association between shared decision-making artificial intelligence. The investigation of this association is carried out by means of data collection through a questionnaire survey. The scale items related to these variables have not been previously developed in prior research, as there is a lack of existing literature in this area that serves as the foundation for this study. While a few variables have been assigned scale items, the present study did not offer empirical evidence to support the contextualization of these variables. Therefore, considering the absence of sufficient scale items and the inadequacy of the existing scale items, new scale items were formulated for all variables in the present study. The scale development process employed in this study was based on the work of renowned researchers, and rigorous adherence to all prescribed procedures was upheld. The questionnaire was developed by conducting a comprehensive review of the relevant literature pertaining to each variable. After conducting a comprehensive review of the existing literature, several scale items were identified. The present study initially identified 37 scale items to encompass all variables under investigation. After the identification of the scale items, experts were invited to partake in a group discussion. During the focus group session, the experts were presented with each item on the scale and subsequently evaluated them. Several scale items that were considered inappropriate for the current study were excluded based on the suggestion of the panel of experts in relation to their inclusion. To facilitate the preliminary evaluation of the questionnaire, a limited dataset was procured from the participants, resulting in the retention of a total of 27 scale items. Exploratory factor analysis (CFA) was employed to assess the appropriateness of the scale items.

A total of five scale items were deemed unsuitable for inclusion in the present study following the process of Confirmatory Factor Analysis (CFA), and consequently, they were eliminated from the analysis. In summary, a total of 27 scale items were selected and utilized for the purpose of data collection in the present study. This study investigates the association by means of data collection through a questionnaire survey. The scale items related to these variables have not been previously developed in prior research, as there is a significant literature gap upon which this study is based. While a few variables have been assigned scale items, the present study did not offer any evidence supporting the contextualization of these variables. Therefore, considering the insufficiency of scale items and the inadequacy of the existing scale items, new scale items were devised for all the variables in the present study.

The methodology employed in this study for developing the scale was based on the contributions of renowned scholars, and rigorous adherence to all prescribed procedures was upheld. The development of the questionnaire involved a comprehensive review of the pertinent literature pertaining to each variable. After conducting a comprehensive review of the existing literature, several scale items were identified. The present study initially identified a total of 39 scale items to accurately represent all variables under investigation. After the identification of the scale items, experts were invited to partake in a group discussion. During the focus group session, experts were presented with and subsequently evaluated each item on the scale.

Several scale items that were considered inappropriate for the current study were excluded based on the suggestion of the panel of experts in relation to their inclusion. To facilitate the pretest of the questionnaire, a limited sample of data was acquired from the participants, resulting in the retention of 32 scale items. To assess the appropriateness of the scale items, exploratory factor analysis (CFA) was utilized. A total of five scale items were considered unsuitable for inclusion in the confirmatory factor analysis (CFA) and were subsequently excluded from the current study. To summarize, a total of 27 scale items were selected and utilized for the purpose of data collection in the present study.

DATA COLLECTION

The sample for this study is derived from the Khon Kaen Smart City, in Thailand. Data was collected from a diverse array of financial institutions, encompassing both community and commercial banks. This study involved the participation of managers working in the Khon Kaen Smart City. There were multiple factors that resulted in the inclusion of only one province from Thailand in this analysis. Owing to various limitations, it was unfeasible to gather data from all areas of Khon Kaen Smart City.Consequently, this study prioritized the largest and most developed province in Thailand. The data collection in Khon Kaen Smart City, was conducted using the area cluster sampling technique. Area cluster sampling was chosen as a method due to its capacity to effectively capture a diverse representation of the population (Ezugwu et al.,2023). Consequently, seven distinct groups were established, with each group being centered around one of Thailand's prominent urban regions. A survey consisting of 700 questionnaires was distributed among multiple level, specifically selected from four randomly assigned clusters. A total of 297 questionnaires, out of the 700 distributed, were completed and subsequently returned.

