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Selection of Technology Acceptance Model for Adoption of Industry 4.0 Technologies in Agri-Fresh Supply Chain

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Abstract: Technology is advancing at a very rapid pace, and it helps the user in predicting things, taking the right decisions, making life less difficult and eventually increasing the profitability of their business. Due to the increasing global population, changing climatic conditions, and other natural factors predominating in nature, agriculture practice is becoming less predictable and as a result, farmers' confidence is being lost, poverty and food insecurity are rising, and other issues are becoming more prevalent. In addition, it affects the sustainability of the food supply chain. So, there is a critical need for agriculture to adopt Industry 4.0 technologies. Here, we want to select a suitable technology acceptance model which comprehensively and robustly defines all the aspects of technology adoption factors in agriculture. From the different adoption theories, we choose one theory that fits our criteria very accurately; for this, we use a hybrid MCDM approach. We utilised fuzzy AHP and fuzzy VIKOR to make the selection logically and systematically correct. Three experts are employed in the study. Fuzzy AHP helps to find the weightage of criteria used by the fuzzy VIKOR technique in ranking the theories. The results showed that the UTAUT ranking comes number one after applying all the suitable criteria and alternatives, and it is the most accurate theory for analysing the adoption of Industry 4.0 technologies in agriculture. This article offers readers a methodical approach for choosing a technology adoption paradigm. The hypothesis that best fits a person's criteria can be determined by comparing them to potential alternatives.

Keywords: adoption models; industry 4.0; Agri-tech; I4.0; agriculture; UTAUT model; fuzzy AHP; fuzzy VIKOR; MCDM

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1. Introduction

In developing nations, the agricultural sector is regarded as the primary industry and contributes to eradicating poverty and increasing food security. However, this industry must deal with several production risks, financial challenges, and human, political, and economic problems [1]. In India, approx. 65–70 percent of the whole population is involved in agriculture and its allied sectors. Additionally, this is made possible by controlling the different flows of the various stakeholders involved to meet the needs of end-users, so as to build an entire Agri-fresh supply chain (AFSC) network. There are multiple stakeholders in AFSC, which are "farmers, consumers, distributors, government systems, non-governmental organisations (NGOs), institutions, national and international agencies" [2]. All stakeholders have a crucial role to play in maintaining the sustainability of the Agri-fresh supply chain. Sustainability has three primary variables that are economic, environmental and social, so if there is an impact on these areas, then there is an effect on sustainability.

As the world's population grows, there is increased pollution and global warming, which harms the environment, causing an unanticipated change in climate and weather changes that damage crops, lower output, and force farmers to lose faith in the AFSC.

Numerous studies have examined on-farm practices such as diversification, irrigation, crop switching, fertiliser switching, and pesticide switching to mitigate the adverse effects of climate change [3]. Additionally, integrating modern technologies into AFSC has become urgent, given the rising public concern over agricultural activities and their safety.

Additionally, the advent of I4.0 in manufacturing has skewed the scales. Other industries undergo a relative change [4]. The key components of the fourth industrial revolution, or I4.0, include decentralisation, digitisation, automation, virtualisation, machine-to-machine communication, and real-time data collecting and processing [5]. During the first industrial revolution (I1.0), the first steam engines and mechanical power systems were employed, and in the second industrial revolution (I2.0), electricity was introduced. I3.0 was powered by electronics and automation, known as Mechatronics, while I4.0 was built on modern technology [6]. So, this revolution is being fueled by I4.0 technology. Therefore, the possibility of applying the I4.0 principle in AFSC is clear because it also reduces waste (Muda), the financial burden of outbreaks, and the likelihood of product failures [7]. By leveraging I4.0 technology, the AFSC can become more networked, intelligent, competent, integrated, data-driven, agile, and autonomous. Additionally, the use of I4.0 technology to improve other industries is well-documented, but there are few comparable uses in the AFSC. To understand how I4.0 technologies are transforming AFSC, further research is required.

Technology enables the user to maximise the value of already available resources. Farmers' use of Industry 4.0 technologies lowers the likelihood that their crops would be harmed by weather, other environmental conditions, or disease and reduces the amount of labour-intensive, time-consuming work that must be done. I4.0 technologies include AI devices, ML algorithms, big data, blockchain technology, smart intelligence, and IoT devices that aid in real-time monitoring, weather prediction, disease diagnosis, and many other advantages. Since these technologies are data-driven, so they produce good results. By promoting information sharing and collaboration, I4.0 technologies assist the Agri-fresh supply chain in becoming more productive, sustainable and having good resilience [8].

A recent study has focused much attention on users' adoption of new technologies. The method used to examine this idea involved examining crucial aspects of user adoption, behavioural intention, and technology use [7]. Numerous adoption models can be used to analyse the variables that influence user's decision making, including the technology adoption model (TAM), theory of planned behaviour (TPB), unified theory of acceptance and use behaviour (UTAUT), theory of reasoned action (TRA), and innovation and diffusion theory (IDT). We must take our needs into account while utilising any technology adoption model because different models work according to different perspectives and standards of the technology domain under consideration.

In earlier studies, researchers embraced specific ideas based on their presumptions and knowledge, but no one ever carefully selected a quantitative method which could objectively consider the attributes of technology adoption theory. Furthermore, our study requires investigation in this field, which was identified through a review of the literature. To select the technology acceptance model that best satisfies our goals, we are utilising an integrated multi-criteria decision-making model (MCDM) in this study. We employ hybrid MCDM, which consists of fuzzy AHP followed by fuzzy VIKOR, to decide which model to use [8].

Fuzzy AHP was used very extensively earlier by researchers for decision making in various fields because it handles imprecise and uncertain data very accurately [9,10]. Each criterion's weight should be fixed using the fuzzy AHP method, and the decision-making process should be ranked using the VIKOR method [11,12]. The decision makers were able to handle decision problems that are hazy and ambiguous and need clear-cut numerical inputs more effectively by using fuzzy AHP and fuzzy VIKOR, as opposed to the standard AHP and VIKOR method. The strength of FVIKOR is to manage a large number of alternatives and generate an e-solution that is very close to the ideal solute ion. In these publications, researchers employed hybrid MCDM for decision making, first in project portfolio selection in the automotive sector and then selecting appropriate storage technology. The effectiveness of combining two MCDM approaches has been well established, and various researchers have provided publications that support this claim [13]. Many researchers compare the different MCDM methods for weighing and ranking purposes, and they generally choose fuzzy VIKOR for ranking it [14]. Many authors commonly use fuzzy TOPSIS for finding the weight of criteria and rely upon fuzzy VIKOR for ranking [15–18]. Additionally, some researchers used hybrid approaches for best selection [19].

