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Article

Analyzing the Critical Parameters for Implementing Sustainable AI Cloud System in an IT Industry Using AHP-ISM-MICMAC Integrated Hybrid MCDM Model

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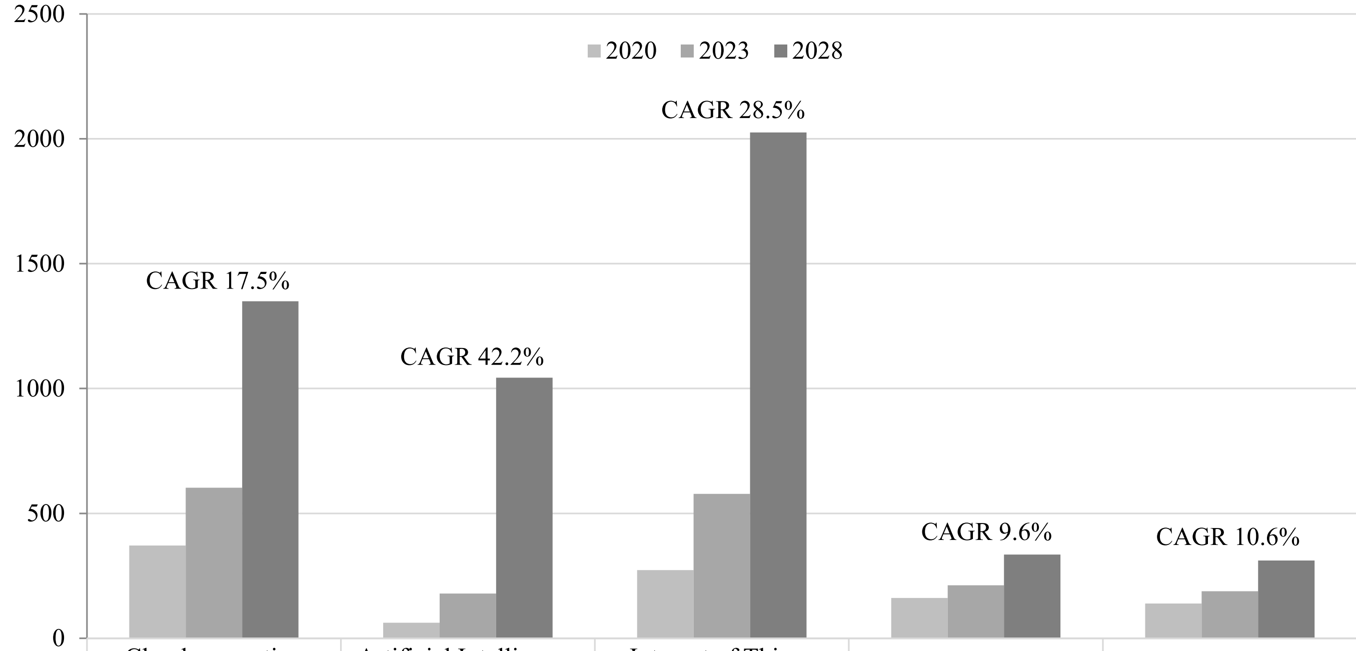
Abstract: This study aims to identify the critical parameters for implementing a sustainable artificial intelligence (AI) cloud system in the information technology industry (IT). To achieve this, an AHP-ISM-MICMAC integrated hybrid multi-criteria decision-making (MCDM) model was developed and implemented. The analytic hierarchy process (AHP) was used to determine the importance of each parameter, while interpretive structural modeling (ISM) was used to establish the interrelationships between the parameters. The cross-impact matrix multiplication applied to classification (MICMAC) analysis was employed to identify the driving and dependent parameters. A total of fifteen important parameters categorized into five major groups have been considered for this analysis from previously published works. The results showed that technological, budget, and environmental issues were the most critical parameters in implementing a sustainable AI cloud system. More specifically, the digitalization of innovative technologies is found to be the most crucial among the group from all aspects, having the highest priority degree and strong driving power. ISM reveals that all the factors are interconnected with each other and act as linkage barriers. This study provides valuable insights for IT industries looking to adopt sustainable AI cloud systems and emphasizes the need to consider environmental and economic factors in decision-making processes.

Keywords: AHP; ISM; MICMAC; MCDM; artificial intelligence; IT industry; sustainability; cloud computing barriers

MSC: 03B52; 90B50; 91B06; 62C86; 94D05; 03E72; 68T27; 68T37

1. Introduction

At present times, most businesses are completely relying on cloud computing (CC) and artificial intelligence (AI) technologies to secure and manage resources properly. With the flow of time, the demand for CC and AI technologies is reaching sky-high because every business owner wants to automate their business [1]. Organizations equipped with advanced technologies are very easy to operate; and at the same time, it also allows high flexibility and scalability. As days pass by, humans started interacting more with different technologies making them completely dependent on new innovations. The cloud computing market is expanding day by day with the goal of achieving fully automated processes and assisting in improving operations, cost reduction, and accelerating business growth [2]. According to recent reports, the global public cloud computing market size is expected to grow from USD 233.4 billion in 2019 to USD 623.3 billion by 2023, at a compound annual growth rate (CAGR) of 18% during the forecast period [3], and it is expected to reach the milestone of USD 1 trillion by 2024. According to a survey conducted by Gartner [4], 81% of organizations are using cloud infrastructure, and this number is expected to increase in the coming years. It is evident from this scenario that most companies are shifting towards digitalization and adopting innovative cloud computing technologies to sustain themselves in this present competitive market. Therefore, information technology (IT) plays an important role in properly organizing business structures and shaping future market strategies [1,2]. Figure 1 clearly illustrates the projected CAGR growth of different cloud computing technologies in the next five years up to 2028.



	Cloud computing (CC)	Artificial Intelligence (AI)	Internet of Things (IoT)	Cybersecurity (CS)	Big Data (BD)
2020	371.4	62.4	272.5	161.07	138.9
2023	602.5	179.4	578.2	212.1	187.9
2028	1349.4	1043.2	2025.8	335.4	311.0

Figure 1. Forecasted CAGR growth of IT sector over next five years. (Source: By different market research organizations).

The IT sector has experienced significant growth over the last few years, with the development of new technologies and the increasing demand for digital services. The sector is expected to continue growing as technology becomes more integrated into our daily lives [5]. Therefore, it is high time for the organization to take immense care of the factors influencing the cloud system. From these aspects, the authors have developed the idea of identifying and analyzing critical AI parameters using MCDM that act as barriers to the implementation of the cloud computing concept.

1.1. Significance of Implementing AI-Enabled Cloud System

AI-enabled cloud systems have significant implications for the IT industry. Here are some of the key ways in which AI-enabled cloud systems are transforming the IT industry [6].

Cost efficiency: Cloud systems enable IT departments to reduce infrastructure and maintenance costs by eliminating the need for on-premises hardware, software, and maintenance. This frees up resources to focus on more strategic initiatives and business growth [7,8].

Scalability: Cloud systems can quickly scale up or down depending on changing business needs. This means companies can respond to changes in demand, usage, and traffic without the need for significant investment in hardware or infrastructure [8].

Flexibility: Cloud systems allow IT departments to deploy and manage applications across multiple environments, including public, private, and hybrid clouds. This offers flexibility in terms of where and how applications are deployed and managed [7,9].

Collaboration: Cloud systems make it easier for teams to work together, share resources, and collaborate on projects, regardless of their location. This improves productivity, communication, and teamwork [8,10].

Security: Cloud systems provide enhanced security features, such as automatic backups, disaster recovery, and encryption. This helps to protect sensitive data and information from unauthorized access or attacks [9,10].

Performance: AI-enabled cloud systems can provide real-time insights and analytics, enabling companies to identify and respond to issues faster than traditional IT systems [7,11].

Innovation: AI-enabled cloud systems are opening up new avenues for innovation, such as the development of advanced algorithms and machine learning models, as well as the ability to integrate with other emerging technologies such as the Internet of Things (IoT) [9,11].

Overall, AI-enabled cloud systems are transforming the IT industries by enabling companies to be more agile, innovative, and efficient, while also improving their ability to manage and secure their IT infrastructure. The stated benefits are so compelling that it inspires the companies to adopt innovative technologies and relish the essence of the Industry 4.0 (I4.0) concept [12,13]. Implementing advanced cloud computing systems within an organization is often considered a critical task to execute. There are numerous factors associated with the cloud concept that need to be examined properly or else it may have a reverse impact on the company's reputation, and the business may suffer huge losses. The following reasons highly motivate the authors to come up with an idea of examining the critical AI factors that vastly influence the cloud computing environment within the IT industry. Due to this fact, the authors have raised three research questions and intend to properly answer all three questions within the context.

(1) Which are the most significant and least sustainable AI factors that highly affect an IT environment?
(2) How are the chosen AI factors interrelated to each other?
(3) How are the chosen factors performed in terms of interdependency?

To address all the research questions raised above, the authors set three objectives that need to be fulfilled to achieve the goal of this research. The objectives can be stated as follows.

(1) To identify the most critical sustainable AI parameters that highly affect the cloud environment within the IT industry.
(2) To study the interrelationship bonding that exists among the selected factors.
(3) To examine the driver and driving performance of the chosen factors.

1.2. Importance of Sustainability in Cloud Computing

Sustainability in cloud computing refers to the adoption of environmentally sustainable practices in the design, deployment, and management of cloud computing systems [14]. Cloud computing is a technology that enables organizations to use shared computing resources, such as servers, storage, and networking, over the Internet, rather than relying on local infrastructure. While cloud computing offers many benefits, such as increased efficiency, scalability, and cost savings, it also has significant environmental impacts, including energy consumption, carbon emissions, and electronic waste [15–17]. Sustainability is important in cloud computing for several reasons.

Environmental Impact: Cloud computing has a significant environmental impact due to the energy consumption, carbon emissions, and electronic waste generated by data centers. By promoting sustainability in cloud computing, we can reduce these negative impacts and contribute to a more sustainable future [16].

- Resource Efficiency: Sustainability in cloud computing promotes resource efficiency by optimizing the use of shared computing resources. This can result in lower energy consumption, reduced carbon emissions, and less electronic waste [15,16].
- Cost Savings: Sustainable practices in cloud computing can result in cost savings for cloud providers and end-users. For example, energy-efficient hardware and cooling systems can reduce energy consumption and lower operating costs, while recycling and reusing hardware can reduce electronic waste and lower replacement costs [15].
- Social Responsibility: Promoting sustainability in cloud computing is a social responsibility for cloud providers, as it shows their commitment to reducing their environmental impact and contributing to a more sustainable future. This can improve their reputation and brand image among environmentally conscious customers [17].
- Regulatory Compliance: Many countries and regions have regulations and standards related to environmental sustainability. By promoting sustainability in cloud computing, cloud providers can comply with these regulations and avoid potential legal or financial penalties [15].

Sustainability is important in cloud computing because it can help to reduce the negative environmental impacts, promote resource efficiency and cost savings, demonstrate social responsibility and comply with regulatory requirements. As a result, environmental-related factors are also considered along with other factors in this ongoing research to promote sustainability in cloud computing [18].

1.3. Role of AHP-ISM-MICMAC for Evaluation of Crucial Parameters

MCDM is a method used to evaluate and compare different options based on multiple criteria or factors. It is an essential tool for decision-makers when dealing with complex and challenging decisions that involve a variety of factors and may be difficult to compare. MCDM helps decision-makers to make well-informed decisions by systematically evaluating all the relevant factors or criteria involved in a decision. It ensures that no important factors are left out, and all the alternatives are considered. MCDM also allows for a transparent decision-making process by clearly outlining the factors and criteria used in the decision-making process [11]. This transparency ensures that the decision-making process is fair and unbiased. MCDM identifies the best option or alternative by weighing the pros and cons of each alternative based on multiple criteria. This ensures that the option selected is the most suitable and the most feasible. Furthermore, MCDM aids in engaging stakeholders by involving them in the decision-making process. It allows them to provide input into the criteria used to evaluate alternatives, and it helps to build consensus around the final decision [19]. MCDM reduces the risk of making a wrong decision by considering multiple criteria and alternatives. This helps to identify the potential risks and drawbacks of each option and select the one that minimizes these risks. Therefore, it can be summarized from the following points that MCDM is the most suitable optimization technique that effectively deals with challenging situations involving several conflicting parameters associated with a problem. It helps to make well-informed, transparent, and fair decisions [20]. Three MCDM techniques, namely AHP-ISM-MICMAC have been adopted in this research article to investigate the 15 parameters. The three chosen MCDM models have some significant features that make these tools superior and preferable over other MCDM methodologies.

The implementation of a sustainable AI cloud system in the IT industry requires the consideration of several critical parameters [21]. To analyze these parameters, an integrated hybrid MCDM model using AHP-ISM-MICMAC can be employed. AHP [22] is a method used to prioritize and compare different criteria and alternatives in decision-making processes. It helps to break down complex decisions into smaller, more manageable ones by structuring the decision problem hierarchically. AHP provides a structured approach to decision-making by breaking down complex problems into smaller components and systematically evaluating each component. It is a flexible and transparent technique that can be used to evaluate different criteria or alternatives. AHP helps decision-makers identify inconsistencies in their thinking and decision-making, promoting consistency and reducing the likelihood of making biased or irrational decisions. It also allows decision-makers to integrate both subjective and objective criteria into the decision-making process, ensuring that all relevant factors are considered [23]. In the context of sustainable AI cloud systems, AHP can be used to identify and prioritize critical parameters such as energy efficiency, resource utilization, and data security.