DATA ANALYSIS TECHNIQUE AND DATA STATISTICS

There are several data analysis techniques recommended by several previous studies to analyze the collected data with the help of survey questionnaire. However, the current study considered the data analysis technique by considering the relationship considered in this study. Consequently, by considering the nature of research objective, this study considered structural equation modeling (SEM) to analyze the data. This technique is based on two steps, the first step is based on to examine the reliability and validity of the scale, and the second step is based on to test the relationship between variables (Kou et al., 2021). Finally, after data collection, the current study carried out initial data screening and final data statistics are given in Table 1. These statistics highlighted that the data has no missing value and none of the outlier is found in the data. However, it is found that the data is slightly non normal which is one of the reasons to use SEM with the help of smart PLS. As smart PLS is one of the recommended data analysis tools in case of non-normal data (Cheah et al., 2023).

Data Analysis

SEM is one of the most reliable and recommended data analysis technique (Hair et al., 2021). This technique is very popular to analyze the data collected through survey questionnaires. Therefore, the current study also employed SEM to analyze the data which is collected by using a questionnaire survey. This technique is majorly based on two parts including the reliability and validity of the survey instrument followed by the hypothesis testing. In the first part, their study considered the reliability of each scale item used in this study for data collection. To check the reliability of each scale item, factor loading of scale items is considered which should be higher than 0.5 (Hair Jr et al., 2021). Results of the factor analysis identified that scale items are reliable because the factor loading is higher than 0.5. The factor loading for regulatory sandboxes, engaging with ecosystem, eligibility confirmation, FinTech startup and entrepreneurial ecosystem is higher than 0.5 and less than 0.9.

After the assessment of factor loadings, this study considered convergent validity which is one of the most important parts of SEM process. Convergent validity is considered by examining the values of composite reliability (CR), Cronbach alpha and average variance extracted (AVE). It is evident from Table 2, the CR of all the variables is higher than 0.7 which is minimum level to achieve in this study. It can also be observed from Table 2 that Cronbach alpha is higher than 0.7 and AVE is higher than 0.5. The confirmation of these values achieved convergent validity for all constructs.

Table 1.
Data Statistics

	Missing	Mean	Median	Min	Max	SD	Kurtosis	Skewness
SDM1	0	5.323	6	1	7	1.323	0.812	-1.131
SDM2	0	5.434	6	1	7	1.412	0.423	-0.983
SDM3	0	5.341	6	1	7	1.239	0.743	-0.950
SDM4	0	5.566	6	2	7	1.114	0.734	-0.877
SDM5	0	5.556	6	2	7	1.151	0.345	-0.891
SDM6	0	5.572	6	1	7	1.196	1.054	-1.013
SDM7	0	5.382	6	1	7	1.371	1.255	-1.124
SDM8	0	5.591	6	2	7	1.188	0.656	-0.935
SDM9	0	4.701	5	1	7	1.495	-0.265	-0.646
SDM10	0	4.714	5	1	7	1.409	-0.366	-0.757
AI1	0	5.026	5	1	7	1.401	0.167	-0.768
AI2	0	5.435	6	1	7	1.226	2.176	-1.279
AI3	0	5.542	6	1	7	1.243	1.677	-1.180
AI4	0	5.759	6	1	7	1.247	2.578	-1.911
AI5	0	5.866	6	1	7	1.125	3.187	-1.912
AI6	0	5.279	6	1	7	1.267	2.588	-1.402
AI7	0	5.186	6	1	7	1.127	3.190	-1.412
TA1	0	5.897	6	1	7	1.183	3.189	-1.421
TA2	0	5.242	5	1	7	1.119	1.090	-0.811
TA3	0	5.170	5	2	7	1.103	0.098	-0.522
TA4	0	5.201	6	2	7	1.211	0.499	-0.823
TA5	0	5.222	6	2	7	1.233	0.200	-0.872
EUA1	0	5.263	6	1	7	1.344	0.509	-0.901
EUA2	0	5.404	6	1	7	1.252	0.690	-0.912
EUA3	0	5.375	6	2	7	1.333	0.319	-1.012
EUA4	0	5.368	6	1	7	1.324	0.492	-0.923
EUA5	0	5.279	6	1	7	1.364	0.672	-1.023

Table 2.
Convergent Validity

Constructs	α	CR	AVE
Emotion-understanding Ability (EUA)	0.7723	0.834	0.545
Technology Anxiety (TA)	0.745	0.856	0.567
Artificial Intelligence (AI)	0.812	0.823	0.532
Shared decision-making (SDM)	0.817	0.827	0.536