This paper provides readers with a systematic way to select a technology adoption model. One can compare their criteria against alternatives and find which theory suits them most. Because theory selection is the initial step before analysis of technology adoption, which is most crucial if a wrong theory is selected, there is the chance that we may not get accurate results, and your time and efforts will be wasted. Earlier researchers took subjective approaches for theory selection, but this study provides an objective approach without any pre-assumption, which is the vital contribution of this study [13].

Opinions of food industry experts are utilised in this study. We took the opinion of experts in criteria selection, in pairwise comparison matrix formation and in the MCDM approach. These experts are from the R&D department, they are above the manager-level designation, and all are technically sound personnel with strong agriculture expertise.

This paper is divided into five sections. We begin by explaining the study's purpose and need, followed by a discussion of the literature related to various acceptance model applications and usage patterns. The third portion introduces the hybrid MCDM approach methodology that we employ here, fuzzy AHP and fuzzy VIKOR. The results portion is covered in the subsequent section, and the entire research project is wrapped up with references and ideas for further research in the last section [20].

2. Literature Study

Over the past ten years, MCDM techniques have swiftly advanced and changed to meet a variety of applications. Various researchers used MCDM in multiple areas and derived good results. This section highlights the work related to technology acceptance models and relevant multi-criterion decision techniques in the extant literature.

2.1. Literature Review on Technology Acceptance Models

Many studies have been conducted on how people accept and use IT systems. In recent years, many theories with fresh perspectives have evolved at individual and organisational levels, each focusing on a single or group of countries [21]. A number of theories and models have been established to understand how end-users choose to use technology. The same dependent variable, usage or intention to use, is present in all models proposed in the literature. Still, different antecedents are used in other models to understand how technology acceptance is understood [22]. The theory of planned behaviour [23], theory of reasoned action (TRA), technology adoption models (TAM), innovation and diffusion theory (IDT), and unified theory of acceptance and use of technology (UTAUT) are among the most well-known theoretical frameworks at the individual level that have made an effort to explain the connection between user beliefs, attitudes, and intentions.

Innovation and diffusion theory (IDT): According to the IDT, personal and technological factors affect how quickly people adopt new technology. Depending on how quickly technology is accepted, people can be classified as innovators, early adopters, early majority, late majority, and laggards, according to the innovation diffusion theory [24]. These categories show the technology acceptance rate of the people. Some essential characteristics influencing IDT are trialability, complexity, relative advantage, compatibility [25]. The IDT details how new technologies and other developments move throughout civilisations and cultures, from introduction to widespread adoption [26]. How quickly diffusion or spreading occurs depends mainly on how innovations are conveyed to various societal segments and the subjective perceptions attached to them.

Theory of planned behaviour (TPB): The theory of reasoned action is expanded by the TPB, which derives from social cognitive theories (TRA) [23]. TPB focuses primarily on perceived behavioural control or the perceived ease or challenge of carrying out the behaviour. The TPB states that whether a behaviour is being carried out depends on the individual's intention to carry it out [24]. The effort a person will put into a particular behaviour is referred to as intention. According to his study, behaviour is affected by three significant factors, which are: (1) attitude towards the behaviour, (2) subjective norms, and (3) perceived behavioral control.

These key factors can be defined in such a way that:

(1) Attitude towards the behaviour: the individual's viewpoints on the expected outcomes of their behaviour, both when they intend to and when they engage in it, as well as the associated favorable or unfavourable outcomes;
(2) Subjective norms: the effect of social influence on an individual's behaviour and the degree to which it affects their decisions is what this term refers to;
(3) Perceived behavioural control: ideas and perceptions of the person regarding the elements that help or hinder their capacity to engage in the behaviour.

Technology adoption model (TAM): The TAM, which was developed to predict information technology acceptance and use in the workplace, with perceived usefulness (PU) and perceived ease (PE) of use as its main predictors of attitudes [27]. PU: a person thinks about to what extent their performance and efficiency are enhanced by employing specific technology. Perceived ease of use (PE): the extent to which someone thinks using a particular technology is effortless/reducing their effort [28,29]. According to the TAM, a person's attitude toward using the system, which perceived usefulness and perceived ease of use define, directly determines whether they intend to utilise and accept technology. TAM is widely employed in various contexts, which makes it highly popular. A further enhanced version of TAM, known as TAM2, is also introduced [24].

The above two models (TPB and TAM) were founded on TRA, which posits that beliefs affect attitudes, which in turn influence intentions, which eventually result in behaviour. [23] Researchers believe that attitudes and the subjective aspect of behaviour drive behaviour in TRA [30]. TAM is widely used in a different context, which shows its results are reliable and accurate [31–33]. Here, we can observe the TAM application in cloud computing adoption by the government in Saudi Arabia and in online shopping adoption.

Theory of reasoned action (TRA): According to TRA, people have a higher desire (motivation) and are more likely to carry out the advised conduct if they perceive it as positive (attitude) and believe others want them to do so (subjective norm). Similarly, attitudes and subjective norms can predict intentions to use technology. In other words, the more highly someone values a particular behaviour or action and the more positively they believe the conduct to be significant to their friends, family, or society, the more probable their decision to partake in it [24].

A unified theory of acceptance and use of technology (UTAUT): Venkatesh, Davis, Davis, and Morris (2003) provide a thorough analysis of eight well-known models and the development of a unified theory of acceptance and use of technology (UTAUT), which can account for up to 80% of the variance. The UTAUT model was created to combine ideas and actual data on people's intentions, acceptance, and adoption of new technology into a unified theoretical model. These researchers examined the following eight models: TRA, TAM, and the motivational model [27]. Constructs of the UTAUT model are performance expectancy, effort expectancy, social influence and facilitating condition. These constructs can be defined as:

Performance expectancy (PE): relates to the extent to which the end-user anticipates that the technology will be beneficial for carrying out specific tasks and improving performance.

Effort expectancy (EE): it shows the degree to which efforts are reduced using a particular technology.

Social influence (SI): it shows society's impact on a decision maker's decisions.

Facilitating condition (FC): the extent to which a person believes that the current technological environment supports employment technology.

It is hypothesised in the model that facilitating conditions are a direct predictor of actual user behaviour, and the other three-parameter model, PE, EE, and SI, are direct predictors of behavioural intention [24]. The literature shows that the UTAUT mode eliminates the various shortcomings of TAM, TRA, and IDT and other models up to a great extent by incorporating the other moderating parameter. It includes gender, sex, the voluntariness of use and experience as moderating variables (Venkatesh et al. (2003), User Acceptance of Information Technology, n.d.). The literature demonstrates that the UTAUT model is quite thorough and integrated, which is why it is beneficial in determining how end-users will embrace new technologies.

Researchers discovered that the UTAUT model has very high accuracy and has been used in many contexts, making its application quite versatile. It was examined and used in numerous instances, such as online bulletin boards [29], learning management system adoption [22], web-based learning adoption [25] and internet banking adoption [22].

