USING PYTHAGOREAN FUZZY ANALYTIC HIERARCHY PROCESS AND PYTHAGOREAN FUZZY INTEGRATED COMPROMISE SOLUTION TO EVALUATE BENEFIT EXPECTATIONS OF ARTIFICIAL INTELLIGENCE IN BUSINESS

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Abstract: Artificial Intelligence (AI) has evolved from a study field to a reality in management. It was evidenced by the fast use of AI technology in enterprises, which has led to more revenue, lower expenses, and enhanced organizational efficiency. Despite this, various organizations are still considering to choose whether or not employ AI. The main objective of this study is to determine and evaluate the anticipated benefits of AI adoption. Pythagorean fuzzy analytic hierarchy process (PF-AHP) and Pythagorean fuzzy compromised solution integration (PF-CoCoSo). PF-AHP computes the relative weights of the significant components, whereas PF-CoCoSo evaluates the benefit expectations (BEs) according to their AI deployment. To exemplify the framework's applicability, a case study of Vietnam Telecom Corporation is done. The most important AI technologies to deploy are "Managerial capability and related advantages" followed by "government involvements" "technical capability and vendor partnership for AI adoption" and "compatibility." The developed model is a step-by-step method for business organizations to strengthen their BEs using AI technology. Conducting sensitivity analysis to evaluate the effectiveness of the recommended framework. This contributions will assist AI researchers and practitioners by providing suggestions and techniques for measuring AI adoption.

Keywords: AI technologies, Pythagorean fuzzy AHP, Score function CoCoSo, telecom industry

JEL Classification: D81, C02, C44, L91.

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Đến tòa soạn: 12/9/2022, chỉnh sửa: 20/12/2022, chấp nhận đăng: 15/1/2023

1. INTRODUCTION

Artificial intelligence (AI) advancements have prompted software and system engineers to devise novel approaches for increasing income, lowering costs, and increasing corporate efficiency. AI is a major competitive trend in business today [1]. AI is defined as 'a collection of tools and technology capable of augmenting and enhancing organizational performance' [2]. This is accomplished through the development of "artificial" systems capable of resolving complex environmental challenges, with "intelligence" referring to the emulation of human intelligence. This intelligence is critical for strategic planning and has been used successfully by firms to obtain a competitive edge over their competitors [3]. It is widely assumed that AI would provide benefits such as human enhancement, which should be considered while considering economic growth [4]. At the federal, industrial, and personal levels, AI has been employed and deployed. Additionally, [1] outlined a clear strategy for implementing AI by 2030, which is progressively gaining traction in the ASEAN area, specifically the Vietnam government, for the public sector [5]. Excellent example of VinAI and Viettel Solutions collaborating with a start-up to develop AI-based novel solutions for future laboratories and implementing a pilot AI distribution system. Examining the importance of government bodies taking the initiative seriously and initiating AI projects within their surroundings that meet their commercial requirements. AI can be defined as the emulation of various human intelligence processes by machines, more specifically computer-related systems [6]. However, [2]asserts that "AI refers to both the intelligence of machines and the branch of computer science devoted to its development." [7], while [2] discusses the history of AI, he defines it as the concept of transforming inanimate objects into intelligent beings capable of reasoning like humans. Computer systems simulate human intelligence processes such as learning, reasoning, problem solving, speech recognition, and planning. From robotic-like game play and knowledge representation to cognitive automation, AI has advanced [8]. AI is having an increasing impact on organizations within the corporate sphere. According to Gartner [9], AI is the top strategic technology for businesses. This is backed up by Google, Amazon, IBM, and Apple, which have all used AI to improve consumer experiences [10]and productivity [3] through simpler cooperation [11]. The global adoption of AI presents a significant opportunity for Vietnamese firms [12]. Additionally, the report projects that the Vietnamese economy might benefit from AI and automation to the amount of 1.2 trillion USD by 2030 [13]. Despite this effective demonstration of AI, an Alphabeta poll of business leaders revealed that only 6% of Vietnamese firms are investing in AI and automation on a sustained basis, compared to more than 25% in the US. Vietnamese enterprises are now falling behind global competitors in adopting AI technologies [14]. Indeed, according to a recent Gartner poll [9], the majority of firms are still gathering data on what and how to adopt AI. Many firms appear to be in the process of determining how to develop a business case for AI deployment, as well as the organizational capabilities required to analyze, construct, and deploy AI solutions, and are unsure about the business applications of AI [4]. As a result, a comprehensive understanding of AI adoption and associated determinants has not yet been developed in the Vietnamese context. As such, this research attempts to gain a thorough understanding of how AI is being adopted by enterprises in the Vietnamese telecom industry. As a result, the organization serves as the unit of analysis. BEs produced as a result of AI adoption are subjective and may be expected to be multidimensional. As a result, a multi-criteria decision-making (MCDM) strategy is necessary to manage the relative importance of applicable AI technologies and BEs. A framework consisting of Pythagorean fuzzy analytic hierarchy process (PF-AHP) and Pythagorean fuzzy integrated compromised solution (PF-CoCoSo) is proposed to accomplish the research objective of ranking all possible parameters affecting the adoption of AI at the organizational level in the Vietnamese setting.

Pythagorean fuzzy sets (PFS) are a class of fuzzy sets that are an extension of intuitionistic fuzzy sets (IFS). PFS gives professionals greater latitude in expressing their views on the vagueness and uncertainty of the MCDM topic under consideration. Experts are not required to grant membership and non-membership degrees with a total value of no more than one. The sum of the squares of these degrees, however, must be no greater than one. As a result, this research applies an analytical hierarchy process (AHP) and a technique known as combined compromise solution (CoCoSo) with PFS extensions. Previous research on AI technologies has examined the conceptual framework for its implementation [15]–[17], but has not examined the impact of AI technologies on their implementation and the associated BEs derived as a result of their adoption. Vietnam's telecom industries can reap a number of significant benefits from implementing the proposed framework in practice. The remaining part of the study is organized as follows: The section 2 provides a literature analysis on AI technologies, critical factors, and BEs, and identifies research objective. The conceptual framework methodology is discussed in Section 3. Section 4 describes the proposed research framework's solution techniques and empirical case study application. Section 5 presents the study's conclusions, commentary, and sensitivity analysis. Section 6 discusses the managerial implications of the study. Section 7 presents the conclusions.