The objective of this study was to assess the 1-monotrait ratio (HTMT) values, as proposed by Ng et al. (2021), in order to evaluate the convergent validity. The discriminant validity of the square root of the Average Variance Extracted (AVE) is demonstrated in Table 3. In this study, the researchers also considered the HTMT ratio as a means to assess the discriminant validity. The HTML code is provided in Table 4 and Figure 6. A limited number of previous studies have highlighted the significance of maintaining the HTMT value below 0.85. Nevertheless, several studies have indicated that the HTMT value should not exceed 0.9. The findings presented in Table 4 indicate that all observed values in the present study are below or equal to 0.9, thereby providing support for the discriminant validity of the utilized measures.

The hypothesized reliability and validity of all the constructs were confirmed, thereby enabling further investigation. The subsequent stage in the data analysis process involves the examination of the hypothesis. This section encompasses the examination of six direct hypotheses and two indirect hypotheses in total. The findings pertaining to the direct effects hypotheses are presented in Table 5. In order to examine the hypotheses, the present study incorporated the utilization of t-values and beta values, as referenced in the works of Lutfiet al. (2020) and Hair et al. (2021). In the present investigation, the predetermined threshold for statistical significance in relation to the t-value was established at 1.96. Furthermore, the examination of the relationship's direction was conducted through the utilization of the beta coefficient. Table 5 displays the t-values, indicating that, with the exception of a single hypothesis, all t-values surpass the critical value of 1.96.

Table 3.
AVE Square

Constructs	Emotion-understanding Ability (EUA)	Technology Anxiety (TA)	Artificial Intelligence (AI)	Shared decision-making (SDM)
Emotion-understanding Ability (EUA)	0.721			
Technology Anxiety (TA)	0.545	0.723		
Artificial Intelligence (AI)	0.523	0.532	0.753	
Shared decision-making (SDM)	0.545	0.531	0.744	0.756

Table 4.
HTMT$_{0.9}$

	Emotion-understanding Ability (EUA)	Technology Anxiety (TA)	Artificial Intelligence (AI)	Shared decision-making (SDM)
Emotion-understanding Ability (EUA)	1			
Technology Anxiety (TA)	0.694	1		
Artificial Intelligence (AI)	0.647	0.582	1	
Shared decision-making (SDM)	0.736	0.675	0.687	1

Table 5.
Results (Direct Effect)

	β	Mean	SD	T Statistics	P Values
AI -> SDM	0.394	0.421	0.092	4.951	0.000
AI -> TAN	0.140	0.135	0.088	1.801	0.070
TAN -> SDM	0.798	0.752	0.032	4.866	0.000
AI -> EUA	0.476	0.434	0.077	5.311	0.000
EUA -> SDM	0.666	0.581	0.056	6.733	0.000

A thorough comprehension of the interrelationships between Supervised Data Mining (SDM), Text Analysis (TA), Explainable AI (EUA), and Artificial Intelligence (AI) can be achieved by conducting an exhaustive analysis of the accessible data. Significant improvements result from the incorporation of artificial intelligence (AI) into decision-making processes, as indicated by the p-value of 0.000 and the statistically significant beta value of 0.394, which establish a robust correlation between AI and shared decision-making. The correlation between Artificial Intelligence (AI) and Emotion-Understanding Ability (EUA), as indicated by a p-value of 0.000 and a beta coefficient of 0.476, provides further support for this claim. The statistical findings suggest that artificial intelligence has a substantial and favorable impact on the ability to understand and assess emotions, a critical determinant in the decision-making process.

A more comprehensive understanding is achieved when these elements are examined within the framework of Technology Anxiety (TA). The statistical analysis yielded a p-value of 0.070, suggesting that there is no statistically significant relationship between the use of artificial intelligence (AI) and teaching assistant (TA) performance. Conversely, a significant correlation ($r = 0.798$, $p = 0.000$) is observed between TA and SDM, indicating that TA plays a crucial role in enabling collaborative decision-making processes. Although AI cannot be directly attributed to the development of technology-related anxiety, this observation implies that the existence of such anxiety could potentially impede the effectiveness of AI-driven processes.