2.2. Literature Review on MCDM Applications in Various Contexts

In diverse farming circumstances, researchers applied the MCDM approach. MCDM strategies were very effective in these scenarios since we have to make many agricultural decisions that directly or indirectly affect a farmer and their resources [1]. This shows the use of the integrated MCDM (FAHP and FTOPSIS) technique to select the best agriculture insurance package based on their criteria [34,35]. In his paper, he employed the MCDM TOPSIS and SAW to prioritise the risk management scenarios [36]. His study uses AHP and the fuzzy method to evaluate the land suitability analysis (LSA) method for agriculture [37]. In his research, he evaluated the effectiveness of two MCDMs fuzzy VIKOR and FOWA, in ranking water-supply system simulations in terms of their ability to meet agricultural water demands and maintain crop patterns. As the crop pattern has a massive impact on the viability of sustainable farming methods, they use fuzzy TOPSIS to choose the best crop pattern in their research [38]. In their study, they use a hybrid decision-making approach, SWARA and VIKOR, to adopt smart waste management techniques in the context of the circular economy in Pakistan to achieve higher sustainability standards. This article aims to identify blockchain drivers to achieve sustainable food security in the Indian context and model them using an integrated MCDM approach.

3. Methodology

The agricultural industry is a very vital and significant one. Here, we wish to use an adoption model to illustrate the adoption of Industry 4.0 technologies into this sector. Our literature review discovered numerous aspects that individuals consider before embracing new technology. As the complexity of the components rises, greater care should be used when choosing theories to achieve good outcomes. As every model has its characteristics and attributes, which appropriately restrict its application to a specific field, we must select a comprehensive and compatible model to match the agricultural sector's needs. Since there is yet to be any scientific research on systematically choosing an adoption model, this study demonstrates model selection based on influencing criteria. There are several adoption theories and many factors to consider while choosing an adoption model. We provide a comprehensive fuzzy AHP-VIKOR approach-based framework for selecting the best technology adoption model that considers all the criteria and all the available options [39]. The considerations, which must be sufficiently extensive, should be used to determine the adoption model. If the decision makers feel that other measures are necessary, they might be added to the suggested procedure. A generic model of MCDM model where M denotes criteria and T denotes theories is presented in Figure 1.

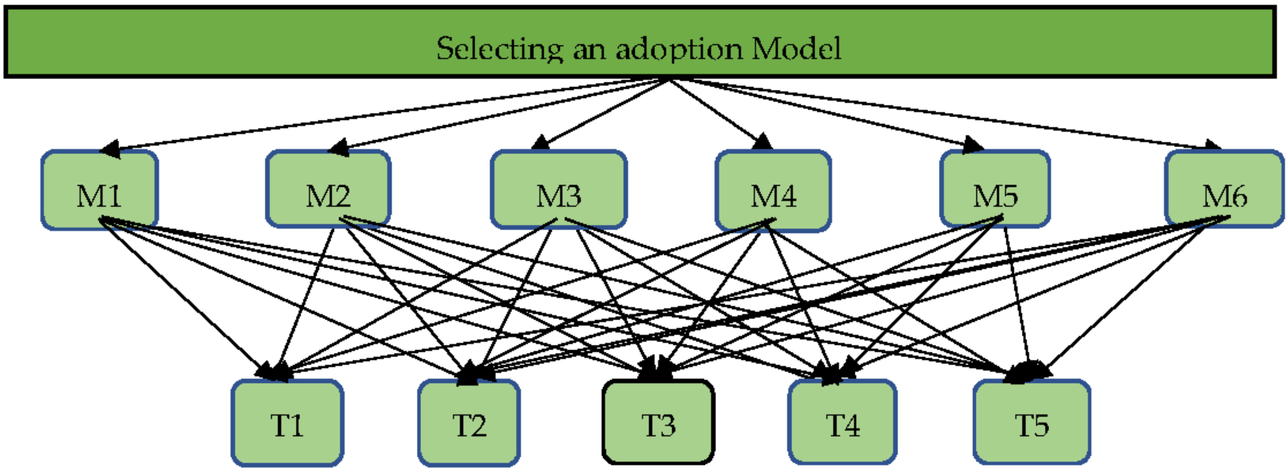

Figure 1. MCDM model where M denotes criteria and T denotes theories.

These are the criteria:

A. **Social Aspect:** Social aspect studies social relations between individuals from a sociological standpoint. In this, we focus on how people affect each other and their impact on the consumer's decisions [30,40], as well as the importance of the social aspect in technology acceptance;
B. **Robustness means** the ability to withstand or overcome adverse conditions or rigorous testing. Robust models are more reliable because their findings are close to correct and can be used in various situations. Ref. [41] indicates the importance of robustness in the adoption of technology and [42] suggests the importance of the robustness of the adoption model;
C. **Comprehensive:** A model must be comprehensive, which means it must consider various elements and yield outstanding accuracy. Ref. [43] suggests how comprehensiveness impacts the accuracy of the results and [44] focuses on the model, which is more comprehensive.
D. **Compatibility:** Compatibility means the adoption model can be applied in different contexts and situations easily and produce good results. Additionally, the model must work with users. It is a crucial factor to consider when selecting any model. Many types of research show compatibility as a vital criterion when working with theories. Ref. [45] consider compatibility a significant criterion while working with the technology adoption model. Ref. [46] also indicates the importance of the model's compatibility.
E. **Technological aspect:** Any model covering the area's technical aspects is always an extra edge. In [47] they used the adoption model, which consists of technical aspects of the system and the model used in [48] majorly focuses on technological aspects.
F. **Human dynamics:** Human dynamics involve actions involving people, such as human effort and behaviour. Many researchers pay close attention to these human dynamics characteristics [22]. This paper uses the adoption model in which human dynamics is an important attribute. In [49] the researcher stated how human dynamics played an essential role in technology adoption decision making.

The flow diagram representing the approach used for the study is exhibited in Figure 2.