The following study objectives are noted based on a review of the literature:

i. Numerous research papers on critical factors / drivers of AI technology adoption are available in the prior literature [87]–[89]. However, only a few articles were able to calculate the influence of identified crucial components on the success of AI adoption using any decision-making technique.

ii. Previous research has identified a variety of success criteria and frameworks. However, fewer papers could point the way to the connection between AI technologies and their BEs.

iii. The majority of articles discussing critical factors affecting AI adoption and frameworks are unverified or unconfirmed, casting doubt on their relevance for AI technologies applied in the telecom industry.

iv. A few of the critical factors affecting AI acceptance and frameworks were studied through case studies and surveys. Simultaneously, none of them used MCDM approaches to enhance its practical application.

v. Only some papers discuss the BEs that have been obtained as a result of the implementation of AI technologies. However, many articles fall short of quantifying their intensity through decision-making techniques.

2. LITERATURE REVIEW

The literature review provides as the foundation of any research project [18]. As a result, the current study uses a systematic literature review (SLR) technique to conduct a review of the literature on critical factors and critical factors affecting the adoption of AI technologies. The Scopus database is searched for articles addressing AI essential aspects and adverse consequences of AI deployment. The forward and backward snowball techniques are used to sift through the literature in this study [18]. This stage aids in the extraction of articles that are more pertinent to the topic of AI. Additionally, the following sub-sections conduct a review of the shortlisted literature in order to have a better knowledge of the AI domain.

2.1 AI technologies

In 1956, during the Dartmouth Conference in the United States, John McCarthy created the phrase artificial intelligence [19]. At the time, AI was defined as the process of using a computer to create a complicated machine that possessed the same fundamental qualities as human intelligence. Later on, the definition of AI shifted. [20], for example, defines AI as an "obscure branch of computer science". According to [21], AI is demonstrated by machines, and they believe that, in contrast to natural intelligence demonstrated by people and other animals, AI is the process of teaching computers to behave intelligently like humans. According to [22], AI is a subfield of computer science concerned with the process through which computers acquire intellectual complexity. According to [23], AI is an area of study that enables robots to identify the optimal solution to complicated problems in a human-like manner. According to [14], AI is neither psychology nor computer science because it places a premium on computation, observation, reasoning, and action.

The advancement of computer capabilities, the accumulation of enormous amounts of data, and theoretical understanding all contribute to the growth of AI technologies in the twenty-first century. Significant progress is made in translating AI research and technology into performant products. At the moment, the primary applications of AI are in large data, visual services, natural language processing, and intelligent robots. The majority of AI applications are found in business, finance, healthcare, and automobiles [24]. Medical imaging, clinical decision support, speech recognition, drug research, health management, and pathology are all examples of intelligent healthcare [25]. AI has the potential to be used in intelligent healthcare. Machine learning, for example, can forecast medicine performance, gene sequencing, and crystal shape. Electronic health records, intelligent queries, and assistance are all made possible by natural language understanding. Medical picture recognition, lesion identification, and self-testing for skin diseases are all possible using machine vision [26], [27]. AI can improve people's health by increasing the efficiency of medical facilities and employees and decreasing medical costs [28], [29].

Additionally, big data-driven AI technologies can be used to accelerate the advancement of financial technology. AI has the potential to restructure the financial industry's ecological framework, thereby making financial services (banking, insurance, wealth management, loans, and investing) more humane and intelligent [26]. Until now, financial services have seen widespread use of artificial neural networks, expert systems, and intelligence systems. Credit evaluation, portfolio management, and financial forecasting and planning are only some of the applications [30]–[32].

Additionally, AI enables robots to exhibit human-like perception, coordination, decision-making, and feedback capabilities. Intelligent robots are classified into three types: intelligent industrial robots, intelligent service robots, and intelligent specialty robots [9], [26]. Industrial robots that are intelligent can execute tasks such as packaging, positioning, sorting, assembling, and detection. Intelligent service robots can be used as a family friend, a business assistant, a healthcare provider, a retail salesperson, or a rehabilitation specialist for impaired persons. Intelligent specialized robots are capable of doing reconnaissance, search and rescue, and firefighting [33]–[35].

Apart from healthcare, finance, and robots, AI has been used in retail [36], [37], education [38], [39], smart home [40]–[42], agriculture [43], [44], manufacturing [42], [45]. Early adopters of AI, such as technology behemoths such as Amazon, Google, and Baidu, reaped the greatest competitive benefit from the technology. They are investing in AI to enhance business processes, such as search engine optimization and targeted marketing. These early adopters have been utilizing AI technology such as natural language processing and machine learning to provide clients with a highly tailored experience.

Due to the pervasive nature of AI and a dearth of research on AI adoption at the organizational level, it is unable to directly build on current theories. Adopting AI is a lengthy process that includes not only the procurement of software and technology but also the establishment of necessary infrastructure and resources over time. However, there is yet no empirical estimate of AI acceptance. As a result, study is required to examine the aspects that influence the proclivity of AI to adopt, as well as an organization's specific organizational competence and environmental circumstances.

Several studies are now being conducted to evaluate the application of AI technologies in specific fields [39], [46]–[48]. Other works examine the theoretical underpinnings of AI [49], [50] as well as its applications [41], [51]. Few studies, on the other hand, examine AI adoption, particularly at the organizational level. For instance, [2] present a study framework for AI adoption, but this framework is not validated across a sample of enterprises in order to discover the elements affecting AI adoption. Additionally, their study lacks hypothesis tests and empirical validation. In the realm of information systems, publications on the subject of AI are also extremely rare.

According to the review of studies on AI adoption, the technological, organizational, and environmental frameworks provide an excellent starting point for investigating AI adoption not only because they highlight the unique context in which the adoption process occurs, but also because they can be used to evaluate the factors affecting AI adoption.

The technological context encompasses characteristics such as technological innovation, technical skill, and technology portfolio [52], [53]. IT characteristics are critical determinants of the IT adoption process [54], [55]. They include perceived benefits and constraints [56], [57], technology integration [58], [59], technological readiness [60], and IT infrastructure [58], [59]. [60]–[63]. [64] contends that the dissemination of a new technology is contingent on a number of the technology's innovative features, including relative advantage, compatibility, complexity, trialability, and observability. When a new technology's relative advantage, compatibility, trialability, and observability improve, the rate of adoption accelerates [65]. Among these innovation traits, trialability and observability are underutilized in research on IT adoption [66]–[68]. Apart from innovation characteristics, three technological elements are shown to influence IT adoption: relative advantage, compatibility, and complexity [66], [68]–[72]. According to this type of literature, the qualities of innovation and technological aspects play a role in IT adoption.