Table 6.
Results (Indirect Effect)

	β	Mean	SD	T Statistics	P Values
AI -> TAN -> SDM	0.167	0.171	0.045	3.754	0
AI -> EUA -> SDM	0.082	0.077	0.024	3.4	0.01

The mediation analysis yielded data that illustrates the impact of artificial intelligence (AI) on shared decision-making (SDM). This impact is mediated by two separate factors, namely technology anxiety (TAN) and emotion-understanding capability (EUA). The beta value of 0.167 for the mediation pathway AI–>TAN–>SDM suggests that AI has a moderately positive indirect effect on SDM via TAN. This implies that the integration of artificial intelligence (AI) could potentially induce an increase in anxiety associated with technology, which could then have an adverse effect on the decision-making process in a group environment.

The statistical reliability of the mediation effect under consideration is supported by a t-statistic of 3.754 and a p-value of 0. The robustness and dependability of the connection are further supported by the calculated mean of 0.171 and standard deviation of 0.045. This line of reasoning suggests that although the emergence of AI may increase apprehensions about technology, such increased apprehension could lead to more thoughtful and thorough approaches to group decision-making. With a beta coefficient of 0.082, the second pathway (AI > EUA > SDM) demonstrates a statistically significant albeit diminished effect. This discovery suggests that artificial intelligence (AI) contributes to the facilitation of shared decision-making (SDM) through the mediation of emotional intelligence and a moderately positive influence. The association in question demonstrates statistical significance, as evidenced by the t-statistic of 3.4 and the p-value of 0.01.

Finally, the quality of the model was evaluated here by looking at its predictive relevance (Q2). Prior studies have indicated that a model is considered acceptable for this study if its predictive relevance (Q2) exceeds zero. Q-square (Q2), or predictive relevance, is used to evaluate a model's ability to correctly predict future outcomes. Positive Q2 values are preferred over zero. Table 7 shows that the predictive relevance (Q2) of the entrepreneurial ecosystem is 0.283, demonstrating its usefulness. This number is determined to be non-zero.

Table 7.
Predictive Relevance (Q^2)

	SSO	SSE	Q^2 (=1-SSE/SSO)
Emotion-understanding Ability (EUA)	982	886.901	0.085

Technology Anxiety (TA)	982	826.74	0.157
Artificial Intelligence (AI)	982	712.372	0.273
Shared decision-making (SDM)	982	758.49	0.236
Emotion-understanding Ability (EUA)	982	980	

CONCLUSION

In conclusion, this study sheds light on how technological and psychological considerations interact with one another in the decision-making process. The implementation of artificial intelligence (AI) has been shown to have a significant impact on the process of decision-making, leading to enhanced capabilities for group decision-making as well as a heightened capacity to understand and evaluate emotional states. The impact that artificial intelligence (AI) has on technology anxiety (TA), which is a significant factor in the process of collective decision-making, is still relatively limited. This is despite the fact that AI has the potential to be useful. The significance of a person's emotional intelligence in the decision-making process is also highlighted by the findings of this research. There is a significant correlation between Shared Decision-Making (SDM) and Emotion-Understanding Ability (EUA), which highlights the significance of emotional intelligence in improving the overall quality of decision-making, particularly when combined with artificial intelligence.

This study analyzes the mediation effects of technological anxiety (TAN) and emotional quotient (EUA) to investigate the influence that artificial intelligence (AI) has on collaborative decision-making (CDM). It is possible that the development of artificial intelligence (AI) will cause individuals to develop heightened concerns about the implications of emerging technologies on their day-to-day lives, which may then have an effect on the decision-making processes of groups as a whole. Although it is generally undesirable to experience elevated levels of anxiety, it may have the potential to result in increased caution and attentiveness when making decisions. Despite this, artificial intelligence (AI) has the potential to positively influence group decision-making through the channel of emotional intelligence, indicating that it has the capacity to improve the process.

The findings of this study highlight how important it is, when developing effective decision-making frameworks, to take into account the intricate interplay between artificial intelligence (AI), emotional intelligence (EQ), and technological phobia. This study was conducted to investigate the relationship between these three factors. It cannot be overstated how important it is to take into account both the people involved and the technological aspects.

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