ISM is a technique used to analyze and model complex systems. It can be used to understand the relationships between different parameters and their relative importance in a system. ISM can help to clarify the relationships between different components of a system and to identify the underlying structure of that system [20]. This can make it easier to understand and communicate about complex systems. ISM helps in constructing a hierarchical structure within a system, which can be useful for prioritizing actions or making decisions. By understanding the relationships between different components, it is possible to identify which components are most important and which ones are less critical. Strategic planning can be conducted using ISM, which helps in identifying key drivers and dependencies within a system [24]. It is possible to identify opportunities and threats, which help in developing strategies that are more likely to succeed. ISM is a collaborative process that involves stakeholders from different parts of an organization. It is possible to develop a more comprehensive understanding of a system by involving a range of perspectives [12,23]. Moreover, ISM is a flexible technique that can be adapted to suit different contexts and purposes. It can be used in a variety of settings, from small-scale projects to large-scale organizational change initiatives. In the context of sustainable AI cloud systems, ISM can be used to analyze the causal relationships between different parameters and identify the key drivers of sustainable AI cloud systems.

MICMAC is a method used to analyze the interdependence and influence of different parameters in a system. MICMAC helps to identify the most important criteria in a decision problem by analyzing the relationships and interdependencies between the criteria. It provides a deeper understanding of the causal relationships between the criteria in a decision problem [20,24]. This helps decision-makers to identify the key drivers of the problem and develop effective strategies to address them. MICMAC is particularly useful for dealing with complex decision problems that involve multiple criteria and interdependencies between them. In the context of sustainable AI cloud systems, MICMAC can be used to identify the direct and indirect impacts of different parameters and their relative importance in the system.

However, every MCDM technique also has some limitations. All three adopted methods AHP, ISM, and MICMAC are qualitative methods and rely on expert judgment, which may introduce biases or inconsistencies in the analysis. It is also time-consuming and may require a significant amount of effort to collect and analyze the data. Despite having some weaknesses, the stated significances of each tool are so convincing that the authors are bound to adopt these three techniques for examining the ongoing analysis. Hence, a comprehensive analysis of the critical parameters for implementing sustainable

AI cloud systems in the IT industry can be conducted by integrating these three methods: AHP–ISM–MICMAC. The results of this analysis can then be used to develop a sustainable AI cloud system that maximizes energy efficiency, resource utilization, and data security while minimizing environmental impact. The AHP–ISM–MICMAC integrated hybrid MCDM model is a useful tool for decision-makers in the IT industry who are looking to implement sustainable AI cloud systems. It provides a structured approach to identify and prioritize critical parameters and helps to ensure that the resulting system is sustainable, efficient, and secure.

2. Literature Review

MCDM is a field of research that deals with decision-making problems involving multiple criteria. The use of MCDM methods has become increasingly popular in various fields, including engineering [24,25], management [18], finance [26], and healthcare [27]. This literature review aims to provide an overview of the MCDM literature, including its history, theoretical foundations, and applications. The history of MCDM can be traced back to the 1960s when researchers began to develop methods for solving decision-making problems with multiple criteria. One of the earliest methods was the AHP developed by Thomas Saaty in 1970 [22]. AHP is a popular MCDM method that allows decision-makers to prioritize criteria and alternatives based on pairwise comparisons. Over the years, many other MCDM methods have been developed, including the technique for order preference by similarity to ideal solution (TOPSIS) [5,28], the preference ranking organization method for enrichment evaluation (PROMETHEE) [29], the simple additive weighting (SAW) [30] method, etc. MCDM methods have been applied to a wide range of decision-making problems, including project selection [26], supplier selection [20], portfolio management [26], and risk management [14]. In the field of engineering, MCDM methods have been used to select the best design alternatives for complex systems, such as power plants and transportation networks [16,20]. In management, MCDM methods have been used to evaluate and select investment projects, as well as to assess the performance of employees and teams [28]. In healthcare, MCDM methods have been used to evaluate the effectiveness of medical treatments and to allocate resources to hospitals and clinics [27].

In recent years, researchers have developed new MCDM methods and improved existing ones. For example, the use of fuzzy logic and neural networks has been integrated into MCDM methods to handle uncertainty and imprecision in decision-making problems. Additionally, researchers have developed new MCDM methods that are more computationally efficient and easier to use. MCDM is a valuable tool for decision-makers facing complex problems involving multiple criteria. The field of MCDM continues to evolve, with new methods and applications being developed. As such, MCDM is likely to play an increasingly important role in decision-making in various fields [31]. However, the authors have identified some of the crucial applications of MCDM in a broad variety of fields as discussed further. While conducting the research, the authors have followed more than 150 articles in this field addressing the analysis of critical AI parameters for various purposes, but it is not possible to refer to each research paper. Therefore, some of the significant MCDM applications are hereby presented with the goal of deriving the research gaps from the recorded published works. Scopus and Web of Science (WoS) databases are mainly utilized for obtaining access to numerous research articles. The best quality articles published in high impact factor (IF) peer-reviewed international journals indexed in Scopus and WoS are mainly followed and referred to in this article. Some of the keywords used to search the databases are “sustainable cloud computing”, “critical AI parameters”, “hybrid MCDM”, “role of MCDM in cloud computing”, “industry 4.0”, “AHP-ISM-MICMAC applications”, “cloud computing barriers”, etc. Searching these keywords resulted in 36,000 (approx.) published results in the ScienceDirect database. The author(s) mainly followed reputed databases from internationally acclaimed publishers like Elsevier, Springer, Wiley, Emerald, Sage, Taylor & Francis, etc. Among the massive list of published articles, the authors sorted around 450 articles based on the core theme of cloud computing. Afterward, the authors eliminated some of the perplexed and irrelevant papers from the list. Later, subsequent numbers of filters have been applied to trim the list further addressing the article themes as "applications of MCDM techniques in cloud computing field", "the sustainability in cloud computing", "applications of AHP-ISM-MICMAC" and "investigation of critical parameters in cloud computing". Finally, around 150 articles have been sorted out and studied properly to identify the crucial parameters that most influence the cloud environment within an industry. However, research papers published in reputable journals with high IF and most relatable to the ongoing research theme are only used in this article. Here are some of the published works highlighting the applicability of various MCDM tools mainly AHP, ISM, and MICMAC in different sectors for analyzing the influential AI factors and promoting sustainability in cloud computing.

2.1. Related Published Works

The increasing popularity of cloud computing has led to a growing demand for sustainable cloud systems. Sustainable AI cloud systems have been introduced to address this issue. These systems aim to provide sustainable cloud computing services while reducing the environmental impact. MCDM is a popular decision-making technique that uses a hierarchical structure to break down complex problems into smaller, more manageable sub-problems. It enables decision-makers to evaluate and prioritize criteria based on their relative importance. This method has been applied in sustainable AI cloud systems to assess the environmental sustainability of cloud computing services [32]. The related published works have been categorized into two further sub-sections highlighting the application of MCDM in diverse areas for analyzing critical parameters and the role of MCDM in promoting sustainability issues. Table 1 also summarizes some of the previous works potentially carried out using different MCDM techniques.

Table 1. Summary of the literature review.

Reference	Tools used	No. of Critical Factors	Area of Application
Sharma et al. [33]	AHP–ISM–MICMAC	28	Supply chain management in manufacturing firm
Kumar and Rahman [34]	ISM–MICMAC–AHP	15	Supply chain management in Indian manufacturing industries
Singh et al. [35]	ISM–MICMAC	12	Green lean practices in Indian manufacturing industries
Singh and Bhanot [36]	DEMATEL–MMDE	10	IoT barriers
Khaba and Bhar [37]	AHP-ISM–SEM	14	Indian mining industry
Khaba et al. [38]	AHP-ISM–SEM	10	Indian mining industry
Sharma et al. [39]	AHP–DEMATEL–ISM	21	Blockchain technology in tourism and hospitality sectors
Duleba et al. [40]	AHP–ISM	24	Public transport systems
Song et al. [41]	AHP–ISM	21	Urban rail transit
Zhang and Yang [42]	ANP, F-TOPSIS	5	Environmental sustainability of big data centers
Rajput and Singh [43]	PCA–DEMATEL–ISM	20	IoT enablers for industry 4.0

Source: Author's own elaboration.

2.1.1. MCDM Applications in Diverse Areas for Examining Critical Parameters

MCDM has been serving as an effective tool in taking efficient judgments for the last few decades. It has been adopted by numerous researchers to achieve various decision-making goals including, ranking prioritization of alternatives, evaluation of lean enablers in green supply chain, assessment of CC and IoT barriers in manufacturing industries, exploring key factors in mining and transportation industries, risk assessment, etc. Here are some of the important applications of different MCDM tools in a wide variety of areas.

Sharma et al. [33] conducted a case study of a manufacturing firm investigating the lean enablers associated with supply chain management (SCM). Initially, they identified 28 leans enablers, which were further filtered using AHP selecting only the top 20 for the analysis according to the global weights. ISM helps to construct the interrelationship hierarchy tree defining the level of each factor, whereas MICMAC helps to evaluate the driving and dependence power of each parameter. Finally, they conclude that the Kanban system, total quality management (TQM), and commitment of top management have the maximum contribution towards lean SCM. Most often, AHP, ISM, and MICMAC are also used to evaluate sustainable supply chain enablers for promoting green SCM. For example, Kumar and Rahman [34] evaluated 15 sustainable factors in SCM using ISM–MICMAC–AHP powered by fuzzy logic to develop an eco-friendly environment. From the context of Indian manufacturing industries, another MCDM framework established by Singh et al. [35] studied twelve critical parameters using the ISM–MICMAC approach and identified two significant factors that mostly influence the implementation of green lean practices in Indian manufacturing industries. Another application to the manufacturing industry by Singh and Bhanot [36] highlights the assessment of 10 potential IoT barriers using an integrated DEMATEL–MMDE (maximum mean de-entropy)–ISM MCDM model.

Khaba and Bhar [37] applied the hybrid model of AHP-ISM to an Indian mining industry for investigating 14 key barriers related to the implementation of the lean concept. Financial and economic restrictions, inadequacy in top management decisions, and absence of cooperation among the inter-departments have been identified as the critical barriers behind lean implementation in the coal mining industry. Following the previous investigation, Khaba et al. [38] further conducted one similar experiment on lean implementation in an Indian mining industry using the same AHP–ISM models considering alternate 10 barriers. This time they found out that top management support, financial performance, motivation, and empowerment of employees were the key lean enablers in the mining industry. However, in both cases, they applied structural equation modeling (SEM) to validate the questionnaire survey used in ISM analysis.

Sharma et al. [39] took the assistance of a hybrid model combining AHP–DEMATEL–ISM together for exploring the drivers and barriers of establishing blockchain technology in the tourism and hospitality sectors. They applied the concept to two geographical locations namely, India and Netherlands, and ultimately conclude the key drivers to be “low cost” and “risk management”. Duleba et al. [40] analyzed 24 crucial factors connected to public transport systems using the concept of AHP–ISM. They found out that “need to transfer” is the most vital criterion and occupies the lowest level in the ISM hierarchy tree that mostly influences other factors directly or indirectly. In another study, Song et al. [41] used AHP–ISM to assess 21 critical urban rail transit factors for promoting sustainable development in cities and assuring safety operations. The five-layered structure clearly signifies that the two management factors in the lowest level influence all other factors above their levels.

2.1.2. Role of MCDM for Promoting Sustainability in Cloud Computing

One study by Zhang and Yang [42] used the analytic network process (ANP) and fuzzy TOPSIS (F-TOPSIS) to evaluate the environmental sustainability of big data centers. The authors carried out the experiment on five critical factors whose relative importance is determined using ANP and F-TOPSIS helps to rate three alternative options. The results showed that carbon footprint, waste heat utilization, and refrigeration system are some of the critical factors that most affect the energy consumption of cloud data centers. Rajput and Singh [43] analyzed 20 essential IoT enablers for Industry 4.0 using an integrated PCA-DEMATEL-ISM approach, where principal component analysis (PCA) is used for cluster formation, DEMATEL is used to study the cause–effect relationship that exists among the factors, and ISM is to define the hierarchical levels. The result concludes that IoT big data and IoT ecosystem are the key Industry 4.0 IoT enablers. Yang et al. [44] conducted a parametric analysis of cloud application services in Taiwan using fused DEMATEL and ANP methods. They conclude that software characteristics factors need special attention for their improvement to prioritize software performance level. Oke et al. [45] investigated CC barriers using exploratory factor analysis (EFA) and partial least square (PLS)-SEM for developing a sustainable construction environment and concluded that social barriers are the most challenging ones. Omer [46] further considered a case study on sustainable construction to analyze 11 CC barriers under a fuzzy environment.

Apart from these, Garg [47] developed a new MCDM framework based on fuzzy Euclidean and Taxicab distances and applied it to an academic organization for the selection of suitable cloud deployment models among four alternative choices based on seventeen sub-factors categorized into three main groups. Yoo and Kim [48] developed an MCDM model consisting of AHP and Delphi to assess twenty-three attributes based on seven parameters for establishing a sustainable CC environment. The exploration of the problem has been executed from both demander and provider perspectives. However, the result reveals that internal pressure and interoperability are the key factors that highly influence the employment of sustainable computing factors. A combined model of fuzzy decision-making trial and evaluation laboratory (F-DEMATEL) and interval-valued additive ratio assessment (IV-ARAS) has been established by Gadekar et al. [14] for evaluating the risk assessment during the implementation of sustainable I4.0. They carried out the analysis based on 16 I4.0 key performance parameters and 6 risk alternatives for implementing the sustainable I4.0 concept. The result reveals that prediction capability and IT infrastructure are the most prominent ones among the 16 chosen factors, whereas the chances of social and technological risks are found to be the maximum among the 6 alternative risks.