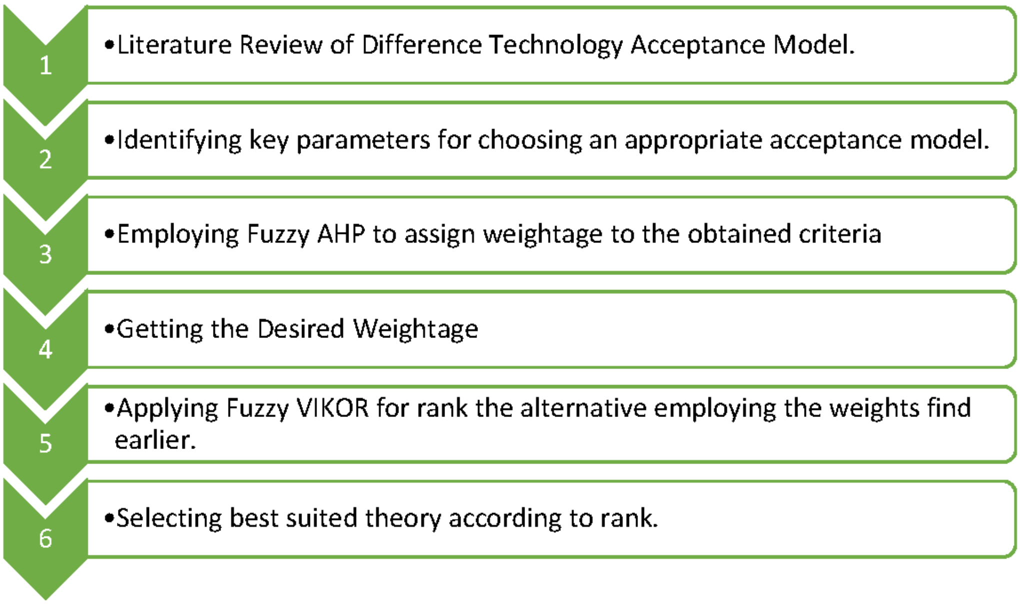

Figure 2. Flow diagram of approach used for the study.

3.1. Fuzzy AHP

A decision-making problem is organised as a hierarchy using the AHP, which Saaty created in 1980. The hierarchy consists of a general objective, a set of alternatives, and criteria that connect the other options to the goal [50]. Laarhoven and Pedrycz proposed the fuzzy analytic hierarchy process in 1983, utilizing a mix of fuzzy theory and the hierarchical process (AHP). The main contribution of fuzzy set theory is its ability to represent ambiguous data. Most of the time, ambiguity is present in decision makers' decisions, so to handle this ambiguity, the fuzzy approach is used [51]. The opinions of experts are transformed by FAHP to fuzzy integers and membership functions. Triangular fuzzy numbers (TFNs) are employed in this work to turn the variables into fuzzy sets, which are then transformed into crisp values [52], indicated in Figure 3 showing the triangular membership function. In the figure 'L' indicated lower value of membership function, 'M' the most occurring and 'U', the upper value. The adoption of the triangular fuzzy membership functions is due to their straightforward application and accurate assessment. In MCDM-based approaches, people usually use the fuzzy number, which follows triangular properties as a mode of representation [53]. A selected membership function accurately determines the nature of inputs.

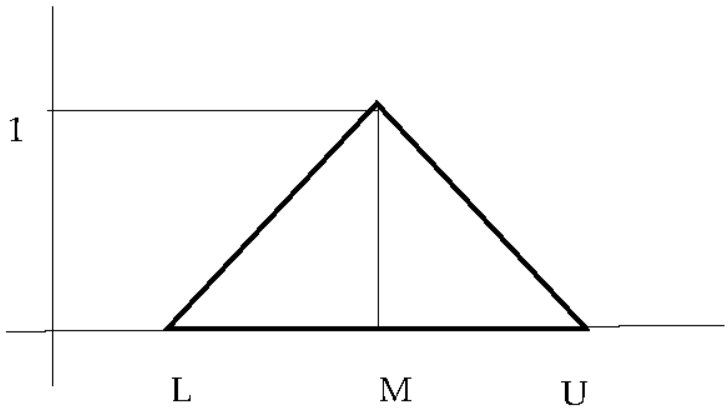

Figure 3. Showing the triangular membership function.

$$\Phi A(X) = \begin{Bmatrix} 0 & X \le L \\ \frac{X-L}{M-L} & L < X \le M \\ \frac{X-U}{M-U} & M < X \le U \\ 1 & X > U \end{Bmatrix}$$

It could ascertain the significance of the under-consideration qualities or the relative pairwise comparison by carrying out particular mathematical operations, including using a predetermined scale from 1 to 9. In a pairwise matrix, the decision maker is traditionally asked to rate the importance of one criterion (C1) in relation to another (C2) with regard to the overall objective [8].

We are computing the weight of these criteria using this fuzzy AHP, which is then employed in ranking alternatives [11]. The linguistic scales and fuzzy triangular numbers are shown in Table 1.

Table 1. Triangular linguistic parameters.

Linguistic Variable	Crisp Value	Triangular Fuzzy Numbers
Equal Importance	1	(1, 1, 1)
Moderate Importance	3	(2, 3, 4)
Strong Importance	5	(4, 5, 6)
Very Strong Importance	7	(6, 7, 8)
Extremely Strong Importance	9	(9, 9, 9)
Intermediate Importance	2	(1, 2, 3)
	4	(3, 4, 5)
	6	(5, 6, 7)
	8	(7, 8, 9)

According to the fuzzy, we need to make a hierarchical structure by decomposing the problem into parts containing the objective, criteria, and alternatives. The experts should approve this hierarchical structure because it may not include all levels of hierarchy depending upon the situation. We have formed a matrix containing pairwise comparison from the Satty scale, which is the first step of applying the AHP. In this matrix, we looked into the dominance of one term over another and formed the whole matrix. Let a total number of criteria be p, which is employed in the problem, and v be the number of decision makers, so for each decision maker a separate matrix is formed. We used the Satty fundamental scale for the best accuracy.

In a general way, for all matrices where e_{ij} = weight of the criterion of i related to j as discussed below:

$$E = \left[e_{ij}^{k}\right] = \begin{bmatrix} e_{11}^{k} & e_{12}^{k} & \cdots & e_{1j}^{k} \\ e_{21}^{k} & e_{22}^{k} & \cdots & e_{2j}^{k} \\ \vdots & \vdots & \ddots & \vdots \\ e_{i1}^{k} & e_{i2}^{k} & \cdots & e_{ij}^{k} \end{bmatrix}_{mxn} \tag{1}$$

The assessments of several decision makers must now be combined. The primary objective of this assemblage is to generate valid findings from the pairwise matrix (PWC). For this, we have to transform the pairwise comparison matrix e^{k} into a fuzzy comparison matrix e^{-k}.

We use a triangular fuzzy number, where $\widetilde{e}_{ij}{}^{k}$= ($e_{ij1}{}^{k}$, $e_{ij2}{}^{k}$, $e_{ij3}{}^{k}$) and $\widetilde{e}_{ji}{}^{k}$= ($1/e_{ij3}{}^{k}$, $1/e_{ij2}{}^{k}$, $1/e_{ij1}{}^{k}$) if $i \neq j$.