The organizational context refers to the qualities of an organization that enable it to pool resources for the purpose of boosting performance. Culture, strategies, managerial abilities, technical abilities, and people considerations are just few of the features [73]–[75]. Organizational variables include the organization's structure and practices, which either inhibit or facilitate the adoption and implementation of innovations [56]. [76] argue that leveraging organizational capabilities sufficiently can help firms establish and sustain competitive advantages, as well as positively affect their cloud computing implementation, based on resource-based theory [77]. [55] emphasizes that the size, maturity, resources, time period, and sophistication of the information system all contribute to the success of the information system.

The environmental context refers to the external environment in which businesses operate their ability to access external resources, and their interactions with the government and other businesses. The environmental context, in particular, encompasses the competitive, legal, and regulatory environment, as well as the market in which businesses operate [75]. These external influences not only create potential for IT breakthroughs, but also constrain them. [78] observes that the higher the competition between businesses, the more likely innovation will be adopted. Intense rivalry can accelerate the diffusion of breakthroughs, and when businesses face a high degree of market uncertainty, they are more likely to pursue aggressive technological initiatives [54], [56], [79]. [54] discovers that government participation through policies and support can significantly affect enterprises' decision to embrace innovative systems. Other environmental determinants, such as government participation [54], regulatory policy [60], industry pressure[57], market uncertainty [56], [61], and competitive pressure, have been highlighted in earlier studies[59], [60], [80].

2.2 Benefit expectations due to adoption of AI technologies

To compete in a worldwide market, the majority of telecom firms are looking forward to implementing breakthrough AI technologies that enhance work performance [81], [82]. AI has the ability to significantly improve corporate performance and productivity [83]. Thus, it is critical to have a thorough understanding of the critical business outcomes that firms can achieve through the use of AI technologies. The BEs can be defined as the metrics that quantify the extent to which an organization's goals are realized through the use of available resources that incorporate AI. [84] discussed how quality-assured inputs and low-cost services have a significant impact on BEs associated with telecom industry activities. [84] built a framework and highlighted the increased efficacy of work. [85] used a decision-making technique to investigate the many main BEs associated with the deployment of AI technologies and to rank these BEs. [17] advanced a holistic conceptual framework for managing AI applications. [86] evaluated the potential for performance enhancement associated with AI adoption in terms of environmental and technological factors.

3. PROPOSED RESEARCH FRAMEWORK

This study provides a PF-AHP and PF-CoCoSo framework for analyzing and ranking the BEs resulting from the use of AI technology. This framework is divided into three stages.

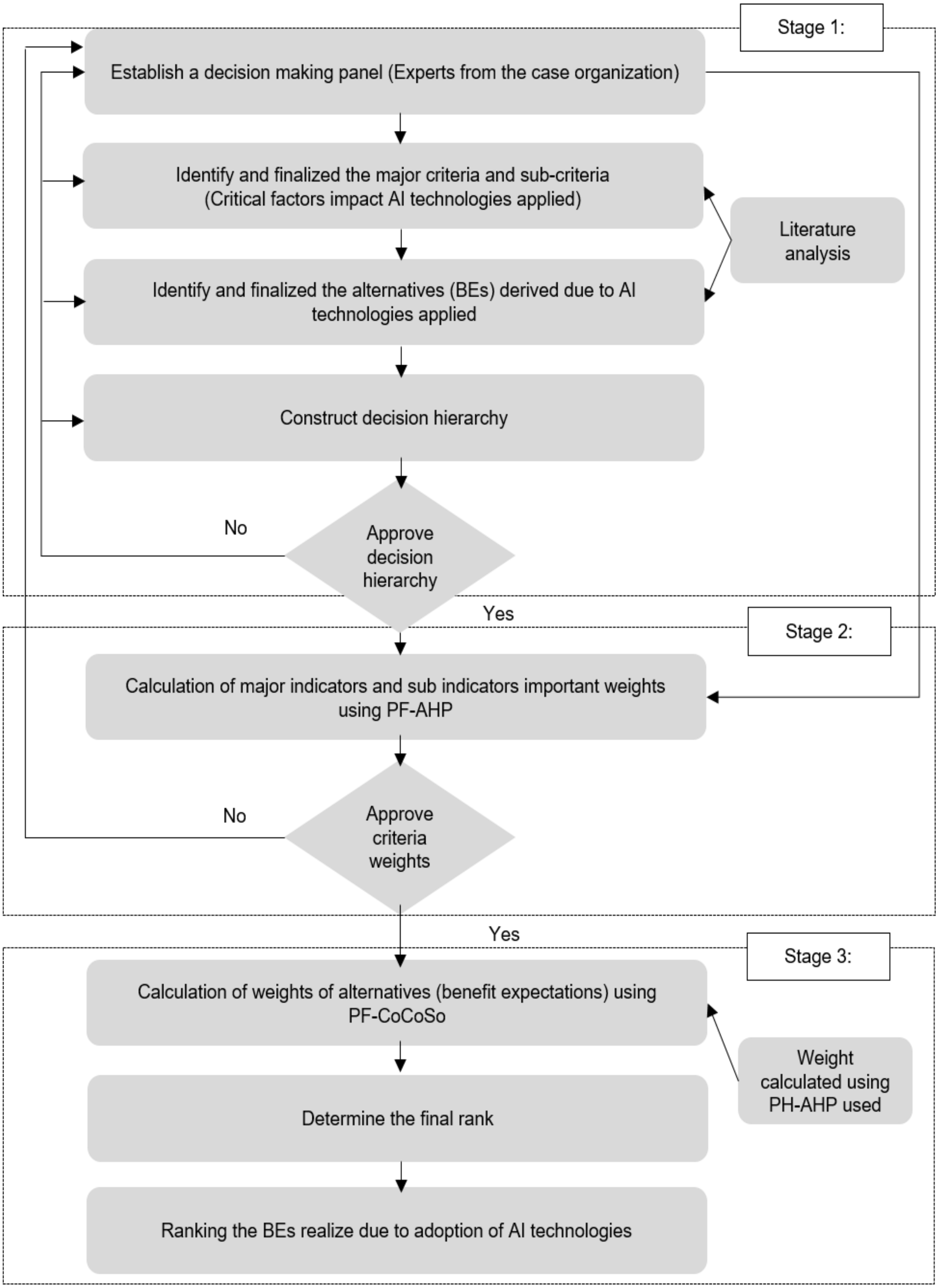
Figure 2 illustrates the suggested framework's flow diagram.

Stage I: Identifying and finalizing the most common critical factors and BEs typically results through the use of AI technologies.

Stage II: Using the PF-AHP technique, calculate the weight of critical major criteria and sub-criteria.

Stage III: Using the PF-CoCoSo approach, rank the BEs collected as a result of AI technology adoption.

Figure 2: *Framework on research methodology*



4. METHODOLOGIES AND CASE STUDY ANALYSIS

This section discusses the research methodologies, especially PF-AHP and PF-CoCoSo, which were used to support the findings.