2.1.3. Research Gaps and Novelty

It is evident from the past literature that MCDM has been utilized for various purposes in different industries including manufacturing, construction, transportation, mining, hospitality, tourism, etc. Moreover, MCDM also plays an important role in achieving the CC goals towards sustainability. Although many works have been conducted on MCDM assessment of critical CC parameters, most of those studies are particularly dedicated to sectors like manufacturing, mining, transportation, etc., other than the IT industry. It has been noticed that very few times researchers have considered the case study of an IT industry involving the critical parameters analysis using MCDM for setting up a sustainable cloud system within the organization. Therefore, exploring barriers using MCDM approaches for setting up a cloud system in the IT industry is a novel contribution to the field. Moreover, it has been noticed that AHP–ISM–MICMAC were very rarely applied together for addressing any parametric evaluation problems. Additionally, there are very limited works recorded in the databases addressing the sustainability issues in cloud computing. The green and sustainable concept in cloud computing is an uprising and unique concept at present times. Thus, this article is an original contribution exploring the sustainable AI parameters in IT industries using an integrated AHP–ISM–MICMAC hybrid MCDM system that happens for the first time.

2.2. Brainstorming Sessions with the Panel Board Members

A committee of thirty expert members from various fields has been formed and divided into three teams containing ten members in each team. The committee members have vast expertise and knowledge of their own profession. While establishing the committee, one eligibility criterion has been set by the authors that all the expert members should have a minimum of 10 years of experience. For taking effective decisions based on practical knowledge the personnel having experience of more than 10 years are only selected. Therefore, all the board members are highly experienced. Each detail of the committee members, e.g., experience, profession, designation, etc., is provided in Table 2. After a systematic and in-depth study of some past published works in the field, several brainstorming stages have been conducted to recognize sustainable cloud computing parameters. In conclusion, the panel experts have finalized the 15 most crucial factors closely related to AI and CC technologies. The first step is to identify most of the possible barriers directly or indirectly associated with cloud computing implementation from the previous research. Initially, the expert members made a list containing 30 associated AI factors that were considered by the previous researchers in their studies. The list is further filtered in the second stage by eliminating some unnecessary weak factors. However, it is not possible to consider all the factors for computational analysis, because the calculation will become complex and difficult to execute. Therefore, for the sake of easiness in the mathematical calculation, the committee members ultimately sorted out the 15 most important AI factors from the list which are finally considered for the analysis. The 15 factors have been further categorized into five broad areas presented in Table 3. The main goal of this research is to examine the 15 factors with the help of the AHP–ISM–MICMAC hybrid MCDM model and identify the strongest, weakest, influential, and dependent parameters among the lists. The 15 potential parameters identified by the experts after thoroughly studying the previous literature can be described as follows.

- Direct cost involved and budget (SF 1): This parameter refers to the total capital cost associated with setting up a cloud environment. It is one of the important barriers that may obstruct CC implementation [7,8,15,17].
- Funding from external bodies (SF 2): Installing advanced CC technologies in an industry is very expensive in nature; in that case, funding or loans may be required from other organizations and banks [7,8].
- Inferred or indirect cost (SF 3): Recruitment of skilled professional staff having sound IT knowledge is required to properly handle and manage the cloud system. Therefore, indirect cost refers to the monthly salaries of the staff, maintenance cost, overhead and administrative expenses [15,17].
- Environmental optimization and management (SF 4): Environmental optimization and management refers to the process of improving and managing the environmental performance of a company or organization. This can involve reducing the environmental impact of operations, minimizing waste, reducing carbon emissions, and ensuring compliance with environmental regulations [49,50].
- Sustainability (SF 5): Sustainability has become an increasingly important issue in recent years, as people have become more aware of the environmental and social impacts of economic development. Governments, businesses, and individuals are now working to incorporate sustainability into their decision-making processes, and to create more sustainable systems and practices [42,45,51,52].
- Focus on social aspects (SF 6): Social sustainability involves promoting cultural diversity and heritage and preserving traditional knowledge and practices. This helps to create a sense of identity and belonging for communities and promotes a rich and diverse cultural heritage for future generations [12–15].
- Tendency of user to learn (SF 7): Implementing the CC system requires knowledgeable and skilled staff that can manage and coordinate the whole system. The employees need to continuously learn new things and stay updated with the technology's growth and gradation [53].
- Collaboration with R&D sectors (SF 8): Collaboration between the R&D sector and the cloud computing industry is crucial for advancing cloud technology and driving innovation. It can lead to new breakthroughs, drive innovation, and ensure that cloud technology is meeting the needs of customers and industries [54,55].
- Training and skill development program (SF 9): Employees and staff should be given proper training to operate and manage a cloud system. Companies should organize skill development programs for the employees to keep them updated with the technology advancements and share proper knowledge about new inventions [51,56].
- Aesthetic values (SF 10): Aesthetic values in cloud computing can refer to several aspects of the technology, including its design, user interface, and overall user expe-

rience. Aesthetic values in cloud computing can play a significant role in how users perceive and interact with the technology, as well as in promoting values such as sustainability and user-centered design [42,57,58].

- Interactive information usage (SF 11): Interactive information usage in cloud computing refers to the ability of users to access, manipulate, and share information stored in the cloud in a collaborative and interactive manner. Interactive information usage in cloud computing can significantly enhance collaboration, productivity, and decision-making, enabling users to access, manipulate and share information more effectively and efficiently [59,60].
- Digitalization of innovative technologies (SF 12): Digitalization of innovative technologies in cloud computing refers to the integration of cutting-edge technologies into cloud computing platforms and services. Digitalization of innovative technologies in cloud computing can significantly enhance the performance and functionality of cloud computing platforms and services. This integration can also lead to the development of new applications and services that were not possible before [61,62].
- Leadership and teamwork (SF 13): Leadership and teamwork are essential components of successful cloud computing projects. Effective leadership can help ensure that projects are completed on time, within budget, and meet the objectives of the organization [49,51].
- Exchange of information (SF 14): Exchange of information is a critical component of cloud computing. Cloud computing enables users to store and access data from anywhere, making it possible to exchange information with others quickly and efficiently. The information exchange in cloud computing enables users to collaborate and share data very easily. By leveraging the capabilities of cloud computing platforms, users can exchange information in real time, making it possible to work together more effectively [36,63].
- Governance of employees (SF 15): Governance of employees in cloud computing refers to the policies, procedures, and controls that organizations put in place to ensure that their employees use cloud computing services in a secure and compliant manner. Governance is essential in cloud computing to mitigate risks such as data breaches, compliance violations, and unauthorized access [64,65].

Table 2. Details of the panel board members.

No of Expert Members	Professional Field	Designation	Experience
	Decision team 1		
1	Manufacturing industry	General manager	20
1	Academician	Research project supervisor	25
4	IT professional	Cloud engineer	15
4	Research institute	Scientist	25
	Decision team 2		
1	IT professional	Technical lead	12
4	University	Professor	22
1	Health sector	Chief medical officer	25
2	IT professional	Data analyst	11
2	IT professional	Project head	20

Table 2. *Cont.*

No of Expert Members	Professional Field	Designation	Experience
Decision team 3			
2	IT professional	Chief digital officer	13
1	Building construction sector	Manager	15
1	Transportation sector	Vice president	18
2	IT professional	Software developer	12
3	IT professional	Data scientist	17
1	IT professional	Senior programmer	15

Source: Author's own elaboration.

Table 3. List of main factors and sub-factors.

Main Factor (MF)	Indicators	Sub Factor (SF)	Indicators
MF 1 Budget Issues	BI	Direct cost involved and budget	SF 1
		Funding from external bodies	SF 2
		Inferred or indirect cost	SF 3
MF 2 Environmental Issues	EI	Environmental optimization and management	SF 4
		Sustainability	SF 5
		Focus on social aspects	SF 6
MF 3 Learning Issues	LI	Tendency of user to learn	SF 7
		Collaboration with R&D sectors	SF 8
		Training and skill development program	SF 9
MF 4 Technological Issues	TI	Aesthetic values	SF 10
		Interactive information usage	SF 11
		Digitalization of innovative technologies	SF 12
MF 5 Organizational Issues	OI	Leadership and teamwork	SF 13
		Exchange of information	SF 14
		Governance of employees	SF 15

Source: Interpreted by the expert team members.

3. Theoretical Framework

This section clearly draws a complete outline of the stated problem step by step. All three applied methods are explained clearly. It also shows how the overall MCDM model is developed from the beginning and helps to meet the objectives. However, before moving into the methodologies let us first formulate the initial stage of the analysis. All the steps are elaborately explained to show the phase-wise steady buildup of the whole decision-making process. The flow diagram shown in Figure 2 portrays the complete framework of the hybrid system.

Step 1: The first and foremost step is to form a panel of expert members for making appropriate judgments and put their opinions on different aspects of the ongoing MCDM analysis. In this present case, a board of thirty members has been formed which is further divided into three teams consisting of ten experts in each team. These three teams provided their own views and opinions about the pair-wise comparison matrix in the case of AHP [66]. During the making of the pair-wise comparison judgments for the AHP process [22], experts are only allowed to meet with their own team members. Each of the three teams should provide their pair-wise comparison judgments after discussing with their own team members only; there is no connection and linkage among the three teams. Hence, in AHP there will be three pair-wise comparison matrices for each case, i.e., main criteria and sub-criteria. The decisions taken by each group are completely kept anonymous from the other groups as well. This will reduce the chances of biasedness to some extent.

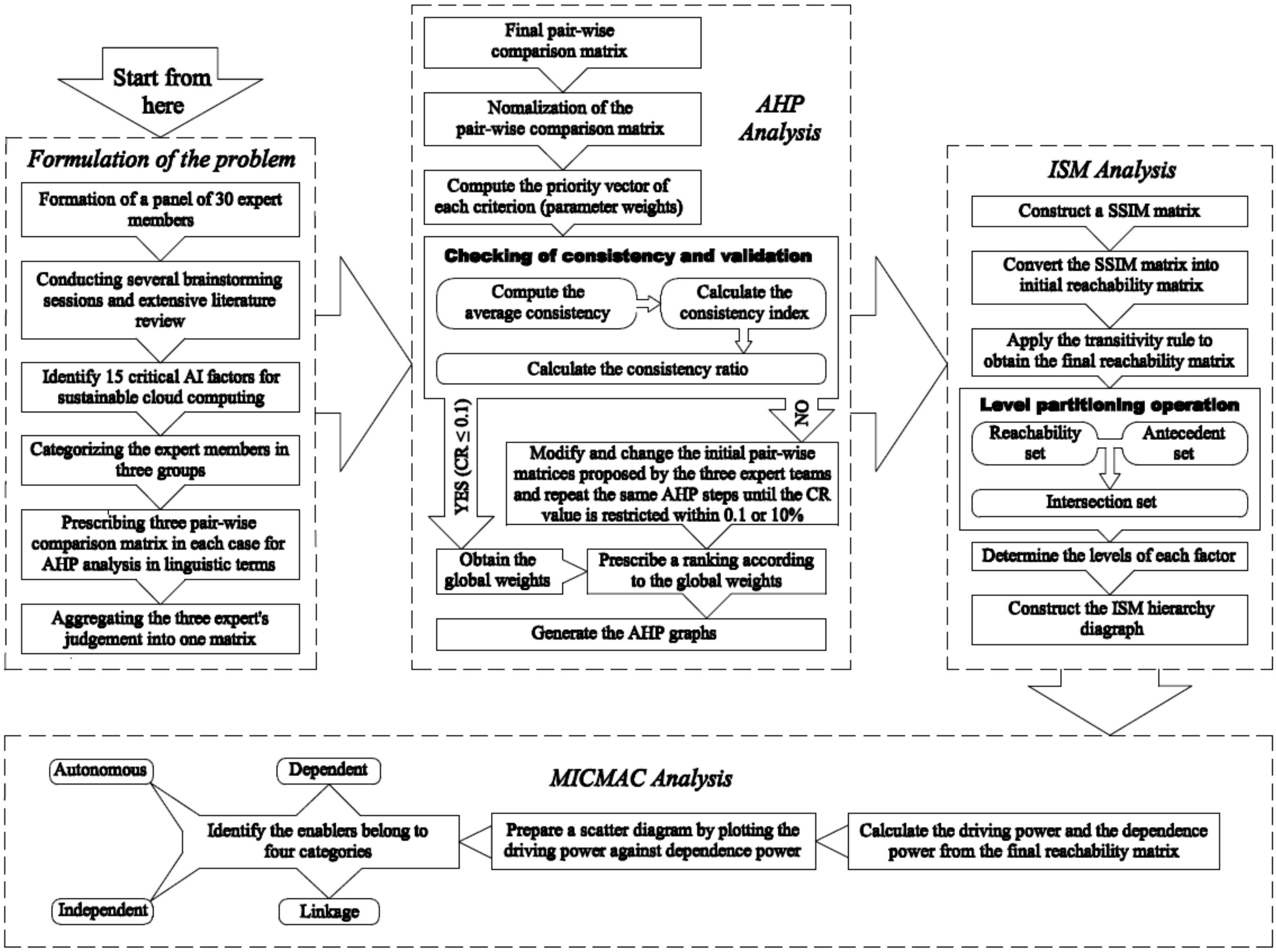


Figure 2. Hierarchy flow diagram of the complete MCDM analysis. (Source: Author's own elaboration; Created using AutoCad 2007).