To determine the fuzzy weights for the criteria, we must combine numerous fuzzy sets from the matrix into a single fuzzy set by combining the fuzzified pairwise comparison matrices $\tilde{e}^{k}$ into an assembled fuzzified pairwise comparison matrix $\tilde{e}$, as stated in Equation (6). We have employed the geometric mean method [1].

$$\tilde{e}_{ij}^{k} = \prod_{k=1}^{n} A_k = \left(e_{ij}{}^{1} \times e_{ij}{}^{2} \times e_{ij}{}^{3} \times \ldots\ldots e_{ij}{}^{k}\right)^{(1/k)} \quad (2)$$

We employ Equation (7) below to determine the fuzzy weights $\tilde{w}_i$ with regard to the ith criterion.

$$\tilde{w}_i = \tilde{e}_{ij} \times \left(\tilde{r}1 + \tilde{r}2 + \tilde{r}3 \ldots\ldots\ldots\ldots + \tilde{r}i\right)^{-1} \quad (3)$$

For checking the consistency of these we use the Satty consistency formula. A defuzzified matrix is deemed sufficiently consistent if its CR value is less than 0.1.

$$\text{CR} = \frac{CI}{RI} \quad (4)$$

$$\text{CI} = \frac{(\lambda \max - p)}{(p - 1)} \quad (5)$$

where CI, CR, and λ_{max} are consistency index, consistency ratio, and max eigenvalue of comparison matrix, respectively. RI denotes the randomised consistency index and its score is computed by the matrix size. Here, we show in Table 2, the Random consistency index RI for n comparisions:

Table 2. Random consistency index RI for n compared.

n	2.0	3.0	4.0	5.0	6.0	7.0	8.0	9.0
RI Value	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45

3.2. Fuzzy VIKOR

Opricovic in Serbia developed the VIKOR method in 1998 to enhance the classification of multi-criteria complex systems [32,54,55]. They contend that it is uncommon for a method to solve a complex system that can fulfil all of the conflicting requirements at the same time. Therefore, the selection of the best feasible compromise solution to satisfy the given criteria, depending on the importance of each of the multi-criteria classification points, which is a method intended to optimise decision making. Therefore, the VIKOR approach creates a suitable ranking that searches for the supreme answer [56,57].

The fuzzy VIKOR uses the criteria weights from the fuzzy AHP to evaluate its scores. Here, it is recommended that decision makers employ linguistic variables to assess how alternatives rate the criteria. The steps of fuzzy VIKOR are given below:

Step 1: create a fuzzy decision matrix from the available criteria and alternatives.

$$\tilde{F} = \begin{bmatrix} \widetilde{X11} & \cdots & \widetilde{X1n} \\ \vdots & \ddots & \vdots \\ \widetilde{Xm1} & \cdots & \widetilde{Xmn} \end{bmatrix} \quad (6)$$

where $\widetilde{Xij}$ is the score of ith alternatives concerning jth criterion and

$$\text{W} = \left[\widetilde{w1}, \widetilde{w2}, \widetilde{w3}, \ldots\ldots\ldots \widetilde{w4}\right] \quad (7)$$

W is the weights matrix and $\widetilde{Wj}$ denotes the weight of the jth criterion.

Step 2: the fuzzy best value (f tilde j*) and fuzzy worst value (f tilde j^{-}) are found for each criterion value ($\tilde{f}_j$*), and fuzzy worst value ($\tilde{f}_j{}^{-}$) are found.

$$\left(\tilde{f}j*\right) = \max(i)\tilde{X}_{ij} \quad (8)$$

$$\widetilde{f}j = \min(i)\widetilde{X_{ij}} \tag{9}$$

Step 3: using the following formulae, the fuzzy separation values $\widetilde{R}_i$ and $\widetilde{S}_i$ are calculated:

$$\widetilde{S}_I = \sum_{j=1}^{n} \widetilde{w}_j \left[\left(\widetilde{f}_j^* - \widetilde{X}_{ij}\right) / \left(\widetilde{f}_j^* - \widetilde{f}_j\right)\right] \tag{10}$$

$$\widetilde{R}_I = \max_j \left[\widetilde{w}_j \left(\widetilde{f}_j^* - \widetilde{X}_{ij}\right) / \left(\widetilde{f}_j^* - \widetilde{f}_{j^-}\right)\right] \tag{11}$$

Step 4: $\widetilde{S}^*$, $\widetilde{S}^-$, $\widetilde{R}^*$, $\widetilde{R}^-$ and $\widetilde{Q}_I$ value are calculated.

$$\widetilde{S}^* = \min_i \widetilde{S}_i \widetilde{S}^- = \max_i \cdot \widetilde{S}_i \tag{12}$$

$$\widetilde{R}^* = \min_i \widetilde{R}_i \widetilde{R}^- = \max_i \cdot \widetilde{R}_i \tag{13}$$

$$\widetilde{Q}_i = v\left(\widetilde{S}_i - \widetilde{S}^*\right) / \left(\widetilde{S} - \widetilde{S}^* + (1-v)\left(\widetilde{R}_i - \widetilde{R}^*\right) / \left(\widetilde{R} - \widetilde{R}^*\right)\right. \tag{14}$$

The indices $\min_i \widetilde{S}_i$ and $\min_i \widetilde{R}_i$ are related to a maximum majority rule and a minimum individual regret of an opponent's strategy, respectively [58]. The parameter v defines the weight for the maximum group utility approach, but the weight for individual regret is determined by the value (1 − v). v is typically believed to be 0.5 in general.

Step 5: now, de-fuzzify the fuzzy number $\widetilde{Q}_i$.

Step 6: The alternatives are sorted according to their $\widetilde{Q}_i$ value. The alternative with the minimum value is considered the best alternative.

All the steps are illustrated by systematic approach flow chart in Figure 4.