4.1 Methodologies

4.1.1 Pythagorean fuzzy sets

The input data necessary to solve any decision-making challenge is incomplete or uncertain. To deal with the uncertainty inherent in decision-making situations, [90] created fuzzy sets, which are defined by a grade of membership function provided to each member ranging from 0 to 1. Later in 1986, Atanassov presented the Intuitionistic fuzzy sets (IFS) in three distinct forms: membership function, non-membership function, and hesitation degree. It is capable of communicating more accurate data than fuzzy sets. However, IFS is unable to meet the criteria for membership and non-membership. As a result, IFS's few extensions, such as the Neu-trosophic set [65], Pythagorean fuzzy set [91], and Orthopair fuzzy set, were produced [92]. These sets were capable of dealing with such scenarios. This study makes use of the PFS, which was established by Yager in 2013. Fig. 1 illustrates the comparison between PFS and IFS spaces.

Let us consider μ_p and v_p are the Pythagorean membership grade, whereas, μ_I and v_I are the Intuitionistic membership grade. In Intuitionistic membership grade all the points are beneath the line $\mu_I + v_I = 1$, whereas, in the Pythagorean membership grade all the points are with the line $\mu_P^2 + v_P^2 = 1$. Therefore, it is clear that the set of Pythagorean membership grades is greater than the set of Intuitionistic membership grades. As a result, PFS give decision-makers more flexibility in formulating their judgments on uncertainty [93]. PFS has recently been used in a variety of research areas, including hydropower plant selection [94], smartcity implementation risks evaluation [95], sustainable supply chain innovation enablers evaluation [96], landfill site selection [97], occupational health and safety [91], information security risk analysis [98].

4.1.2 Algorithm 1 Pythagorean fuzzy analytical hierarchy process

AHP is often regarded as the most effective and powerful MCDM technique for resolving complicated problems with several competing criteria [99]. It evaluates all decision-making criteria in order to organize complex topics in a hierarchical sequence [100]. When calculating the weight of criteria, the AHP method has a lot of advantages over other related techniques such as ANP, entropy, and SWARA. AHP can be used for both quantitative and qualitative data. It develops difficult choice issues using a hierarchical architecture. Decision-makers can use AHP to calculate the consistency of the evaluation approach. As a result, the AHP approach is used for CSCE evaluation in this study. Furthermore, the AHP method is incorporated into the PFS theory to eliminate ambiguity and imprecision in MCDM situations. As a result, the weights of CSCEs are determined using a PF-AHP technique in this study. The following are the steps involved in the PF-AHP method:

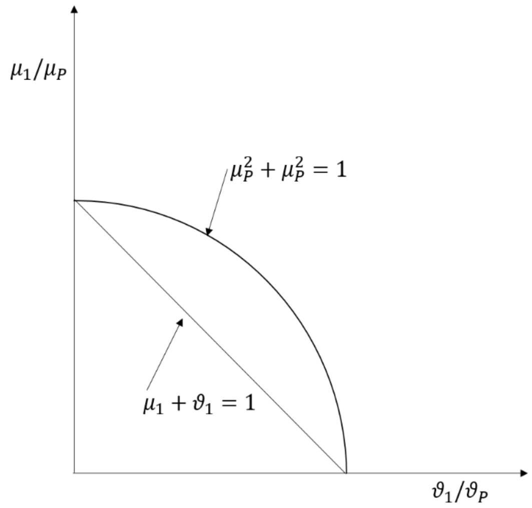
1: Construct a pairwise comparison matrix $A = (a_{ik})_{m\times n}$ in accordance to responses taken from decision-making panel with the help of linguistic variables provided.

2: Compute the differences matrix $D = (d_{ik})_{m\times n}$ between the lower and upper values of the membership and nonmembership functions using Eqs. (1) and (2):

$$d_{ik_L} = \mu_{ik_\perp}^2 - v_{ik_U}^2$$
$$d_{ik_U} = \mu_{ik_U}^2 - v_{ik_\perp}^2$$

3: Compute the Interval multiplicative matrix $S = (s_{ik})_{m\times n}$ using Eqs. (3) and (4):

***Figure 1:** Difference of spaces of P.F.Ns and I.F.Ns (Source: [92]).*



$$S_{ik_L} = \sqrt{1000^{d_{ik_L}}}$$

$$S_{ik_U} = \sqrt{1000^{d_{ik_L}}}$$

4: Calculate determinacy value $\tau = (\tau_{ik})_{m\times n}$ of the a_{ik} using Eq. (5):

$$\tau_{ik} = 1 - \left(\mu_{ik_U}^2 - \mu_{ik_L}^2\right) - \left(v_{ik_U}^2 - v_{ik_L}^2\right)$$

5: Compute the matrix of weights, $T = (t_{ik})_{m\times m}$ before normalization by multiplying the determinacy degrees with $S = (s_{ik})_{m\times m}$ matrix using Eq. (6):

$$t_{ik} = \left(\frac{S_{ik_L} + S_{ik_U}}{2}\right)\tau_{ik}$$

6: Compute the normalized priority weight, w_i using Eq. (7):

$$w_i = \frac{\sum_{k=1}^{m} t_{ik}}{\sum_{i=1}^{m}\sum_{k=1}^{m} t_{ik}}$$

4.1.3. Algorithm 2 Pythagorean fuzzy combined compromised solution

[101], [102] proposed CoCoSo, an innovative and effective MCDM technique. The CoCoSo approach combines the simple additive weighting and exponentially weighted product decision making algorithms with aggregation strategies to produce a multidimensional compromise solution that is consistent with changes in weight distribution criteria. As a result, when compared to other MCDM methodologies, the CoCoSo method has advantages in terms of decision-making dependability and stability [103]. As a result, the CoCoSo technique has recently garnered a lot of attention from researchers for handling difficult decision-making problems like risk evaluation [104], electric car evaluation (Biswas et al., 2019), and telecom technology assessment [103].

[102] apply the PFS theory to the CoCoSo technique. The PF-CoCoSo is a decision assistance tool that addresses uncertain concerns in decision-making challenges. Because of the presence of PFS, it has a strong ability to distinguish the best choices from other existing MCDM techniques [105]. The following is the computational process used in PF-CoCoSo [104]:

1: Construct the decision matrix $D = \left(D_{ij}\right)_{m\times n}(i = 1{,}2 \ldots m;\ \mathrm{j} = 1{,}2 \ldots n)$ with the help of experts opinion by assigning linguistic scale of PF-CoCoSo is given.