Step 2: The next responsibility of the board members is to identify the most important parameters. After having a massive brainstorming session, the expert members sort out all the parameters associated with the cloud system. Since the decision-makers are highly experienced professionals having high knowledge and expertise in the field, they identified 15 critical parameters from the list shown in Table 3 that mostly influences the cloud infrastructure. The 15 factors are further categorized into 5 major groups shown in Figure 3. All the factors and sub-factors considered for this analysis are depicted with the help of a diagram in Figure 3.

Step 3: After sorting out all the critical factors associated with the cloud architecture, the three tools, i.e., AHP, ISM, and MICMAC are applied to study the interrelationship that exists among the factors. AHP is used to measure the importance of each criterion, whereas ISM and MICMAC are used to examine the driving and dependence power of each criterion [33,40,41]. The steps of each adopted technique are explained thoroughly in the following sub-sections.

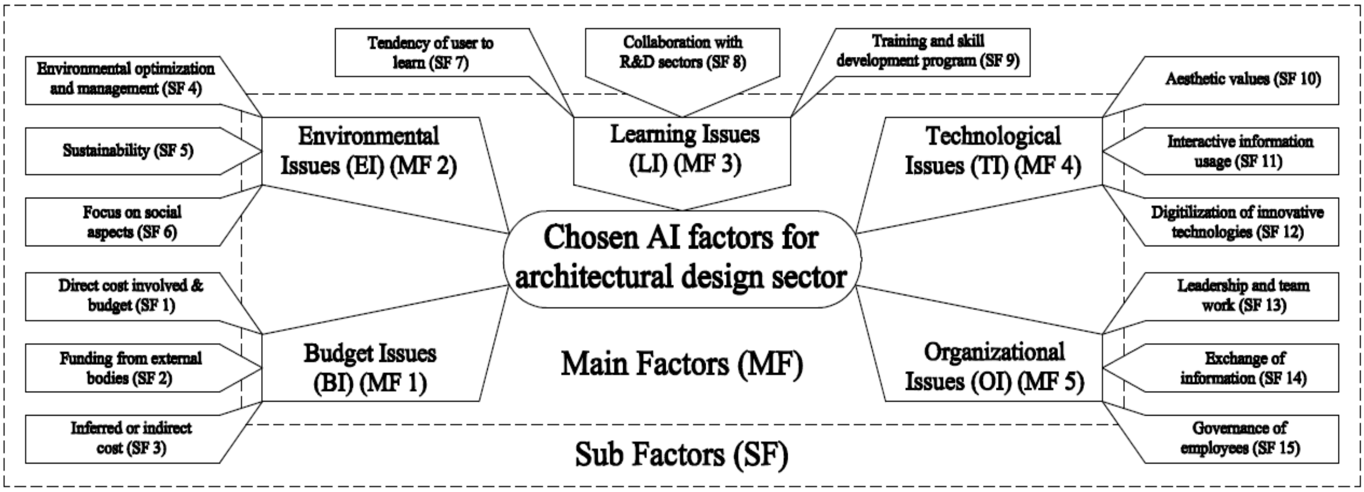


Figure 3. Classification of the main parameters and sub-parameters group. (Source: Author's own elaboration; Created using AutoCad 2007).

3.1. Analytic Hierarchy Process (AHP)

AHP was invented by Thomas. L. Saaty in 1970s [22]. AHP deals with pair-wise comparisons of the factors linked with the associated problem. In AHP, all the considered factors are compared with each other following the Saaty linguistic scale shown in Table 4. The linguistic scale helps to identify the degree of importance of each factor over other factors. AHP also allows decision-makers to check the consistency of their judgment by computing the consistency ratio (CR). AHP is a very simple and easy to understand method utilized to measure the parametric weights, which ultimately signifies the importance of each factor. Saaty [22] proposed the following steps that may be applied to execute the AHP analysis.

Table 4. Linguistic scale and RI values.

RI Values				Linguistic Scale		
n	**RI**	**n**	**RI**	**Qualitative Terms**	**Notations**	**Quantitative Scale**
1	0	8	1.41	Same importance	SI	1
2	0	9	1.45	Moderate importance	MI	2
3	0.58	10	1.49	Adequate importance	AI	3
4	0.9	11	1.51	Importance	I	5
5	1.12	12	1.58	High importance	HI	7
6	1.24	7	1.32	Very high importance	VHI	8
				Extreme importance	EI	9

Source: Saaty, 1980; Author's own elaboration.

Step 1: Create a pair-wise comparison matrix ($n_i \times n_j$) according to Equation (1) in Table 5. "n" is the total number of parameters considered for the pair-wise comparison and "p_{ij}" symbolizes the decision elements of the main criteria pair-wise matrix illustrated in Table 6.

$$P\ (n_i \times n_j) = \begin{bmatrix} p_{11}\ p_{12} \cdots p_{1j} \\ p_{21}\ p_{22} \cdots p_{2j} \\ \cdots\ \cdots \cdots \cdots \\ p_{i1}\ \ p_{i2}\ \cdots\ p_{ij} \end{bmatrix} \quad (1)$$

Step 2: Obtain the normalized values (N_{ij}) using Equation (2) in Table 7.

$$N_{ij} = \frac{p_{ij}}{\sum_{i=1}^{n} p_{ij}} \tag{2}$$

Step 3: The priority vector (w_j) of each criterion is computed using Equation (3). These priority vectors are nothing but the weights of the factors. The weights of the main factors are presented in Table 8.

$$w_j = \frac{\sum_{j=1}^{n} N_{ij}}{n} \tag{3}$$

Step 4: The final step is to check the consistency of the pair-wise comparison matrix shown in Table 8. This step involves two stages, one is to calculate the consistency index (CI) and the other one is to find the consistency ratio (CR). CI and CR can be calculated using Equation (4) and Equation (5), respectively. CR value is used to make a judgment about whether the pair-wise matrix is consistent or not. The maximum permissible limit of CR is 0.1, i.e., 10%. If the CR value lies within the limit CR $\leq$ 0.1 or 10% then the three expert team's qualitative judgment provided in Table 5 for the main criteria comparison may be accepted as consistent. Similarly, CR > 0.1 signifies an inconsistent pair-wise matrix; in such case, the expert opinions need to be altered and the pair-wise matrix requires modification until the CR value restricts itself within the allowable range of 0.1.

$$CI = \frac{(\lambda_{max} - n)}{(n - 1)} \tag{4}$$

$$CR = \frac{CI}{RI} \tag{5}$$

"RI" represents the randomly generated index, whose values can be obtained from Table 4. The same AHP steps have been followed to compute the sub-criteria weights and the pair-wise comparisons for the sub-criteria are shown in Table 9.

Table 5. Pair-wise judgments of the three decision teams for main criteria.

	Decision Team 1						Decision Team 2						Decision Team 3				
	BI	**EI**	**LI**	**TI**	**OI**		**BI**	**EI**	**LI**	**TI**	**OI**		**BI**	**EI**	**LI**	**TI**	**OI**
BI	SI	MI	I		AI	BI	SI	AI	HI		I	BI	SI	MI	VHI		AI
	1	2	5		3		1	3	7		5		1	2	8		3
EI		SI	AI		MI	EI		SI	I		AI	EI		SI	AI		MI
		1	3		2			1	5		3			1	3		2
LI			SI			LI			SI			LI			SI		
			1						1						1		
TI	MI	AI	EI	SI	I	TI	MI	AI	EI	SI	HI	TI	MI	I	VHI	SI	HI
	2	3	9	1	5		2	3	9	1	7		2	5	8	1	7
OI			MI		SI	OI			AI		SI	OI			MI		SI
			2		1				3		1				2		1

Source: Judgments given by three decision teams.

Table 6. Final pair-wise judgments.

Main Factors	BI	EI	LI	TI	OI
BI	1	2.33333	6.66667	0.50000	3.66667
EI	0.42857	1	3.66667	0.27273	2.33333
LI	0.15000	0.27273	1	0.11538	0.42857
TI	2.00000	3.66667	8.66667	1	6.33333
OI	0.27273	0.42857	2.33333	0.15789	1
Sum	3.85130	7.70130	22.33333	2.04601	13.76190

Source: Author's own elaboration.

Table 7. Criteria weights using AHP.

Main Factors	BI	EI	LI	TI	OI	Priority Vector (PV)
BI	0.25965	0.30298	0.29851	0.24438	0.26644	0.27439
EI	0.11128	0.12985	0.16418	0.13330	0.16955	0.14163
LI	0.03895	0.03541	0.04478	0.05640	0.03114	0.04133
TI	0.51931	0.47611	0.38806	0.48876	0.46021	0.46649
OI	0.07081	0.05565	0.10448	0.07717	0.07266	0.07616
Sum	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000

Source: Author's own elaboration.

Table 8. Consistency checking.

Main Factors	Consistency of Each Factor	Consistency Terminologies	
BI	5.07637	No of comparisons (n)	5
EI	5.05333	Average consistency (λ max)	5.05131
LI	5.02201	CI	0.01283
TI	5.09153	RI	1.12
OI	5.01332	CR	0.01145 or 1.145% $\leq$ 0.1 or 10%
Sum	25.25656	Consistent	yes

Source: Author's own elaboration.

3.2. Interpretive Structural Modeling (ISM)

ISM is an MCDM method that aims to analyze the interrelationships between different criteria or factors in a decision problem. The method was first proposed by Warfield in the 1970s [67,68] and has since been widely applied in various fields, including management, engineering, and environmental studies. The ISM method consists of the following steps.

Step 1: A structural self-interaction matrix (SSIM) is proposed by the expert team members in terms of qualitative expressions as shown in Table 10. The linguistic terms are defined in four ways represented by the letters "V", "A", "X", "O". The direct and indirect relationships among the 15 factors are portrayed with the help of a line diagram in Figure 4 showing the influence of 1 factor over another by arrow point head. As can be seen in Table 10, only the upper triangular matrix is formed, and consecutively the values in the lower triangular can be determined accordingly as follows.

- Letter "V" in a cell denotes that ith criteria help to achieve the jth criteria, therefore 1 is allotted in the upper triangular cell ij, and simultaneously lower triangular cell ji will be 0.
- Letter "A" represents that ith criteria will be achieved by jth criteria. In easy words, the jth criteria help to achieve ith criteria, hence cell ij on the upper side will be 0, and cell ji on the lower side will be 1.

- Letter "X" signifies that both ith criteria and jth criteria will help to achieve each other, therefore both the cells, i.e., ij and ji in the upper and lower triangular side will be 1.
- Letter "O" indicates that the ith criteria and the jth criteria are not related to each other, hence in this case, 0 will be allotted in ij and ji cells on both triangular sides.

Step 2: Initial reachability matrix (A) shown in Table 11 is formed by replacing all the linguistic terms with the binary digits 0 and 1 as per the rules explained in step 1.

Step 3: Transitivity must be checked confirming that all the criteria hold a direct or indirect relationship with each other. During transitivity, the value 0 is replaced by 1* indicating the transitive relationship exists among the factors. After checking the transitivity relationship among the factors, the matrix obtained is known as the final reachability matrix indicated in Table 12.

Step 4: Level partitioning is executed in Table 13 to determine the levels of each factor. This step also helps the experts to observe the driving and dependence ability of each factor and to build a structural framework like Figure 5 showing the interrelationship among the parameters.

Table 9. Pair-wise judgments of the three decision teams for sub-criteria.

Budget Issues (BI)											
	Decision Team 1				**Decision Team 2**				**Decision Team 3**		
	SF 1	**SF 2**	**SF 3**		**SF 1**	**SF 2**	**SF 3**		**SF 1**	**SF 2**	**SF 3**
SF 1	**SI**		**MI**	**SF 1**	**SI**		**AI**	**SF 1**	**SI**		**MI**
SF 2	**I**	**SI**	**HI**	**SF 2**	**I**	**SI**	**VHI**	**SF 2**	**AI**	**SI**	**HI**
SF 3			**SI**	**SF 3**			**SI**	**SF 3**			**SI**
Environmental Issues (EI)											
	Decision Team 1				**Decision Team 2**				**Decision Team 3**		
	SF 4	**SF 5**	**SF 6**		**SF 4**	**SF 5**	**SF 6**		**SF 4**	**SF 5**	**SF 6**
SF 4	SI	AI	I	**SF 4**	SI	MI	I	**SF 4**	SI	MI	AI
SF 5		SI	MI	**SF 5**		SI	AI	**SF 5**		SI	MI
SF 6			SI	**SF 6**			SI	**SF 6**			SI
Learning Issues (LI)											
	Decision Team 1				**Decision Team 2**				**Decision Team 3**		
	SF 7	**SF 8**	**SF 9**		**SF 7**	**SF 8**	**SF 9**		**SF 7**	**SF 8**	**SF 9**
SF 7	SI			**SF 7**	SI			**SF 7**	SI		
SF 8	HI	SI	I	**SF 8**	VHI	SI	I	**SF 8**	VHI	SI	AI
SF 9	MI		SI	**SF 9**	AI		SI	**SF 9**	MI		SI
Technological Issues (TI)											
	Decision Team 1				**Decision Team 2**				**Decision Team 3**		
	SF 10	**SF 11**	**SF 12**		**SF 10**	**SF 11**	**SF 12**		**SF 10**	**SF 11**	**SF 12**
SF 10	SI			**SF 10**	SI			**SF 10**	SI		
SF 11	MI	SI		**SF 11**	MI	SI		**SF 11**	MI	SI	
SF 12	EI	I	SI	**SF 12**	EI	HI	SI	**SF 12**	VHI	I	SI
Organizational Issues (OI)											
	Decision Team 1				**Decision Team 2**				**Decision Team 3**		
	SF 13	**SF 14**	**SF 15**		**SF 13**	**SF 14**	**SF 15**		**SF 13**	**SF 14**	**SF 15**
SF 13	SI	VHI	I	**SF 13**	SI	EI	I	**SF 13**	SI	HI	AI
SF 14		SI		**SF 14**		SI		**SF 14**		SI	
SF 15		MI	SI	**SF 15**		AI	SI	**SF 15**		MI	SI

Source: Judgments given by three decision teams.