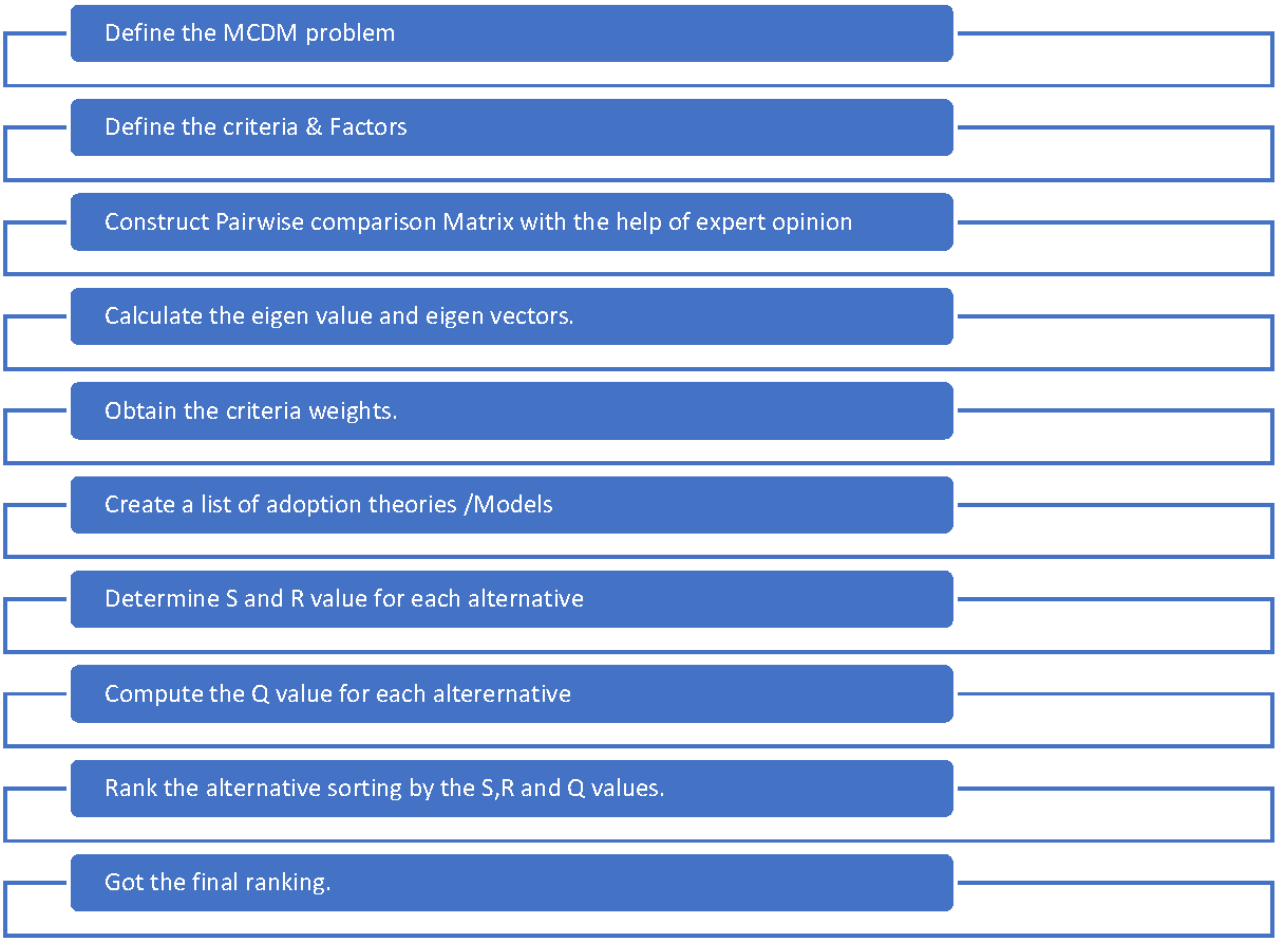

Figure 4. Systematic approach flow chart.

4. Case

Three experts worked with us to analyse five theories (T1, T2, T3, T4, T5) utilising the six criteria, which are social aspect (M1), robustness (M2), comprehensiveness (M3), compatibility (M4), technical aspect (M5), and human dynamics (M6). Here, the symbol "T" is used for adoption theories, and "M" stands for selection criteria.

We started the fuzzy-AHP method using the criteria that had been established, allowing us to choose weights for each criterion. For assigning weights, we followed the procedures below[1].

Step 1: First, we compare each criterion with one another and make the pairwise comparison matrix. We have asked the expert to create a pairwise comparison matrix individually. Below are the tables showing the pairwise comparison by all three experts as in Tables 3–5.

Table 3. Pairwise comparison (D1).

	M1	**M2**	**M3**	**M4**	**M5**	**M6**
M1	1	1/6	1/4	1/3	1/2	1/3
M2	6	1	4	5	6	9
M3	4	1/4	1	3	4	5
M4	3	1/5	1/3	1	3	2
M5	2	1/6	1/4	1/3	1	2
M6	3	1/9	1/5	1/2	1/2	1

Table 4. Pairwise comparison (D2).

	M1	**M2**	**M3**	**M4**	**M5**	**M6**
M1	1	1/5	1/4	1/4	1/3	1/2
M2	5	1	3	6	5	9
M3	4	1/3	1	3	5	4
M4	4	1/6	1/3	1	2	3
M5	3	1/5	1/5	1/2	1	2
M6	2	1/9	1/4	1/3	1/2	1

Table 5. Pairwise comparison (D3).

	M1	**M2**	**M3**	**M4**	**M5**	**M6**
M1	1	1/7	1/2	1/3	1/4	1/2
M2	4	1	3	5	9	6
M3	2	1/3	1	4	5	5
M4	3	1/5	1/2	1	3	2
M5	4	1/9	1/5	1/3	1	2
M6	2	1/6	1/5	1/2	1/2	1

Step 2: After making the pairwise comparison matrix, we convert these crisp values into fuzzy numbers by using the triangular membership function to reduce the ambiguity in the decision maker's decision. For converting these crisp values into fuzzy numbers, we use Table 1; Tables 6–8 show the converted values.

Table 6. Fuzzy evaluation matrix.

	M1	M2	M3	M4	M5	M6
M1	(1, 1, 1)	(1/7, 1/6, 1/5)	(1/5, 1/4, 1/3)	(1/4, 1/3, 1/2)	(1/3, 1/2, 1)	(1/4, 1/3, 1/2)
M2	(5, 6, 7)	(1, 1, 1)	(3, 4, 5)	(4, 5, 6)	(5, 6, 7)	(9, 9, 9)
M3	(3, 4, 5)	(1/5, 1/4, 1/3)	(1, 1, 1)	(2, 3, 4)	(3, 4, 5)	(4, 5, 6)
M4	(2, 3, 4)	(1/6, 1/5, 1/4)	(1/4, 1/3, 1/2)	(1, 1, 1)	(2, 3, 4)	(1, 2, 3)
M5	(1, 2, 3)	(1/7, 1/6, 1/5)	(1/5, 1/4, 1/3)	(1/4, 1/3, 1/2)	(1, 1, 1)	(1, 2, 3)
M6	(2, 3, 4)	(1/9, 1/9, 1/9)	(1/6, 1/5, 1/4)	(1/3, 1/2, 1)	(1/3, 1/2, 1)	(1, 1, 1)

Table 7. Fuzzy evaluation matrix.