2: Convert the linguistic decision matrix into the Pythagorean fuzzy decision matrix using Eq. (8).

$$P = \left(P_{ij}\right)m \times n(\mathrm{i} = 1{,}2 \ldots \mathrm{m};\mathrm{j} = 1{,}2 \ldots \mathrm{n})$$

3: Calculate the score function $R = \left(r_{ij}\right)_{m\times n}$ of each PFN $p_{ij} = \left(\mu_{ij}, v_{ij}\right)$ using Eq. (9).

$$r_{ij} = \mu^2{}_{ij} - v_{ij}^2 - \ln\left(1 + \pi^2{}_{ij}\right)$$

4: Convert the score function matrix $R = \left(r_{ij}\right)_{m\times n}$ into an orthonormal Pythagorean fuzzy matrix $R' = \left(r'_{ij}\right)_{m\times n}$ using Eq. (10).

$$r'_{ij} = \begin{cases} \dfrac{r_{ij} - r_j^-}{r^r{}_j - r_j}, \text{ifjeB,} \\ \dfrac{r_j{}^+ - r_{ij}}{r_{\ j\ j} - r_j}, \text{ifjeC} \end{cases}$$

where,

$$r_j^- = \min_i r_{ij}, \text{ and } r_j^+ = \max_i r_{ij}$$

5: Determine the total of the weighted comparability sequence for each alternative using Eq. (11).

$$S_i = \sum_{j=1}^{n} w_j * r'_{ij}$$

6: Calculate the whole of the power weight of comparability sequences for each alternatives using Eq. (12).

$$P_i = \sum_{j=1}^{n} \left(r'_{ij}\right)^{w_j}$$

7: Determine the relative weight of the alternatives using aggregation score strategies with the help of Eqs. (13)-(15).

$$K_{ia} = \frac{P_i + S_i}{\sum_{i=1}^{m}(P_i + S_i)}$$

$$K_{ib} = \frac{S_i}{\min_i S_i} + \frac{P_i}{\min_i P_i}$$

$$K_{ic} = \frac{\lambda S_i + (1-\lambda)P_i}{\lambda \max_i S_i + (1-\lambda)\max_i P_i} 0 \leq \lambda \leq 1,$$

where,

(i) K_{ia} = Arithmetic mean of sums of weighted sum method (WSM) and weighted product model (WPM) scores.

(ii) K_{ib} = Denote a sum of relative scores of WSM and WPM compared to the best.

(iii) K_{ic} = Balanced compromise of WSM and WPM models scores.

8: Determine the assessment value K_i using Eq. (16).

$$K_i = \sqrt[3]{K_{ia}K_{ib}K_{ic}} + \frac{K_{ia} + K_{ib} + K_{ic}}{3}$$

9: Rank the alternative based on the decreasing value of $\mathrm{K_i} (\mathrm{i} = 1,2 \dots \mathrm{m})$.

4.2 A case study of Vietnam Telecom Corporation

4.2.1 The case introduction and the problem analysis

The suggested PF-AHP and PFCoCoSo frameworks are empirically validated for a Vietnamese telecommunications organization. The VNMI organization was founded in 1985 and currently has several units scattered over 20 different places around Vietnam. The organization employs more than 50,000 people and generates over 11.5 billion US dollars in yearly revenue. VNMI is a Vietnamese telecommunications company. This case study was conducted at the VNMI organization's telecom section in Hanoi and Ho Chi Minh City, Vietnam. As a result, VNMI executives are extremely interested in using AI techniques across their multi-service operations and distribution. Implementing an AI technologies plan is viewed as an innovative sustainable technique that will assist the example organization in enhancing its technology adoption practices in its service operations. The VNMI organization's executives agreed to contribute to this research.

4.2.2 Stage 1: Identification and finalization of the most common critical factors AI technologies adoption and BEs derived due to adoption of AI technologies.

52 critical factors relating to AI and 15 BEs were identified in the literature. Following that, a questionnaire containing the criteria and BEs was created and delivered to the VNMI's decision-making (DM) panel for validation. The DM panel is composed of fifteen specialists, including the head of production, the head of environmental management, the head of AI technological, quality, and maintenance, the head of operations and planning, and the head of logistics and supply chain. These professionals are highly qualified, knowledgeable, and have more than ten years of industrial experience. After numerous rounds of discussion among the DM panel's experts, a final list of 34 important elements for AI adoption was selected. Tables 1 and 2 provide a detailed list of selected 34 critical factors and 15 BEs.

4.2.3 Stage 2: Calculate the major criteria and sub-criteria weight

The relative weights of criteria and their sub-criteria are calculated in this phase using the PF-AHP approach. The selected DM panel provides a pairwise comparison matrix of key enablers and sub enablers using the linguistic scale. Additionally, the decision matrix mode is calculated in order to acquire a single decision matrix before proceeding with the remainder of the calculations. Calculations were performed in accordance with the procedures outlined in Section 3.2. The following is a sample calculation using data obtained from expert 1 for PF-AHP. The final determined worldwide weights for each significant aspect affecting the adoption of AI technology are presented in Table 3. All key parameters were weighted equally, but relative advantage (RAD) received strongest weight.

4.2.4 Stage 3: Ranking the BEs derived due to adoption of AI Technologies

The final stage employs the PF-CoCoSo approach to rank the BEs obtained from significant factors affecting AI technology adoption. In the PF-CoCoSo approach, the weight computed in PF-AHP is used. The same DM panel is presented with a set of questionnaires in the form of a decision matrix. Before to doing further calculations, the decision matrix mode is calculated to obtain a single decision matrix. Calculations were performed in accordance with the procedures outlined in Section 3.3. The following is a sample computation using data obtained from expert 1 for PFCoCoSo. Table 4 summarizes the final ranking of BEs according to their *Ki* values.

5. RESULTS AND SENSITIVITY ANALYSIS

5.1 Analysis results

The use of AI technologies assists the company in carrying out operational duties in a more effective and efficient manner. The study attempts to prioritize the BEs by the effective use of AI technologies. 15 BEs were ranked against the 34 essential variables influencing decision-making in the Vietnam telecom industry for the use of AI technologies. According to the findings, technical capability (TCPs) are the most important major criteria influencing at once adopted AI technologies. Complexity (CPLs), Organizational readiness (OREs), Government involvement (GIVs), Relative advantage (RADs), Compatibility (CPAs), Market uncertainty (MUCs), Managerial capability (MCPs) and Vendor partnership (VPAs) come next. The priority ranking of sub criteria is presented in Table 3. The most critical Technical capability for adopting AI technology in a telecom corporation is Flexibility and integration can be facilitated by the use of AI (TCP1). TCP2 require the company has clear information technology strategies assist their in achieving our company goals in implementation AI technologies in their business segment.