Table 10. Structural self-interaction matrix (SSIM).

	SF 1	**SF 2**	**SF 3**	**SF 4**	**SF 5**	**SF 6**	**SF 7**	**SF 8**	**SF 9**	**SF 10**	**SF 11**	**SF 12**	**SF 13**	**SF 14**	**SF 15**
SF 1	1	V	A	V	A	O	A	V	X	A	O	A	V	A	O
SF 2		1	V	A	O	A	X	O	V	A	A	O	A	O	X
SF 3			1	O	A	V	A	V	A	V	X	A	V	A	V
SF 4				1	X	O	V	A	O	A	V	A	A	X	A
SF 5					1	V	A	O	A	X	A	O	A	A	O
SF 6						1	V	X	V	A	O	A	V	A	X
SF 7							1	O	X	V	A	V	O	O	A
SF 8								1	O	A	O	A	V	A	V
SF 9									1	V	A	O	X	V	A
SF 10										1	V	A	V	A	O
SF 11											1	X	A	O	X
SF 12												1	V	A	V
SF 13													1	X	A
SF 14														1	V
SF 15															1

Source: Judgments given by three decision teams.

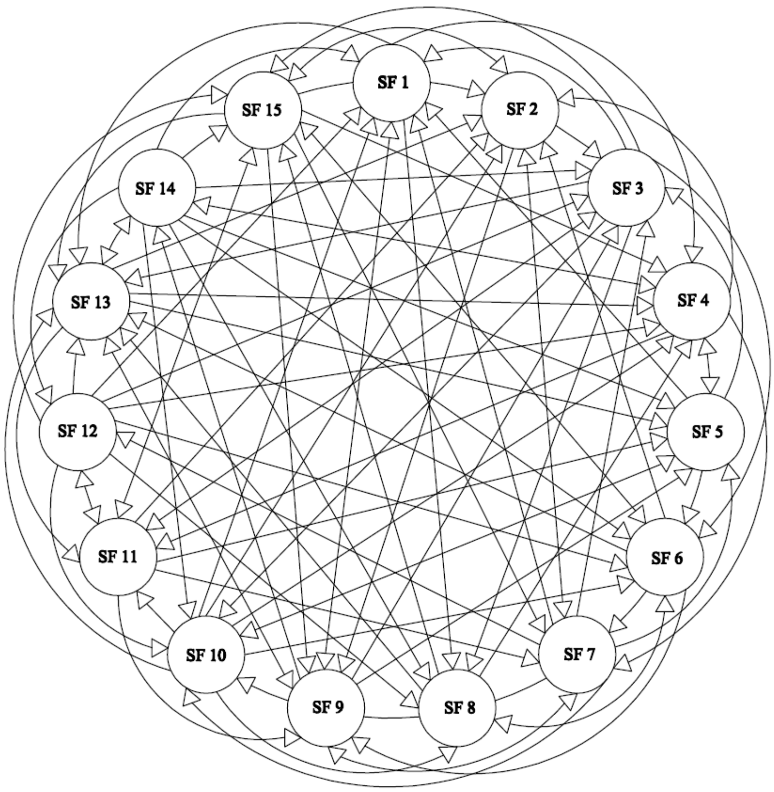


Figure 4. Line digraph of ISM model. (Source: Author's own elaboration; Created using AutoCad 2007).

Table 11. Initial reachability matrix.

	SF 1	SF 2	SF 3	SF 4	SF 5	SF 6	SF 7	SF 8	SF 9	SF 10	SF 11	SF 12	SF 13	SF 14	SF 15
SF 1	1	1	0	1	0	0	0	1	1	0	0	0	1	0	0
SF 2	0	1	1	0	0	0	1	0	1	0	0	0	0	0	1
SF 3	1	0	1	0	0	1	0	1	0	1	1	0	1	0	1
SF 4	0	1	0	1	1	0	1	0	0	0	1	0	0	1	0
SF 5	1	0	1	1	1	1	0	0	0	1	0	0	0	0	0
SF 6	0	1	0	0	0	1	1	1	1	0	0	0	1	0	1
SF 7	1	1	1	0	1	0	1	0	1	1	0	1	0	0	0
SF 8	0	0	0	1	0	1	0	1	0	0	0	0	1	0	1
SF 9	1	0	1	0	1	0	1	0	1	1	0	0	1	1	0
SF 10	1	1	0	1	1	1	0	1	0	1	1	0	1	0	0
SF 11	0	1	1	0	1	0	1	0	1	0	1	1	0	0	1
SF 12	1	0	1	1	0	1	0	1	0	1	1	1	1	0	1
SF 13	0	1	0	1	1	0	0	0	1	0	1	0	1	1	0
SF 14	1	0	1	1	1	1	0	1	0	1	0	1	1	1	1
SF 15	0	1	0	1	0	1	1	0	1	0	1	0	1	0	1

Source: Author's own elaboration.

Table 12. Final reachability matrix.

	SF 1	SF 2	SF 3	SF 4	SF 5	SF 6	SF 7	SF 8	SF 9	SF 10	SF 11	SF 12	SF 13	SF 14	SF 15	DrP	Rank
SF 1	1	1	1*	1	1*	1*	1*	1	1	1*	1*	0	1	1*	1*	14	12
SF 2	1*	1	1	1*	1*	1*	1	1*	1	1*	1*	1*	1*	1*	1	15	1
SF 3	1	1*	1	1*	1*	1	1*	1	1*	1	1	1*	1	1*	1	15	1
SF 4	1*	1	1*	1	1	1*	1	1*	1*	1*	1	1*	1*	1	1*	15	1
SF 5	1	1*	1	1	1	1	1*	1*	1*	1	1*	0	1*	1*	1*	14	12
SF 6	1*	1	1*	1*	1*	1	1	1	1	1*	1*	1*	1	1*	1	15	1
SF 7	1	1	1	1*	1	1*	1	1*	1	1	1*	1	1*	1*	1*	15	1
SF 8	0	1*	0	1	1*	1	1*	1	1*	0	1*	0	1	1*	1	11	14
SF 9	1	1*	1	1*	1	1*	1	1*	1	1	1*	1*	1	1	1*	15	1
SF 10	1	1	1*	1	1	1	1*	1	1*	1	1	1*	1	1*	1*	15	1
SF 11	1*	1	1	1*	1	1*	1	1*	1	1*	1	1	1*	1*	1	15	1
SF 12	1	1*	1	1	1*	1	1*	1	1*	1	1	1	1	1*	1	15	1
SF 13	1*	1	1*	1	1	1*	1*	1*	1	1*	1	1*	1	1	1*	15	1
SF 14	1	1*	1	1	1	1	1*	1	1*	1	1*	1	1	1	1	15	1
SF 15	0	1	0	1	0	1	1	0	1	0	1	0	1	0	1	8	15
DeP	13	15	13	15	14	15	15	14	15	13	15	11	15	14	15		
Rank	12	1	12	1	9	1	1	9	1	12	1	15	1	9	1		

Source: Author's own elaboration.

Table 13. Iteration process.

Factor	Reachability	Antecedent	Intersection	Level
		1st iteration		
SF 1	1,2,3,4,5,6,7,8,9,10,11,13,14,15	1,2,3,4,5,6,7,9,10,11,12,13,14	1,2,3,4,5,6,7,9,10,11,13,14	
SF 2	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15	Level 1
SF 3	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15	1,2,3,4,5,6,7,9,10,11,12,13,14	1,2,3,4,5,6,7,9,10,11,12,13,14	
SF 4	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15	Level 1
SF 5	1,2,3,4,5,6,7,8,9,10,11,13,14,15	1,2,3,4,5,6,7,8,9,10,11,12,13,14	1,2,3,4,5,6,7,8,9,10,11,13,14	
SF 6	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15	Level 1
SF 7	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15	Level 1
SF 8	2,4,5,6,7,8,9,11,13,14,15	1,2,3,4,5,6,7,8,9,10,11,12,13,14	2,4,5,6,7,8,9,11,13,14,15	
SF 9	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15	Level 1
SF 10	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15	1,2,3,4,5,6,7,9,10,11,12,13,14	1,2,3,4,5,6,7,9,10,11,12,13,14	
SF 11	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15	Level 1
SF 12	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15	2,3,4,6,7,9,10,11,12,13,14	2,3,4,6,7,9,10,11,12,13,14	
SF 13	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15	Level 1
SF 14	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15	1,2,3,4,5,6,7,8,9,10,11,12,13,14	1,2,3,4,5,6,7,8,9,10,11,12,13,14	
SF 15	2,4,6,7,9,11,13,15	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15	2,4,6,7,9,11,13,15	Level 1
		2nd iteration		
SF 1	1,3,5,8,10,14	1,3,5,10,12,14	1,3,5,10,14	
SF 3	1,3,5,8,10,12,14	1,3,5,10,12,14	1,3,5,10,12,14	
SF 5	1,3,5,8,10,14	1,3,5,8,10,12,14	1,3,5,8,10,14	Level 2
SF 8	5,8,14	1,3,5,8,10,12,14	5,8,14	Level 2
SF 10	1,3,5,8,10,12,14	1,3,5,10,12,14	1,3,5,10,12,14	
SF 12	1,3,5,8,10,12,14	3,10,12,14	3,10,12,14	
SF 14	1,3,5,8,10,12,14	1,3,5,8,10,12,14	1,3,5,8,10,12,14	Level 2
		3rd iteration		
SF 1	1,3,10	1,3,10,12	1,3,10	Level 3
SF 3	1,3,10,12	1,3,10,12	1,3,10,12	Level 3
SF 10	1,3,10,12	1,3,10,12	1,3,10,12	Level 3
SF 12	1,3,10,12	3,10,12	3,10,12	
		4th iteration		
SF 12	12	12	12	Level 4

Source: Author's own elaboration.

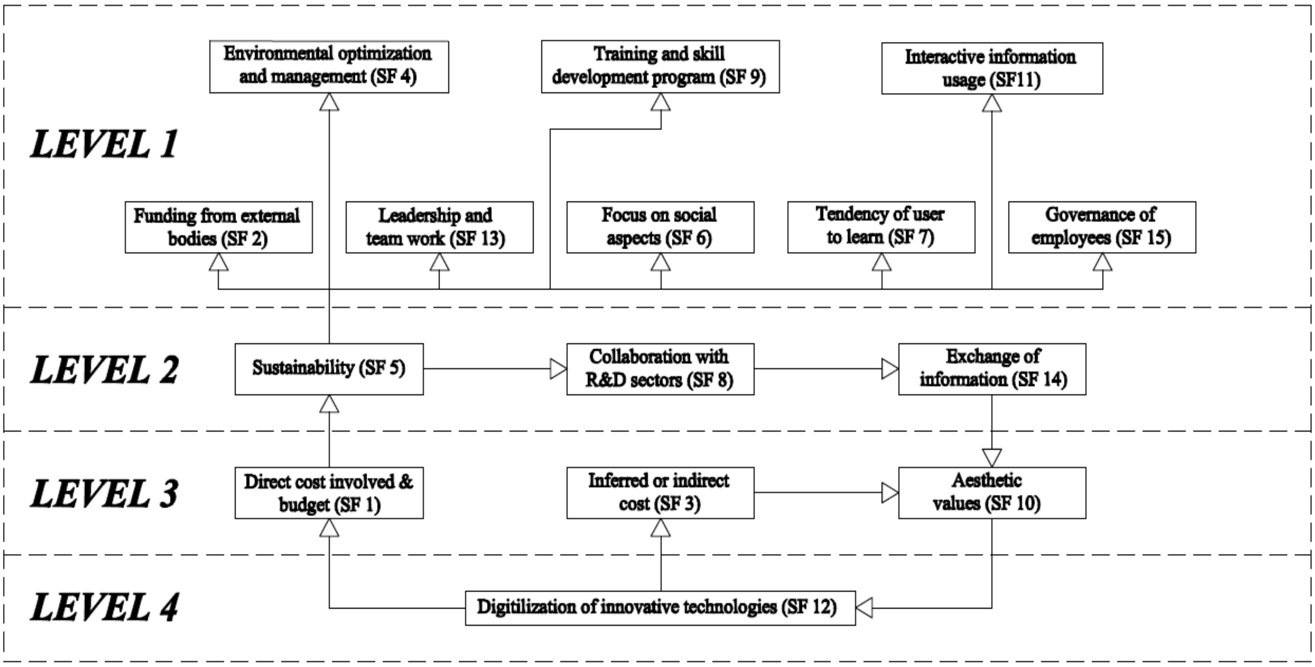


Figure 5. ISM hierarchy tree showing level partitioning. (Source: Author's own elaboration; created using AutoCad 2007).

3.3. Cross-Impact Matrix Multiplication Applied to Classification (MICMAC)

MICMAC stands for "Matrice d'Impacts Croisés-Multiplication Appliquée à un Classement" in French, which roughly translates to "Cross-Impact Matrix Multiplication Applied to Classification". It is a method used to analyze the interactions between factors in a complex system. In other words, it helps to identify the key drivers or factors that influence a particular outcome. The method involves constructing a matrix of the relationship between the factors, and then using matrix multiplication to calculate the importance of each factor [37,38]. MICMAC was used to distinguish the factors into four categories based on the driving and dependence power of the criteria calculated in Table 12. However, MICMAC is closely associated with ISM and involves the following steps.