	M1	M2	M3	M4	M5	M6
M1	(1, 1, 1)	(1/6, 1/5, 1/4)	(1/5, 1/4, 1/3)	(1/5, 1/4, 1/3)	(1/4, 1/3, 1/2)	(1/3, 1/2, 1)
M2	(4, 5, 6)	(1, 1, 1)	(2, 3, 4)	(5, 6, 7)	(4, 5, 6)	(9, 9, 9)
M3	(3, 4, 5)	(1/4, 1/3, 1/2)	(1, 1, 1)	(2, 3, 4)	(4, 5, 6)	(3, 4, 5)
M4	(3, 4, 5)	(1/7, 1/6, 1/5)	(1/4, 1/3, 1/2)	(1, 1, 1)	(1, 2, 3)	(2, 3, 4)
M5	(2, 3, 4)	(1/6, 1/5, 1/4)	(1/6, 1/5, 1/4)	(1/3, 1/2, 1)	(1, 1, 1)	(1, 2, 3)
M6	(1, 2, 3)	(1/9, 1/9, 1/9)	(1/5, 1/4, 1/3)	(1/4, 1/3, 1/2)	(1/3, 1/2, 1)	(1, 1, 1)

Table 8. Fuzzy evaluation matrix.

	M1	M2	M3	M4	M5	M6
M1	(1, 1, 1)	(1/8, 1/7, 1/6)	(1/3, 1/2, 1)	(1/4, 1/3, 1/2)	(1/5, 1/4, 1/3)	(1/3, 1/2, 1)
M2	(3, 4, 5)	(1, 1, 1)	(2, 3, 4)	(4, 5, 6)	(9, 9, 9)	(5, 6, 7)
M3	(1, 2, 3)	(1/4, 1/3, 1/2)	(1, 1, 1)	(3, 4, 5)	(4, 5, 6)	(4, 5, 6)
M4	(2, 3, 4)	(1/6, 1/5, 1/4)	(1/5, 1/4, 1/3)	(1, 1, 1)	(2, 3, 4)	(1, 2, 3)
M5	(3, 4, 5)	(1/9, 1/9, 1/9)	(1/6, 1/5, 1/4)	(1/3, 1/2, 1)	(1, 1, 1)	(1, 2, 3)
M6	(1, 2, 3)	(1/7, 1/6, 1/5)	(1/6, 1/5, 1/4)	(1/3, 1/2, 1)	(1/3, 1/2, 1)	(1, 1, 1)

Step 3: By using the geometric mean, we have calculated the final weightage of all the criteria. We have used the equation mentioned in the above fuzzy method for calculation. Below, Table 9 shows the weight of each decision maker, and then the final weightage is obtained by taking the arithmetic mean of all [59].

Table 9. Weights of criteria with different decision maker.

	D1	D2	D3	Final Weight
M1	0.050494	0.046512	0.058035	0.05168
M2	0.504867	0.48064	0.47926	0.488256
M3	0.235488	0.256126	0.256856	0.24949
M4	0.124576	0.129986	0.125553	0.126705
M5	0.074955	0.08936	0.079398	0.081238
M6	0.063724	0.058569	0.068791	0.063694

Step 4: for checking the consistency, we used the equation mentioned in the above section. Table 10 indicates model consistency result.

Table 10. Model consistency result.

	λmax	CI	CR
D1	6.451236	0.090247	0.07278
D2	6.408808	0.081762	0.065937
D3	6.311023	0.062212	0.050164

From the above tables, criteria weights are obtained using the equations of fuzzy AHP, and then consistency is checked with the consistency equations of AHP.

Fuzzy VIKOR

The FVIKOR method will be applied to generate a prioritizing ranking for the technology adoption models proposed in this work using the weighted criteria that have already been constructed and validated using the FAHP Method. These symbols are used as indicated by symbol meaning in Table 11.

Table 11. Symbol meaning.

Symbol	Theory
T1	Innovation and Diffusion Theory (IDT)
T2	Theory of Planned Behaviour (TPB)
T3	Technology Adoption Model (TAM)
T4	Theory of Reasoned Action (TRA)
T5	Unified Theory of Acceptance and Use Technology (UTAUT)

Here, for this Fuzzy VIKOR, we use trapezoidal linguistic parameters. Due to their ease of mathematical handling and intuitive interpretation, trapezoidal numbers are particularly popular. The profile of Trapezoidal membership function is shown in Figure 5, where 'a' is the lower most vale of function, 'b' and 'c' are middle range limits and 'd' is the highest value. Because of their conceptual and computational simplicity—largely responsible for their widespread use—trapezoidal fuzzy numbers are used here [42]. Additionally, the previous study discovered that trapezoidal numbers, as opposed to triangular fuzzy numbers, can better represent the most likely scenario when it involves considerable ambiguity [43]. Trapezoidal linguistic parameter are shown in Table 12.

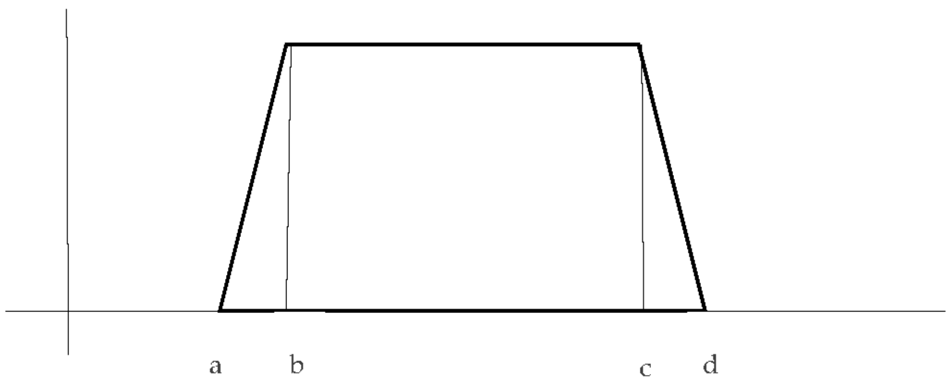

Figure 5. Trapezoidal membership function.

Table 12. Trapezoidal linguistic parameter.

Linguistic Parameter	Trapezoidal Fuzzy Number Scale
Very Poor (VP)	(0.0,0.0,0.1,0.2)
Poor (P)	(0.1,0.2,0.2,0.3)
Medium Poor (MP)	(0.2,0.3,0.4,0.5)
Fair (F)	(0.4,0.5,0.5,0.6)
Medium Good (MG)	(0.5,0.6,0.7,0.8)
Good (G)	(0.7,0.8,0.8,0.9)
Very Good (VG)	(0.8,0.9,1.0,1.0)

Step1: formed the decision matrix with the help of decision makers in the form of the linguistic term. Table 13 indicates Fuzzy pairwise comparison matrix (D1) and Table 14 represents Fuzzy pairwise comparison matrix (D2).

Table 13. Fuzzy pairwise comparison matrix (D1).

Decision Maker		M1	M2	M3	M4	M5	M6
D1	A1	VP	MP	P	P	VG	MG
	A2	F	MG	G	F	VP	G
	A3	VP	MG	F	G	VP	VG
	A4	MG	MG	G	MG	VP	VG
	A5	VG	VG	VG	VG	G	VG

Table 14. Fuzzy pairwise comparison matrix (D2).