In Vietnam, AI is heavily utilized in a variety of industries, including health, education, agriculture, transportation, and e-commerce. AI has been regarded as a critical technology for achieving a breakthrough and requires further development and investment. Data is critical for AI development. This entails a focus on the development of huge databases and on ensuring that the proper processes and laws for this massive data flow are shared favorably by domestic and international entities. The Prime Minister's Directive No. 16 / CT-TTg dated May 4, 2017 on strengthening access capacity to the Fourth Industrial Revolution affirms that Vietnam must make efforts to strengthen capacity to access Industry 4.0, one of the critical pillars of which is AI, which has fundamentally changed the world's production. Additionally, the legal framework and laws governing AI development are being developed and applied progressively. Additionally, the Government has tasked the Ministry of Planning and Investment with developing a National Strategy for Industrial Revolution 4.0, which lists AI as a priority technology industry for policymakers to focus on in order to foster development. As a result, the Government involvement is ranked fourth and their sub-criteria are classified as follows: GIV1>GIV2>GIV3. Among all critical factors, Relative advantage (RAD), Compatibility (CPA), Market uncertainty (MUC) and Competitive pressure (CPR) are critical which came in fifth place.

Managerial capability (MCP) and Vendor partnership (VPA) are ranked ninth and tenth, respectively. MCP sub-criteria are ranked as follows: MCP3 > MCP2 > MCP1. The sub-criteria of VPA are ranked as follows: VPA4 > VPA3 > VPA1 > VPA2. BEs obtained as a result of AI technologies adoption are ranked using the evaluation value K_i. K_i for AI can aid workplace safety, smart and sustainable production and operations (BE11) is the highest, whereas K_i for BE1 is the lowest. BE11 > BE7 > BE12 > BE9 > BE6 > BE8 > BE4 > BE2 > BE10 > BE5 > BE3 > BE15 > BE14 > BE13 > BE1 are the additional BEs listed in descending order. The ranking of BEs aids organizational decision-makers in exploring the primary complex that arise while using AI technology and setting appropriate policy guidelines to improve their benefits in several dimensions in telecom industry.

5.2 The sensitivity analysis of weight information

It is usually preferable to run the sensitivity analysis test to ensure the robustness of the given framework [106]. The BEs (alternatives) are ranked based on changes in the importance weight of discovered essential elements in sensitivity analysis. Twenty experiments are carried out in this study. The importance weight of each key component is set higher one by one in the first 18 experiments, while the weight of other critical factors is set to low and assigned identical values. Based on the results of the sensitivity analysis, the weight of factor GIV1 is set to 0.6, and the weights of the remaining 33 factors are assumed to be of equal relevance and set to 0.0095. The order of BEs (alternatives) is established. Similarly, the weights of other components were changed in the subsequent calculations, and the results are shown. Figures 3 show how the weights of the important criteria affect the final ranking of the BEs (alternatives). BE6 obtained the highest assessment value K_i in 6 experiments (i.e., experiments 7, 8, 9, 10, 15, 19) and was reported as the best outcome.

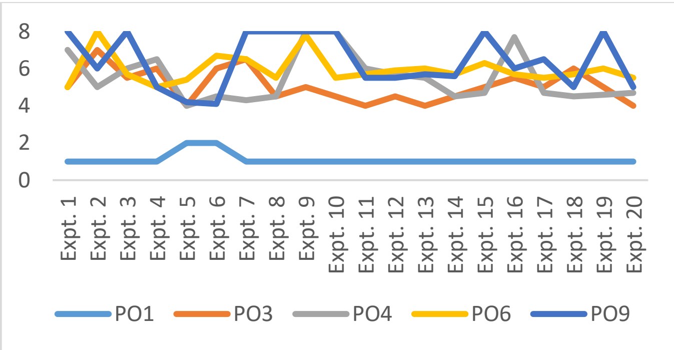


Figure 3 *Result of sensitivity analysis (k_i score)*

6. MANAGERIAL IMPLICATIONS

This research work makes a significant theoretical and practical contribution to the AI sector. The implications of this study for researchers and practitioners, as well as the benefits of the proposed model to society, are examined in the sub-sections that follow. In addition, a proposal to policymakers and sensitivity analysis are explored in the next sub-section. This study produced significant contributions to the AI sector, both for researchers and for industrial practitioners, in the following ways:

i. The ongoing research and use of new technologies has encouraged researchers and industrial practitioners to discover and execute essential critical variables that can aid in the implementation of AI in an industry.

Table 1: *List of 34 selected critical factors AI technologies adoption.*

Major criteria	Code	Sub-criteria	Reference
Organizational readiness (ORE)	ORE1	A roadmap for the timely implementation of AI technology and application migration has been devised.	[56], [107]; Expert's opinion
	ORE2	Managers have already endorsed the plan.	
	ORE3	A financial budget has been approved, as well as a migration schedule.	
	ORE4	Our clients excitedly embrace new goods and services that incorporate AI advances.	
Compatibility(CPA)	CPA1	Our existing communication/network environment is compatible with AI applications.	[66], [108]; Expert's opinion
	CPA2	Our existing hardware environment is compatible with AI applications.	
	CPA3	Our infrastructure is suitable with AI applications.	
	CPA4	AI applications are compatible with digital data sources.	
Competitive pressure (CPR)	CPR1	In our primary industry, the rate of innovation in terms of new operating methods and new products or services has accelerated substantially.	[63], [109]; Expert's opinion
	CPR2	Our industry faces intense price competition. Competitors are fierce in terms of product/service quality.	
Complexity (CPL)	CPL1	Adopting AI innovation is immature in terms of application maturity.	[56], [107]; Expert's opinion
	CPL2	The cost of AI application and migration has been too expensive.	
	CPL3	Adopting AI innovation requires time.	
	CPL4	Inadequate work force and people shortages are significant barriers to embracing AI innovation.	
Government involvement (GIV)	GIV1	The government provides pertinent data.	(Chang et al., 2007; Chau & Tam, 1997; Oliveira et al., 2014); Expert's opinion
	GIV2	We should strive to preserve cordial relations with the local government.	
	GIV3	Government support and assistance are critical to our ability to innovate.	
Managerial capability (MCP)	MCP1	Inter-departmental collaboration is critical for the adoption of AI technologies.	[76], [109]; Expert's opinion
	MCP2	Inter-departmental communication is critical for the adoption of AI technologies.	
	MCP3	Formal education and training programs for all user classes, from managers to shop floor controllers, can be designed.	
Market uncertainty (MUC)	MUC1	In our primary industry, there is a trend toward more use of AI technology for company development and application development.	[54]; Expert's opinion
	MUC2	In our primary industry, AI has a vast range of application possibilities.	