Step 1: Compute the driving power (DrP) and dependence power (DeP) of the alternatives using Equation (6) as depicted in Table 12.

$$\begin{cases} \mathrm{DrP_i} = \sum_{j=1}^{n} \mathrm{a_{ij}^f} \\ \mathrm{DeP_j} = \sum_{i=1}^{n} \mathrm{a_{ij}^f} \end{cases} \tag{6}$$

Step 2: Plot the driving power against the dependence power for each alternative in a scatter diagram shown in Figure 6 to identify the nature and distinguish the factors into four different quadrants as follows.

- Autonomous: The factors occupying the first quadrant space are termed autonomous enablers. These are mainly isolated from the system. Autonomous enablers are basically weak drivers, and they also have weak dependence power.
- Dependent: Dependent factors lie in the second quadrant and are basically highly dependent on the lower-level factors. These factors occupy the top-most level in the ISM hierarchy. These have weak driving power and high dependence power.
- Linkage: These factors act as linkage enablers connecting the ISM levels among each other. These enablers lie in the third quadrant of the scatter plot diagram and have high driving and dependence power.
- Driving or independent: These are the lowest level factors in the ISM hierarchy used to drive all the parameters above their levels. These mainly lie in the fourth quadrant and have strong driving power. These enablers are mainly independent in nature.

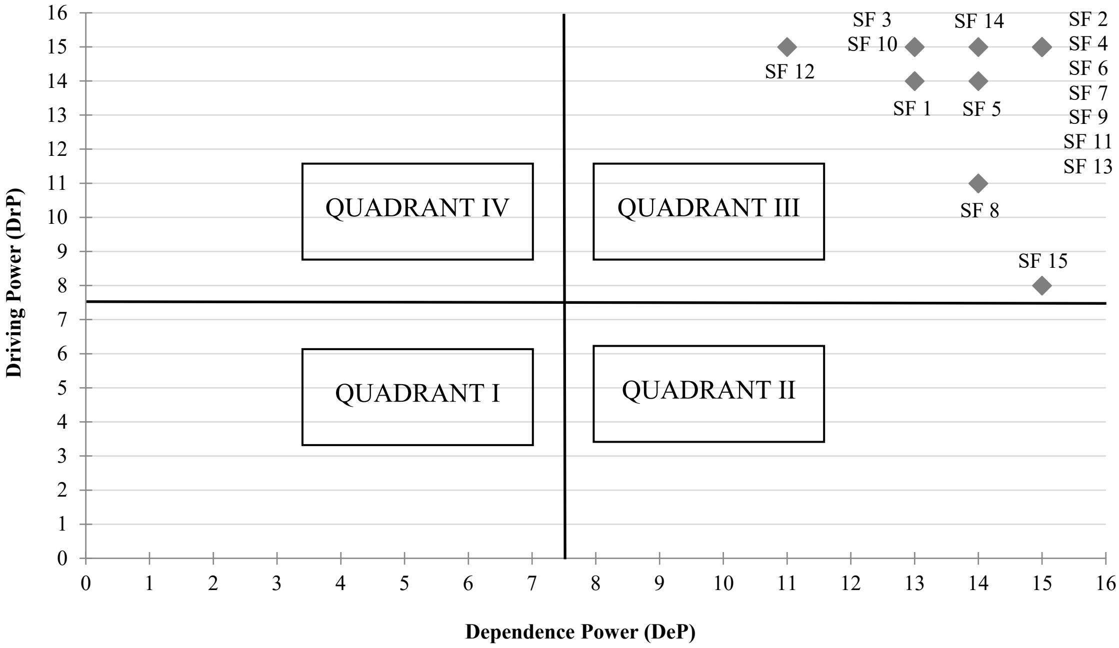


Figure 6. Scatter plot diagram of MICMAC analysis. (Source: Author's own elaboration; Created using MS Word 2010).

4. Research Methodology

The section mainly deals with the computational analysis and mathematical calculations of the three applied tools, i.e., AHP, ISM, and MICMAC. The basic outline of the whole analysis is already formulated in the previous section identifying all the critical factors that influence the cloud infrastructure within the IT industry. Now, all three tools will be applied to measure the performance of each involved factor. First, AHP is applied to calculate the weights of the parameters followed by ISM and MICMAC. ISM is used to examine the interrelationship that exists among the factors; finally, MICMAC is used to calculate the driving and dependence power of the factors and helps to categorize it into four different categories according to the nature of the parameters [69]. The calculation details of all three MCDM analyses are shown in detail in the following sub-sections. Let us first start with the AHP analysis followed by ISM and MICMAC.

4.1. Data Analysis of AHP

To start with the AHP analysis, we need to first prepare the pair-wise comparison matrix according to Equation (1). To compute the weights of each main factor and sub-factor, pair-wise comparison has to be conducted for each case considering the main factors and sub-factors within each primary factor separately. Therefore, there will be one 5×5 matrixes for the main criteria and five 3×3 sub-criteria matrices for each main criteria group. However, the opinions of the three decision teams for the main criteria 5×5 pair-wise matrix are provided in Table 5. The qualitative terms of the experts are further converted into quantitative values according to the scale given in Table 4.

The three pair-wise comparison matrices shown in Table 5 are now combined by taking the average values for each cell to obtain the final pair-wise comparison matrix depicted in Table 6. The empty cells in Table 5 are filled up by taking the reciprocal of their opposite cells, for example, "p_{12}" and "p_{21}" in Equation (1) can be related as $p_{12} = \frac{1}{p_{21}}$ and $p_{21} = \frac{1}{p_{12}}$, respectively.

Using Equation (2), normalize Table 6 to stabilize the data and equally distribute the data to unity. Following the normalization process, the priority vector of the parameters is calculated using Equation (3) and portrayed in Table 7.

The PV of the five main factors can be treated as actual weights once the consistency checking stage is qualified. Using Equations (3) and 4, the consistency procedure has been carried out and all the calculated results are presented in Table 8.

It is evident from Table 8 that the CR ratio is 0.01145 (or 1.145%) which is well within the limit, i.e., 10%; hence, it can be concluded that the pair-wise comparisons given by the expert team's members are consistent. Additionally, the PV values calculated in Table 7 may be treated as the final weights of the main criteria.

Now, the sub-criteria weights are also evaluated in the same manner using the same equations applied for generating the main criteria weights. The judgments given by the decision-makers for the sub-criteria group within each main criteria group are presented in Table 9. By applying all the steps of AHP, the weights of the sub-criteria may also be computed as well like the main criteria. Here also, the consistencies of the pair-wise matrices for the sub-criteria are also checked to confirm the inconsistencies associated with the problem. All the final outcomes from Table 9, e.g., CI and CR values are presented in Table 14.

Table 14. Summary of results obtained from AHP analysis.

MF	Weights	Rank	CR (MF)	SF	Local Weights	Local Rank	CR (SF)	Global Weights	Global Rank
				SF 1	0.18703	2		0.05132	6
BI	0.27439	2		SF 2	0.72367	1	0.00992	0.19857	2
				SF 3	0.08929	3		0.02450	10
				Sum	1		Sum	0.27439	
				SF 4	0.59604	1		0.08442	3
EI	0.14163	3		SF 5	0.27615	2	0.00500	0.03911	7
				SF 6	0.12781	3		0.01810	11
				Sum	1		Sum	0.14163	
				SF 7	0.08704	3		0.00360	15
LI	0.04133	5	0.01145	SF 8	0.72789	1	0.00736	0.03009	9
				SF 9	0.18507	2		0.00765	13
				Sum	1		Sum	0.04133	
				SF 10	0.08160	3		0.03807	8
TI	0.46649	1		SF 11	0.14919	2	0.00691	0.06959	4
				SF 12	0.76921	1		0.35883	1
				Sum	1		Sum	0.46649	
				SF 13	0.73185	1		0.05573	5
OI	0.07616	4		SF 14	0.08494	3	0.00526	0.00647	14
				SF 15	0.18322	2		0.01395	12
Sum	1			Sum	1		Sum	0.07616	

Source: Author's own elaboration.

4.2. Data Analysis of ISM

ISM analysis starts with the formation of the SSIM matrix as shown in Table 10. After having a massive brainstorming session, all the panel members put their own opinions and views to create the SSIM matrix in verbal expressions. According to step 1 of ISM analysis, the linguistic terms of Table 10 are replaced by the binary digits 0 and 1 to create the initial reachability matrix shown in Table 11. The relationship that exists among different factors is represented using line diagram shown in Figure 4. In Figure 4, the arrow from criteria SF 1 pointing towards SF 2 indicates that the sub-factor SF 1 influences or leads to the achievement of sub-factor SF 2; alternatively, SF 2 will be achieved by SF 1. Similarly, arrow pointing towards both criteria as in case of SF 1 and SF 9 represents that both SF 1 and SF 9 will help to achieve each other. Moreover, no interconnecting lines between the factors represent that there is no relationship that exists between those two factors as in case between SF 1 and SF 6. Therefore, it is very easy to interpret the SSIM in Table 10 from Figure 4.

Following the Boolean algorithm, transitivity of the reachability matrix in Table 11 is checked to find out the indirect relationship exists among different parameters. Numeric digit 1 denotes the influential behavior of one parameter over the other, whereas 0 signifies the missing relationship between two factors. After checking the transitivity, all the indirect relationships among the parameters are denoted by 1* replacing all the 0 values in Table 11 thus obtaining the final reachability matrix depicted in Table 12.

Level partitioning operation has been conducted for determining the levels of different factors. Each level in Figure 5 of the ISM hierarchical framework shows the ability of a criterion to drive other criteria, and at the same time, it also measures the dependence tendency of a criterion on other criteria. However, the iteration process to categorize 15 factors into different levels is portrayed in Table 13. An ISM hierarchy tree illustrated diagrammatically in Figure 5 is built to represent all the levels of 15 parameters and the interrelationship that exists among them. If we notice closely the ISM hierarchy in Figure 5, it can be observed that two loops have been formed among the parameters present in level 2, level 3, and level 4. One closed loop is formed among the parameters SF 12, SF 3, and SF 10, and another one exists among the parameters SF 12, SF 1, SF 5, SF 8, SF 14, and SF 10. This scenario clearly depicts that all seven elements are intimately linked to each other, and changes in any one of them may have an effect on other factors.

4.3. Data Analysis of MICMAC

MICMAC is a part of ISM analysis used to categorize the considered factors into four different classes as already discussed under the MICMAC theoretical analysis section. MICMAC analysis does not demand any separate computation steps like AHP and ISM. The first and foremost step of MICMAC is to calculate the driving power and the dependence power of the factors from the final reachability matrix shown in Table 12. The last step is to prepare the scatter diagram shown in Figure 6 by plotting all the driving power on y-axis against the dependence power on x-axis. From Figure 6, the belonging quadrants of the parameters can also be determined depicting the nature of each factor. The coordinates of the horizontal and the vertical line separating the four quadrants can be set in different ways; in this present case, the coordinates of both lines are taken exactly at the middle of the highest driving and dependence power, i.e., 7.5 in each case, since the highest value in both cases is 15.

5. Results and Discussions

The mathematical computation of three MCDM tools has been carried out in the previous sections. This section primarily highlights the core outcome results from the three applied tools. From the AHP analysis, we have computed the weights of each main criterion as well as the sub-criteria. Furthermore, all the consistencies are also checked to validate the expert's judgments. However, Table 14 summarizes all the outcomes from the AHP analysis.

Now, let us derive some of the important remarks from Table 14. It can be observed that rankings of the main and sub-factors are prescribed in Table 14 according to the weights received from AHP analysis. The factors with the highest weights may be treated as the most important factors and allotted the position rank 1; similarly, the rating order is performed based on decreasing weight values. Among the main factors, technological issues come with the highest weight value of 0.46649 and hence it can be termed as the most important factor among the group. It is also true that an IT industry highly depends on technologies that mostly influence the cloud system within a sector. Therefore, technological issues are one of the critical factors that most influence the cloud infrastructure of an IT industry. The main factor that occupies the second-rank and third-rank position are the budget issue and environmental issue having weight values of 0.27439 and 0.14163. Budget is also one of the important factors that are closely associated with the business along with sustainable factors. The learning issue is in the last rank position having weight 0.04133 portraying that it is the least important aspect among the group. However, learning aspects may come with the lowest degree of importance but they cannot be ignored completely.

IT professionals require enough skills and knowledge to drive an IT sector smoothly. Moreover, the adaptation of the cloud concept demands high expertise in the field to operate. Hence, learning and gathering skills is equally important to the other factors, but somehow other parameters like technology, budget, and environment added more value than learning to some extent. All five main factors are crucial and closely linked with the cloud infrastructure, but AHP analysis helps to determine the degree of importance of each factor and rate the parameters according to their weights. Now if we examine the main criteria weights from a general point of view it can be observed that technological aspects contribute nearly about 46.6% followed by budget aspects at 27.4% and environmental aspects at 14.2%; organizational and learning aspects contribute around 7.6% and 4.1% each for implementing and maintaining a cloud environment within an IT sector. Figure 7 clearly portrays the main criteria weights along with the contribution % of each sub-factor within their main criteria group.

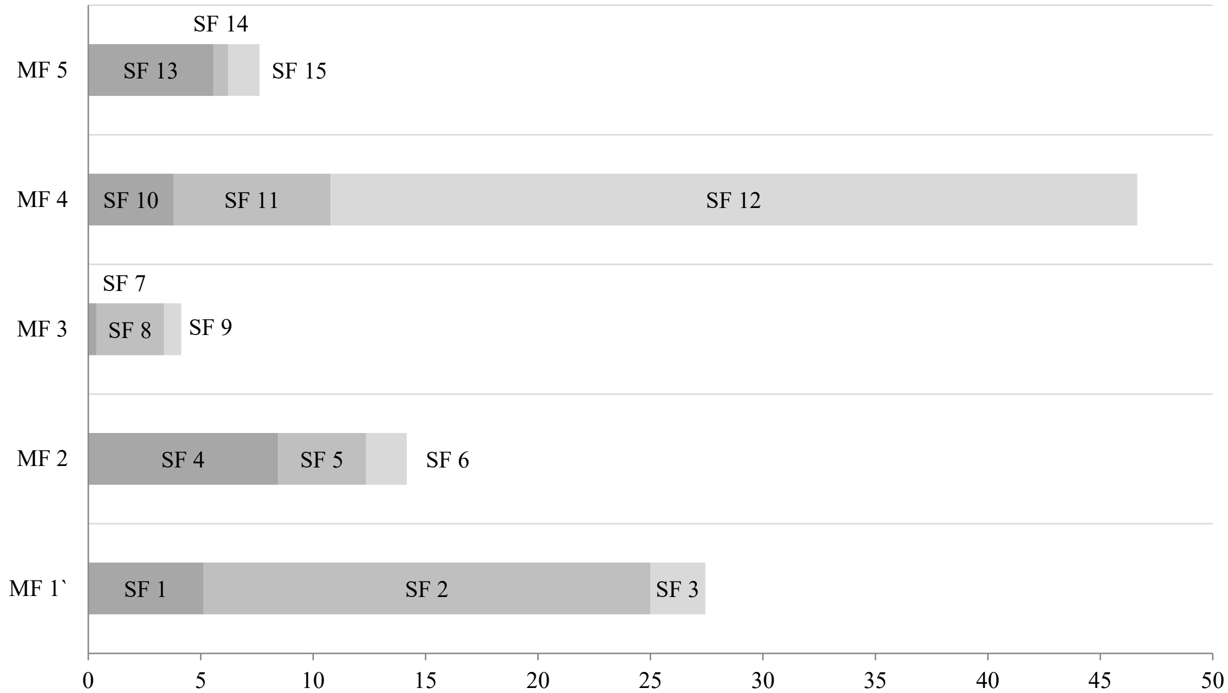


Figure 7. Representation of the main criteria weights along with the contribution % of each sub-criterion. (Source: Author's own elaboration; Created using MS Word 2010).

The sub-factors within each main factor also grab the attention of the readers in a similar way. From Table 13, it can be observed that rankings have been prescribed as well to the three sub-factors within each main factor according to the sub-criteria local weights (LW) obtained using AHP. The local ranks (LR) of the sub-criteria reveal the most superior and inferior aspects within each main factor category. Digitalization of innovative technologies (SF 12) is the most important parameter within technology field, and aesthetic values are the inferior one among the three sub-factors within TI category. Similarly, funding, optimizing environment, leadership, and collaboration hold the top position with the highest weight and indirect cost and focus on social aspects, information exchange, and learning tendency of user are the least important aspects within BI, EI, OI, and LI main categories, respectively. Overall, the parameter coming with the highest weight value will have the greatest influence, and the parameters with the lowest weight will influence the cloud framework less comparatively. The local weights of each sub-factor are also portrayed graphically, as shown in Figure 8. One more thing to note, the CR values presented in Table 14 also reveal that the CR in each case is well below the upper bound limit, i.e., 10%. Hence, all six pair-wise comparisons including all main and sub-criteria are consistent and stable.

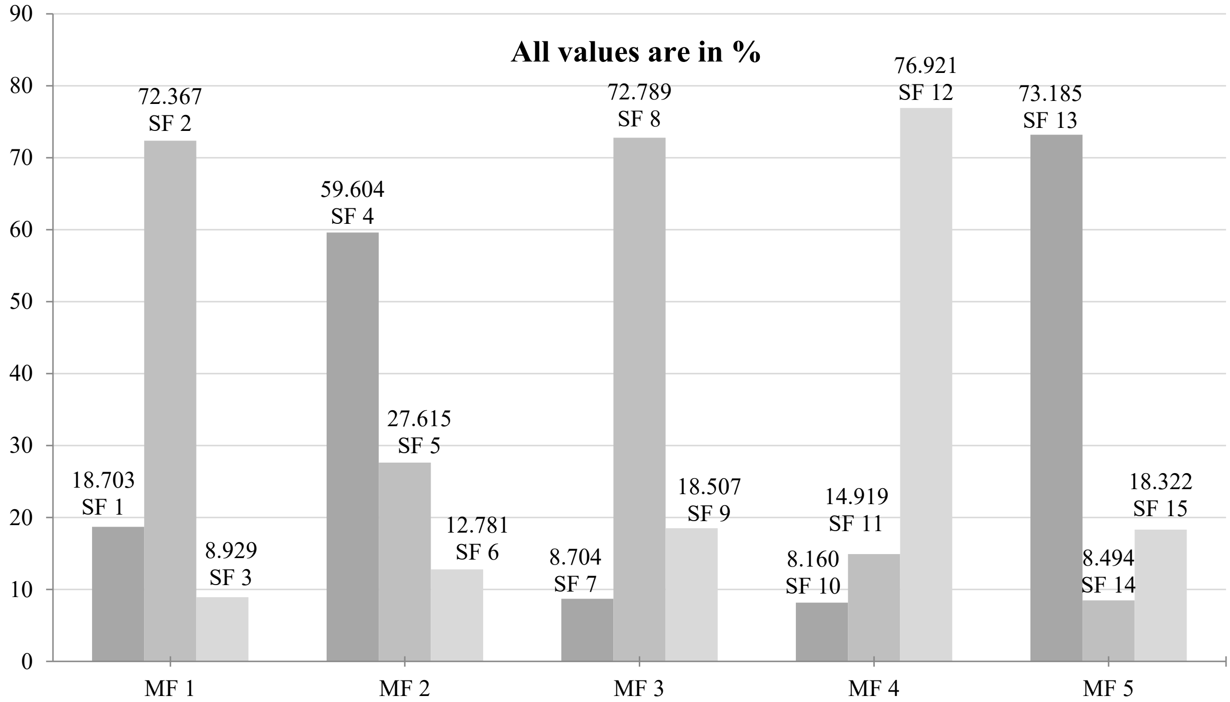


Figure 8. Representation of the local weights of the sub-factors. (Source: Author's own elaboration; Created using MS Word 2010).

From Table 14, it is also evident that the global weights (GW) have been calculated for each sub-criterion. GW helps expert members to draw an outline about the most crucial one on an overall basis. GW represents the most superior one and their contribution towards the analysis among all 15 factors considered in this study. Furthermore, a global rank (GR) is also prescribed indicating that digitalized technologies (SF 12) are the most crucial one followed by external body funding (SF 2) and environmental management (SF 4) that mostly influence the cloud environment within an organization. On the other hand, user tendency to earn (SF 7), information exchange (SF 14), and skill development program (SF 9) occupy the last three positions from least, i.e., rank 15, rank 14, rank 13; thus, can be considered as the least important and may have small contribution behind fulfilling the objectives. LW and GW both have their own benefits; LW contributes to recognizing the importance of each sub-factor within each main criteria category, whereas GW helps in identifying the most critical parameters that influence the overall analysis globally. However, the global weights of the 15 parameters are depicted graphically with the help of a bar chart diagram shown in Figure 9. From Figure 9, it is also easy to judge the global ranking and assessment of the 15 parameters according to the global weights.

As we can observe, AHP analysis fulfills all its objectives and handles the weightage computation phase in a very responsible way. AHP mainly took the responsibility of evaluating the parametric importance and sorting out the ranking from the highest priority to the lowest. AHP also helps the decision-makers to examine the contribution and influence of each involved parameter within the analysis. Hence, all three tools, i.e., AHP, ISM, and

MICMAC have been applied for some reasons to meet some specific goals. Every utilized technique in this study has its own significance and contribution. Let us now focus on the objectives accomplished using ISM and MICMAC models.

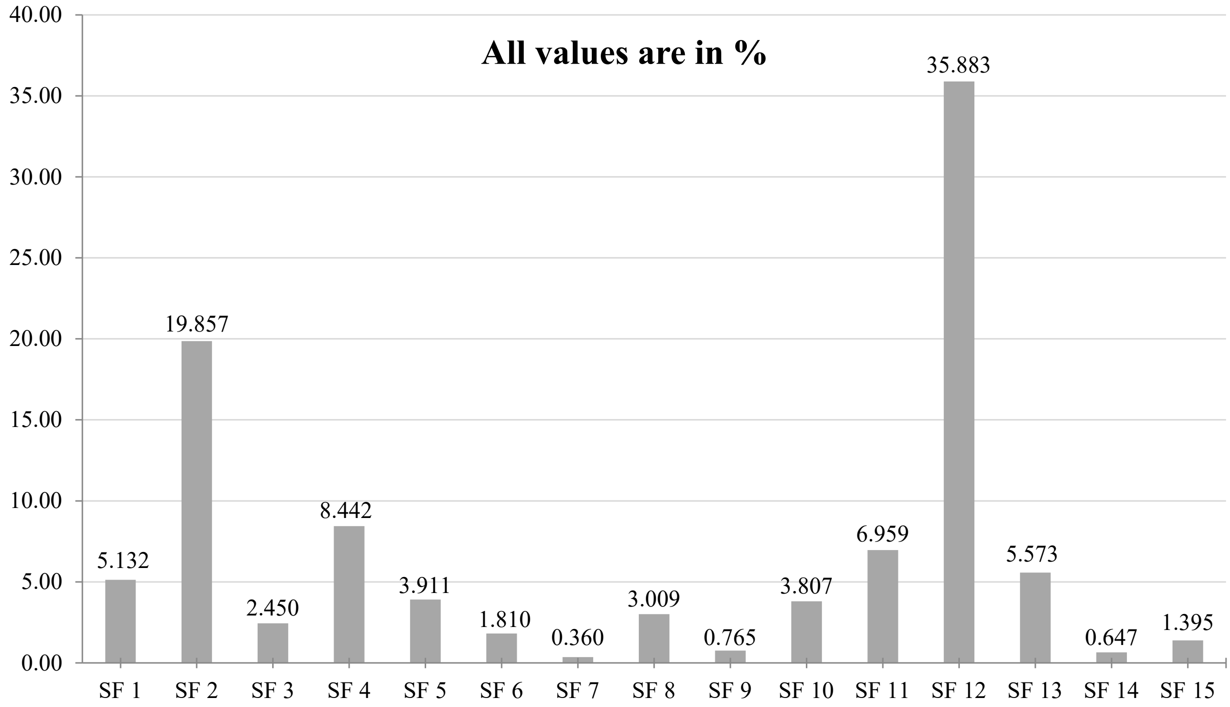


Figure 9. Representation of the global weights of 15 parameters. (Source: Author's own elaboration; Created using MS Word 2010).

With the help of ISM analysis, the belonging levels of all the 15 parameters are determined as can be seen in Figure 5. All the parameters are allocated into different levels according to their behavioral characteristics. From Figure 5 it is evident that the ISM hierarchy consists of four levels, and the fifteen factors are adjusted into different levels according to their driving and dependence tendencies. Thus, ISM helps the decision-makers to determine the hierarchical levels of the involved parameters within the stated problem. As we can observe from Figure 5, SF 12, i.e., digitalization of innovative technologies holds the lowest level 4 followed by three factors in the intermediate level 3 namely, aesthetic values (SF 10), direct (SF 1) and indirect cost (SF 3). Exchange of information (SF 14), collaboration (SF 8), and sustainability (SF 5) are another three intermediate factors that settle down in level 2; and the topmost level 1 contains the maximum number of factors. The ISM hierarchy tree shown in Figure 5 depicts the driving and the dependence ability of each factor. The lowest level factors in the hierarchy tree are the most influencing ones that mostly drive other factors above their levels. Here, in this case, SF 12 is the most powerful one that not only highly influences other factors but also helps to drive the factors above its levels. From the AHP analysis, it has been observed that SF 12 obtained the first global rank position with the highest global weights indicating the most important one among the group; from ISM analysis, it has been examined that SF 12 has the powerful driving ability as well and the most influencing parameter in the list. The lowest level 4 acts as the root of the ISM tree based on which the whole structure is erected. The lowest level factor SF 12 controls all the upper-level factors.

The factors present in the intermediate level 2 and level 3 act as a linkage among the factors. Level 2 and level 3 parameters interconnect the lowest level parameters with the highest level portraying the driving and dependence abilities. The intermediate factors generally have strong driving as well as strong dependence power. As in this case, six parameters, three in each level 2 and level 3 act as interconnecting links in Figure 5. It is obvious from Figure 5 that all six intermediate factors directly or indirectly depend on SF 12 in level 1. In the general case, SF 12 in level 1 is driving the three factors SF 1, SF 3, and SF 10 in level 3, and level 3 is driving SF 5, SF 8, and SF 14 in level 2 situated above level 3. Hence, parameters in level 2 and level 3 depend on the other factors situated below their respective levels. Now, if we look at the driving abilities of level 2 and level 3 factors, it is evident from Figure 5 that level 3 is directly or indirectly driving the above level 2 and level 1. Similarly, level 2 is also directly driving the eight elements situated in level 1. Therefore, both level 2 and level 3 factors possess driving as well as dependence quality, since they are driving the other factors above their levels, and simultaneously they are also dependent on SF 12 of level 4. Finally, the eight factors present in the top-most level 1 signify the high dependency on the lower-level factors, since these eight factors are being driven by the rest of the seven parameters situated in the lower levels as shown in Figure 5. Level 1 parameters are directly or indirectly dependent on level 2, level 3, and level 4; thus, these are called dependent variables. Moreover, they are very weak drivers as these level 1 factors did not contribute to driving other factors as can be seen in Figure 5.