Major criteria	**Code**	**Sub-criteria**	**Reference**
	MUC3	AI has the potential to help our business become more competitive.	
Relative advantage (RAD)	RAD1	Increased staff productivity can be achieved through the use of AI applications.	[66], [108]; Expert's opinion
	RAD2	Customer service can be enhanced with the use of AI applications.	
	RAD3	AI applications can improve the efficiency of information technology resources.	
	RAD4	AI application can promote flexibility and integration.	
Technical capability (TCP)	TCP1	Flexibility and integration can be facilitated by the use of AI.	[54], [66], [108]; Expert's opinion
	TCP2	Our information technology strategies assist us in achieving our company goals.	
	TCP3	We have the necessary hardware/software in place to safeguard our systems' and networks' security and privacy.	
Vendor partnership (VPA)	VPA1	We have encountered no trouble obtaining support or relying on the services of our vendors/partners.	[76], [112]; Expert's opinion
	VPA2	Our suppliers and partners are reputable.	
	VPA3	Vendor makes decisions beneficial to our organization.	
	VPA4	Our vendors/partners are extremely important to us.	

ii. A structural framework for AI technology adoption and its influence on BEs utilizing any decision-making approach is uncommon in the literature. As a result, the proposed framework will assist company executives in efficiently using AI.

iii. The current study looks into the 34 crucial elements, which are divided into 9 primary criteria. It is a comprehensive study on the adoption of AI technologies and a one-of-a-kind study that integrates DM and BEs in the AI adoption literature. The detailed understanding and outcome of each criterion would assist industry practitioners in successfully using AI.

Table 2: *Benefit expectations realized due to adoption of AI technologies*

Code	**Benefit expectations realized as a result of AI technology adoption**	**Reference**
BE1	Improved work performance.	[81], [113]; Expert's opinion.
BE2	Increased productivity.	[83]; Expert's opinion.
BE3	Increased work effectiveness.	[84]; Expert's opinion.
BE4	Quality ensured raw inputs, services at low cost.	[84]; Expert's opinion.
BE5	Attract environmentally conscious customers.	[113], [114]; Expert's opinion.
BE6	Rise in sales and enhances after sale service.	[115]; Expert's opinion.
BE7	Decrease employment rate.	[85]; Expert's opinion.
BE8	Decrease cost of operations.	[85]; Expert's opinion.
BE9	Increased competitive advantage.	[73], [107]; Expert's opinion.

Code	Benefit expectations realized as a result of AI technology adoption	Reference
BE10	Increases efficiency and refocuses daily tasks and efforts with an emphasis on creation and creativity.	[2]; Expert's opinion.
BE11	AI can aid workplace safety, smart and sustainable production and operations.	[2]; Expert's opinion.
BE12	AI will present new opportunities and capabilities to improve the human experience.	[43], Expert's opinion.
BE13	AI can derive better business insights from the data through the process of predictive analytics.	[2]; Expert's opinion.
BE14	AI plays an essential role in telecommunications digital transformation across all verticals.	[2]; Expert's opinion.
BE15	AI can optimize of the operational support services and development of highly personalized products and services.	[2]; Expert's opinion.

iv. It is difficult to apply all of the AI technologies in an organization at the same time. As a result, the ranking of essential parameters acquired through the use of PF-AHP allows practitioners to focus on high weightage criteria for the efficient deployment of AI.

v. The ranking of BEs generated from the use of AI technologies in PF-CoCoSo enables practitioners to design an innovative action plan from the start. It reduces the probability of failure while increasing the likelihood of success with AI adoption.

vi. Adoption of AI technologies is still in its early stages in underdeveloped countries such as Vietnam. The suggested framework's empirical relevance is tested in the Vietnamese telecom industry. With certain modifications, the proposed framework will assist academicians and industrialists in other geographical regions in improving organizational performance.

Table 3: *The final ranking of sub-criteria.*

Major criteria	Relative weights	Sub-criteria	Globalize weight	Rank
Organizational readiness (ORE)	0.11268	ORE1	0.0500	5
		ORE2	0.0325	11
		ORE3	0.0383	8
		ORE4	0.0305	15
Compatibility(CPA)	0.09342	CPA1	0.0308	14
		CPA2	0.0320	12
		CPA3	0.0176	27
		CPA4	0.0312	13
Competitive pressure (CPR)	0.08932	CPR1	0.0170	28
		CPR2	0.0235	24
Complexity (CPL)	0.12312	CPL1	0.0350	10
		CPL2	0.0516	3
		CPL3	0.0502	4
		CPL4	0.0223	25
Government involvement (GIV)	0.10142	GIV1	0.0460	6
		GIV2	0.0352	9
		GIV3	0.0261	20
Managerial capability (MCP)	0.08446	MCP1	0.0111	32
		MCP2	0.0168	29

Major criteria	Relative weights	Sub-criteria	Globalize weight	Rank
		MCP3	0.0241	22
Market uncertainty (MUC)	0.09245	MUC1	0.0177	26
		MUC2	0.0249	21
		MUC3	0.0295	17
Relative advantage (RAD)	0.09543	RAD1	0.0278	18
		RAD2	0.0123	31
		RAD3	0.0304	16
		RAD4	0.0263	19
Technical capability (TCP)	0.12421	TCP1	0.0564	1
		TCP2	0.0531	2
		TCP3	0.0431	7
Vendor partnership (VPA)	0.08349	VPA1	0.0097	33
		VPA2	0.0082	34
		VPA3	0.0146	30
		VPA4	0.0240	23

Table 4: *The final ranking of BEs based on evaluation value K_i*

Code	Benefit expectations realized as a result of AI technology adoption	K_{ia}	K_{ib}	K_{ic}	K_i	Rank
BE1	Improved work performance.	0.0115	1.9997	0.1470	0.8695	15
BE2	Increased productivity.	0.0738	9.9557	0.9942	4.5775	8
BE3	Increased work effectiveness.	0.0670	9.4962	0.9029	4.3230	11
BE4	Quality ensured raw inputs, services at low cost.	0.0709	10.1684	0.9543	4.6163	7
BE5	Attract environmentally conscious customers.	0.0695	9.5775	0.9245	4.3734	10
BE6	Rise in sales and enhances after sale service.	0.0694	10.6533	0.9352	4.7729	5
BE7	Decrease employment rate.	0.0731	11.3485	0.9847	5.0724	2
BE8	Decrease cost of operations.	0.0692	10.3733	0.9323	4.6689	6
BE9	Increased competitive advantage.	0.0693	10.6602	0.9337	4.7739	4
BE10	Increases efficiency and refocuses daily tasks and efforts with an emphasis on creation and creativity.	0.0720	9.7832	0.9700	4.4917	9
BE11	AI can aid workplace safety, smart and sustainable production and operations.	0.0795	11.4210	0.9640	5.0781	1
BE12	AI will present new opportunities and capabilities to improve the human experience.	0.0708	10.6141	0.9541	4.7772	3
BE13	AI can derive better business insights from the data through the process of predictive analytics.	0.0564	8.2591	0.7608	3.7370	14
BE14	AI plays an essential role in telecommunications digital transformation across all verticals.	0.0600	8.6437	0.8093	3.9234	13
BE15	AI can optimize of the operational support services and development of highly personalized products and services.	0.0651	9.2450	0.8777	4.2076	12

7. CONCLUSIONS

This study is an early investigation of AI adoption at the organizational level, incorporating well-established theories into a novel innovation. Our research provides a foundation for future research on why and how organizations use AI. It can be used as a starting point for further study on AI adoption in various directions. This contribution figure out the importance of offering guidance and tools for investigating the topic of AI adoption. Using the limits stated, the degree of abstraction provides an overview of potential study topics. Our findings have a variety of practical consequences. First, the current study proposes that the AI adoption framework may be used effectively to assist Vietnamese firms in preparing to adopt AI and in overcoming the obstacles and challenges involved with such a process. Second, we offer assistance in overcoming the management barriers to AI adoption that have a direct impact on such acceptance. As previously noted, while the tremendous benefits of AI are recognized and accepted by organizations, worries about a lack of leadership support and a lack of clarity about which components of AI can be exploited have hampered widespread AI adoption.

As a result, it reduces the need for resource inputs and waste generation, and it encourages green development to attain sustainability in the telecom company. The current study aims to identify and assess the essential elements influencing AI technology adoption, as well as the BEs obtained as a result of its deployment. Following a review of the literature and advice from experts, 34 important criteria and 15 BEs were determined. The PF-AHP and PF-CoCoSo methods were used in this study to create a structural framework for grading the BEs resulting from the use of AI technology. Initially, the PF-AHP approach was used to calculate the relative important weight of crucial factors' influence, and critical factors were ordered based on the results. The results show that among the essential critical criteria, 'government involvements,' 'technical capability and vendor cooperation,' and 'compatibility' for AI adoption are the most important. It is followed by improved work performance, increased productivity, increased work effectiveness, quality-assured raw materials, low-cost services, attracting environmentally conscious customers, an increase in sales and improved after-sales service, a decrease in employment, a decrease in operating costs, and an increase in competitiveness. To test the robustness of the proposed framework, sensitivity analysis was undertaken.

The proposed research methodology for this study has several limits, but it can be viewed as an open door for future researchers. The suggested framework's input data for computation is based on DM panel responses, which can be subjective. Any prejudice on the part of the experts judging the important elements will influence the outcome. As a result, it is expected that the outcome will be estimated with considerable caution. The application and findings of the suggested framework in this study are limited to a single empirical case organization in Vietnam telecom enterprises. As a result, with certain modifications for generalizations of results, the suggested framework can also be extended to telecom businesses in various geographical areas. Furthermore, the findings of this study may be compared and evaluated with those of other MCDM approaches, such as Pythagorean fuzzy preference ranking organization method for enrichment of evaluations (PF-PROMETHEE), Pythagorean fuzzy vlsekriterijums kaoptimizacijai kompromisno Resenje (PF-VIKOR), Pythagorean fuzzy technique for order of preference by similarity to ideal solution (PF-

TOPSIS) and Pythagorean fuzzy elimination et choice translating reality (PF-ELECTRE).

Funding: This work was supported by the Posts and Telecommunications Institute of Technology (Grant Number: 09-HV-2022-RD_QT2.

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SỬ DỤNG QUY TRÌNH PHÂN TÍCH PHÂN TÍCH MỜ PYTHAGORE VÀ GIẢI PHÁP THỎA HIỆP TÍCH HỢP MỜ PYTHAGORE ĐỂ ĐÁNH GIÁ CÁC KỲ VỌNG VỀ LỢI ÍCH CỦA TRÍ TUỆ NHÂN TẠO TRONG KINH DOANH

Tóm tắt: Trí tuệ nhân tạo (AI) đã phát triển từ một lĩnh vực nghiên cứu thành hiện thực trong quản lý. Bằng chứng là việc sử dụng nhanh chóng công nghệ AI trong các doanh nghiệp, giúp tăng doanh thu, giảm chi phí và nâng cao hiệu quả tổ chức. Mặc dù vậy, các tổ chức khác nhau vẫn đang cân nhắc để lựa chọn có nên hay không sử dụng trí tuệ nhân tạo. Mục tiêu chính của nghiên cứu này là xác định và đánh giá những lợi ích dự kiến của việc áp dụng AI. Quy trình phân cấp phân tích mờ Pythagore (PF-AHP) và tích hợp giải pháp thỏa hiệp mờ Pythagore (PF-CoCoSo). PF-AHP tính toán trọng số tương đối của các thành phần quan trọng, trong khi PF-CoCoSo đánh giá các kỳ vọng lợi ích (BE) theo việc triển khai AI của họ. Để chứng minh khả năng ứng dụng của khung nghiên cứu đề xuất, tình huống nghiên cứu điển hình tại Tổng công ty Viễn thông Việt Nam đã được thực hiện. Các yếu tố quản trọng ảnh hưởng đến hoạt động triển khai và ứng dụng AI là "*Khả năng quản lý và các lợi thế liên quan"*, tiếp theo là *"Sự tham gia của chính phủ" "Năng lực kỹ thuật và quan hệ đối tác với nhà cung cấp để áp dụng AI"* và *"Khả năng tương thích"*. Mô hình nghiên cứu đề xuất được phát triển là nhằm hình thành phương pháp thích hợp để từng bước áp dụng tại các công ty nhằm tiếp cận và cải thiện lợi ích kỳ vọng (BE) của họ trong việc ứng dụng công nghệ AI. Tiến hành phân tích độ nhạy để đánh giá hiệu quả của mô hình nghiên cứu khuyến nghị. Những đóng góp trong nghiên cứu sẽ hỗ trợ các nhà nghiên cứu và doanh nghiệp ứng dụng, triển khai AI thông qua các đề xuất và kỹ thuật để đo lường việc áp dụng AI.

Từ khóa: Công nghệ AI, phương pháp phân tích thứ bậc (AHP), tập mờ Pytago, giải pháp thỏa hiệp kết hợp (CoCoSo)

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