Next, we come to the MICMAC analysis to discuss the primary outcomes from it. As already discussed under MICMAC analysis in the theoretical framework section MICMAC is a part of ISM that helps to categorize the selected factors into four groups. Figure 6 clearly suggests that all the 15 parameters fit into Quadrant-III representing the inter-level linkage behavior. Hence, MICMAC suggests that all the 15 chosen parameters for the present analysis have both strong driving and dependent qualities. All the factors are somehow interconnected among each other and help to drive other factors directly or indirectly, and at the same time, they are also dependent on or being driven by other factors. Moreover, Figure 6 also denotes that the parameters that are close to the horizontal and vertical divider lines like SF 12 (close to the vertical line) and SF 15 (close to the horizontal line) have the tendency to become independent (for SF 12) and dependent (SF 15), respectively. Therefore, no parameters are present that are completely dependent and independent, since all 15 factors are somehow interrelated and have an influence on each other.

ISM helps to design and construct the entire architecture of the hierarchy tree that clearly illustrates different levels constituted by some factors signifying the influential ability and the tendency of getting influenced for each of the 15 parameters. The ISM hierarchy tree clearly represents how all the factors are linked and interconnected to each other. Parameters present in each level possess different characteristics, and it can be concluded that only one factor, namely digitalization of the innovative technologies, belongs to level 4, which constitutes the base of the ISM hierarchy tree considered the most influential and independent factor. The factors present in the top three levels above level 4 directly or indirectly depend on the level 4 factor; hence, all 14 factors are dependent on digitalization of the innovative technologies. Level 4 factors directly or indirectly influence other factors present in the levels above level 4. Similarly, the eight factors present in the top-most level 1 are considered as the most dependent factors, since these eight factors are established on seven other factors occupying the levels situated below level 1. The level 1 factor has the highest tendency of being influenced by the other level factors present below level 1. The six parameters present in the intermediate levels, level 2 and level 3, generally possess both the influencing and dependency tendency at the same time. As a result, the second objective of the study is also fulfilled addressing the entire interrelationship framework model of the chosen factors.

MICMAC analysis ultimately helps in achieving the final objective of this study by examining the performance of the 15 factors chosen for the present analysis. MICMAC analysis contributes to evaluating the driving and dependence power of each alternative. From MICMAC analysis it can be concluded that digitalization of innovative technologies is coming with the highest driving power and lowest dependence power simultaneously, thus revealing this factor as the strong driver among the group. It is also evident from ISM analysis that SF 12 holds the bottom level 4 in the ISM hierarchy and also depicts the exact same scenario that it drives all the other factors directly or indirectly above its levels; at the same time, SF 12 has also the lowest dependence tendency among the group of 15. Likewise, the governance of employees is the weak driver and the most dependent one among the group having the lowest driving power and highest dependence power simultaneously. It is also obvious from the ISM hierarchy that SF 15 shares its position in the top level 1 hierarchy along with other seven factors. However, all the eight factors present in the top level 1 hierarchy are considered dependent factors, but MICMAC revealed SF 15 as the most dependent and weak driver among the lists. The rest of the factors present in level 2 and level 3 hold good driving as well as dependence power thus exhibiting the properties of being a good driver and reliant on other factors both at the same time. Utmost care should be taken to the strong drivers because factors with high driving power strongly influence other AI factors and affect the whole CC environment. Strong drivers help to achieve other factors with strong dependence power, therefore strong drivers and highly dependent factors behave like input and output to a system. However, the MICMAC analysis digraph also reveals that all the 15 parameters retain some driving and dependence characteristics simultaneously, thus occupying the linkage quadrant-III in the MICMAC diagram.

AHP, ISM, and MICMAC are all MCDM techniques that can be used in the field of cloud computing to aid decision-making processes. Here are some significant contributions of each technique.

- AHP can be used to determine the relative importance of different criteria that are used to evaluate cloud computing options. For example, when deciding between different cloud providers, AHP can help managers determine which criteria are most important, such as security, cost, and scalability. By using AHP, managers can make more informed decisions and ensure that the most important criteria are given appropriate consideration.
- ISM can be used to understand the relationships between different factors that impact cloud computing. This can help managers identify key drivers of cloud computing success or failure, as well as potential roadblocks. By using ISM, managers can develop a better understanding of how different factors interact and affect each other and make more informed decisions as a result.
- MICMAC can be used to identify the most influential factors impacting cloud computing, and how they are interconnected. It can help managers identify critical factors that need to be addressed in order to improve cloud computing performance. By using MICMAC, managers can gain insights into the underlying factors that affect cloud computing success or failure and develop strategies to address them.

These MCDM techniques can help managers make better decisions in the field of cloud computing, by providing a structured approach to evaluating options, understanding the relationships between different factors, and identifying critical factors for success.

As already discussed, the authors have raised three research questions and intended to find the answers through this research. To achieve the predetermined goal, the authors identified some significant flaws after studying and doing extensive research on the previous literature and designed three research objectives simultaneously. Therefore, theoretical contributions can be presented as follows, fulfilling all the research objectives.

- Paying the highest effort and conducting several intense brainstorming sessions, the expert members narrowed down 15 crucial factors that act as barriers against the implementation of sustainable cloud computing systems in the IT industry.
- Firstly, the most important factors among 15 sustainable AI parameters have been identified using AHP that highly affect the cloud environment within the IT industry.
- Secondly, ISM helps in establishing the interrelationship among the 15 factors and defining their hierarchical levels.
- Finally, the dependence and driving performance of all 15 parameters are determined using MICMAC analysis.

Therefore, managers can shape their businesses accordingly by taking care of the strong drivers and the most important parameters that have the strongest influence on cloud computing implementation.

Since the MCDM study is completely based on computational and data analysis, the prescribed judgment may not always match the expectations with reality. Moreover, the above analysis is highly reliable on expert's judgment and decisions; hence, there is a chance of biasedness in the verdicts of the decision-maker. MCDM methods are often based on subjective judgments, such as the weights assigned to the criteria, or the ratings given to the alternatives. The subjectivity of these judgments can introduce biases and errors into the decision-making process. It is also true that only 15 parameters have been examined in this present study; however, other AI factors are also present that may have an influence or impact on the cloud environment. The ongoing investigation provides one broad idea regarding the most critical parameters that may impact the cloud system within an organization. Additionally, all three MCDM models, i.e., AHP, ISM, and MICMAC require data on the interrelationships between the elements in the system. Collecting this data can be time-consuming and expensive. MCDM methods can be quite complex, especially when dealing with many criteria or alternatives. As the number of elements increases, the complexity of the analysis increases, making it difficult to draw meaningful conclusions.

6. Conclusions

The present article mainly deals with the sustainable AI factors that need to be implemented in every IT sector to improve the cloud-based system environment. The present analysis is completely established on a total of fifteen parameters that are categorized into five major (or main) criteria followed by the sub-categorization into three sub-factors (or sub-criteria) within each main criterion. The following decision problem starts with AHP analysis for evaluating the criteria weights. AHP helps us to identify the most important parameters among the 15 selected ones according to the priority vector weights obtained. AHP clearly reveals that digitalization of innovative technologies is the most important factor on the list followed by funding from external bodies in second and environmental optimization and management in third. Among the five main factors, technological issues may be treated as the most critical major group that should be managed to improve the AI-enabled cloud system environment. Consecutively, the tendency of the user to learn, exchange information, and use skill development training programs holds the last three positions 15, 14, and 13 indicating the least significant factors among the group, respectively. As a result, the factors coming with the highest weightage should be given maximum priority, because these factors are the most significant and have the highest contribution in the field of cloud computing. Similarly, the factors with the least weight values can be completely ignored. Therefore, the first research question formulated previously is hereby answered. Here comes the answer to the second question. The ranking of the 15 factors has also been proposed based on the reducing weight magnitude that clearly highlighted the most important and the least important factors in the list. All 15 considered factors are also examined based on both local weights and global weights to judge how the selected parameters performed locally within their own main group as well as how they performed globally. As a result, the first objective of this research study is met successfully.

6.1. Managerial Implications

The AHP–ISM–MICMAC integrated hybrid MCDM model is a sophisticated decision-making framework that combines AHP, ISM, and MICMAC approaches to examine essential factors for developing a long-term AI cloud system in the IT business. This paradigm has some major managerial consequences, which are discussed more below.

- The integrated model can assist in identifying and prioritizing crucial parameters that have a substantial impact on the successful implementation of a long-term AI cloud system. These data are critical for managers in directing their resources and efforts toward the most influential factors.

- The output results can help managers allocate resources more efficiently. Organizations can allocate cash, time, and people to address the most crucial factors first by understanding the interrelationships and dependencies between parameters.
- Implementing long-term AI cloud systems entails inherent risks. The model can help evaluate potential risks linked with various parameters and their effects on the overall system. This enables managers to establish risk-mitigation strategies in advance.
- The model sheds light on the cause-and-effect interactions that exist between various parameters. This data can help in developing comprehensive and effective strategic plans for the implementation of long-term AI cloud systems.
- As the AI cloud system deployment progresses toward advancement, the model's findings can be used to compare the system's performance to projected outcomes. Managers can take corrective actions if certain parameters do not behave as intended.
- The integrated model can help managers make decisions by giving a structured way to consider many criteria and their interconnections. It assists in making educated and impartial decisions based on the model's outcomes.
- Collaboration with diverse stakeholders is required for the implementation of sustainable AI cloud systems. The model can help in understanding the concerns and interests of many stakeholders, which can lead to better participation and consensus-building.
- The model encourages businesses to seek novel solutions by understanding the complicated interactions between factors. It has the potential to encourage research and development activities to overcome fundamental issues in building long-term AI cloud systems.
- Organizations can obtain a competitive edge by prioritizing crucial factors that differentiate them from competitors in terms of sustainability, efficiency, and performance.
- The integrated model prioritizes sustainability as a critical decision-making factor. Managers may assure the long-term viability and profitability of their AI cloud system implementations by taking environmental, social, and economic considerations into account.

It is vital to note that the successful deployment of this integrated model necessitates a thorough comprehension of the underlying procedures as well as reliable data. Managers should also be prepared to modify their strategies and actions in response to the changing nature of the AI and cloud industries, as well as emerging sustainability issues and possibilities.

6.2. Limitations

While the AHP–ISM–MICMAC integrated hybrid MCDM model provides useful insights and benefits for examining critical factors for creating a sustainable AI cloud system in an IT industry, there are also some limitations that cannot be completely overlooked.

- The model primarily relies on data for parameter evaluation and interrelationship analysis. The precision and validity of the model's results can be limited by a lack of trustworthy and comprehensive data.
- AHP relies on expert assessments during pairwise comparisons, which can induce biases and variations in the results. The experts' viewpoints and comprehension of the parameters influence the model's conclusions.
- The model is complex and time-consuming due to the incorporation of different approaches. Data collection, analysis, and interpretation can be time-consuming and expensive.
- While the model aims to describe parameter interdependencies, real-world interactions among parameters may be more complex and difficult to correctly express in a model.
- The IT industry, including AI and cloud technologies, is fast evolving. The model's validity may be reduced over time as technology, industry standards, and best practices evolve.

- Despite its ability to identify crucial factors, the model may not provide a deeper knowledge of the underlying causes of interrelationships and consequences. Additional qualitative analysis may be required for comprehensive interaction.
- During pairwise comparisons, AHP implies independence between criteria, which may not always be true. Some criteria may be dependent on others, affecting the ultimate outcomes.
- Some crucial parameters may have complex interactions that the model is unable to fully capture. This may result in oversimplification of some components of the analysis.
- The usefulness of the model may vary across different geographical areas or organizational contexts, and the generalization of outcomes may be limited.
- While the model seeks to assess sustainable characteristics, it may not address all aspects of sustainability, such as ethical issues, social impact, or long-term environmental implications.
- The model may not fully encompass all key stakeholders' perspectives, thus leading to the omission of some critical aspects or opportunities.

To solve these constraints, decision-makers must use the model's outputs as a relevant reference but not rely exclusively on them. Complementing the study with real-world insights, stakeholder feedback, and more qualitative research can improve the overall decision-making process for adopting long-term AI cloud systems in the IT business.

6.3. Scope of Future Work

The following research may be extended in the future by introducing some new MCDM tools and encouraging a greater number of participants to contribute to the survey. Although a panel board of 30 members from different professional fields is constituted, this is not enough to take appropriate decisions. A greater number of participants from diverse areas having vast experiences should be involved in the survey to identify the barriers more precisely. Furthermore, more optimization techniques may be applied along with AHP–ISM–MICMAC like SEM, PCA, and DEMATEL to filter the barriers and examine the decision-making procedure more closely and accurately. The potential and ability of the established hybrid model of AHP–ISM–MICMAC can also be verified by applying it to other industries including the health sector, educational sector, transportation sector, electronics industry, mining industry, etc., who are seeking to implement an AI-enabled cloud concept within their organization.

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