Decision Maker		M1	M2	M3	M4	M5	M6
D2	A1	P	MP	MP	MP	VG	MG
	A2	F	F	MG	F	VP	G
	A3	VP	F	MP	MG	P	G
	A4	G	MG	G	MG	P	VG
	A5	VG	VG	VG	G	G	VG
Decision Maker		**M1**	**M2**	**M3**	**M4**	**M5**	**M6**
D3	A1	P	P	P	MP	VG	MG
	A2	MG	MG	G	F	VP	VG
	A3	P	F	F	G	P	G
	A4	G	F	G	G	VP	VG
	A5	VG	VG	G	G	VG	G

Step 2: Now, these linguistic variables of all decision makers are converted into trapezoidal fuzzy linguistic numbers. Fuzzy number conversion from the linguistic term are shown in the Table 15.

Table 15. Fuzzy number conversion from the linguistic term.

Decision Maker		M1	M2	M3	M4	M5	M6
D1	A1	(0.0, 0.0, 0.1, 0.2)	(0.2, 0.3, 0.4, 0.5)	(0.1, 0.2, 0.2, 0.3)	(0.1, 0.2, 0.2, 0.3)	(0.8, 0.9,1,1)	(0.5, 0.6, 0.7, 0.8)
	A2	(0.4, 0.5, 0.5, 0.6)	(0.5, 0.6, 0.7, 0.8)	(0.7, 0.8, 0.8, 0.9)	(0.4, 0.5, 0.5, 0.6)	(0.0, 0.0, 0.1, 0.2)	(0.7, 0.8, 0.8, 0.9)
	A3	(0.0, 0.0, 0.1, 0.2)	(0.5, 0.6, 0.7, 0.8)	(0.4, 0.5, 0.5, 0.6)	(0.7, 0.8, 0.8, 0.9)	(0.0, 0.0, 0.1, 0.2)	(0.8, 0.9,1,1)
	A4	(0.5, 0.6, 0.7, 0.8)	(0.5, 0.6, 0.7, 0.8)	(0.7, 0.8, 0.8, 0.9)	(0.5, 0.6, 0.7, 0.8)	(0.0, 0.0, 0.1, 0.2)	(0.8, 0.9,1,1)
	A5	(0.8, 0.9,1,1)	(0.8, 0.9,1,1)	(0.8, 0.9,1,1)	(0.8, 0.9,1,1)	(0.7, 0.8, 0.8, 0.9)	(0.8, 0.9,1,1)
Decision Maker		**M1**	**M2**	**M3**	**M4**	**M5**	**M6**
D2	A1	(0.1, 0.2, 0.2, 0.3)	(0.2, 0.3, 0.4, 0.5)	(0.2, 0.3, 0.4, 0.5)	(0.2, 0.3, 0.4, 0.5)	(0.8, 0.9,1,1)	(0.5, 0.6, 0.7, 0.8)
	A2	(0.4, 0.5, 0.5, 0.6)	(0.4, 0.5, 0.5, 0.6)	(0.5, 0.6, 0.7, 0.8)	(0.4, 0.5, 0.5, 0.6)	(0.0, 0.0, 0.1, 0.2)	(0.7, 0.8, 0.8, 0.9)
	A3	(0.0, 0.0, 0.1, 0.2)	(0.4, 0.5, 0.5, 0.6)	(0.2, 0.3, 0.4, 0.5)	(0.5, 0.6, 0.7, 0.8)	(0.1, 0.2, 0.2, 0.3)	(0.7, 0.8, 0.8, 0.9)
	A4	(0.7, 0.8, 0.8, 0.9)	(0.5, 0.6, 0.7, 0.8)	(0.7, 0.8, 0.8, 0.9)	(0.5, 0.6, 0.7, 0.8)	(0.1, 0.2, 0.2, 0.3)	(0.8, 0.9,1,1)
	A5	(0.8, 0.9,1,1)	(0.8, 0.9,1,1)	(0.8, 0.9,1,1)	(0.7, 0.8, 0.8, 0.9)	(0.7, 0.8, 0.8, 0.9)	(0.8, 0.9,1,1)
Decision Maker		**M1**	**M2**	**M3**	**M4**	**M5**	**M6**
D3	A1	(0.1, 0.2, 0.2, 0.3)	(0.1, 0.2, 0.2, 0.3)	(0.1, 0.2, 0.2, 0.3)	(0.2, 0.3, 0.4, 0.5)	(0.8, 0.9,1,1)	(0.5, 0.6, 0.7, 0.8)
	A2	(0.5, 0.6, 0.7, 0.8)	(0.5, 0.6, 0.7, 0.8)	(0.7, 0.8, 0.8, 0.9)	(0.4, 0.5, 0.5, 0.6)	(0.0, 0.0, 0.1, 0.2)	(0.8, 0.9,1,1)
	A3	(0.1, 0.2, 0.2, 0.3)	(0.4, 0.5, 0.5, 0.6)	(0.4, 0.5, 0.5, 0.6)	(0.7, 0.8, 0.8, 0.9)	(0.1, 0.2, 0.2, 0.3)	(0.7, 0.8, 0.8, 0.9)
	A4	(0.7, 0.8, 0.8, 0.9)	(0.4, 0.5, 0.5, 0.6)	(0.7, 0.8, 0.8, 0.9)	(0.7, 0.8, 0.8, 0.9)	(0.0, 0.0, 0.1, 0.2)	(0.8, 0.9,1,1)
	A5	(0.8, 0.9,1,1)	(0.8, 0.9,1,1)	(0.7, 0.8, 0.8, 0.9)	(0.7, 0.8, 0.8, 0.9)	(0.8, 0.9,1,1)	(0.7, 0.8, 0.8, 0.9)

Step 3: With the equation of vikor we converted these fuzzy numbers into the crips values for further analysis. Here, weightage is carried forward from the earlier stage (by fuzzy AHP). Fuzzy number conversion from the linguistic term are indicated in Table 16.

Table 16. Convert to crisp numerical value.

Weight	0.05168	0.488256	0.24949	0.126705	0.081238	0.063694
	M1	**M2**	**M3**	**M4**	**M5**	**M6**
T1	0.15	0.29	0.27	0.3	0.93	0.65
T2	0.57	0.6	0.72	0.5	0.08	0.85
T3	0.12	0.57	0.42	0.73	0.15	0.87
T4	0.72	0.6	0.8	0.7	0.13	0.93
T5	0.93	0.93	0.88	0.85	0.85	0.88

Step 4: Using the matrix that has previously been built, as indicated in the Table 17, it is feasible to find the highest and lowest values of each variable. For beneficial criteria, we regarded the greatest value to be the best; for non-beneficial criteria, we considered the lowest value to be the best.

Table 17. Finding the f_{min} and f_{max}.

	M1	M2	M3	M4	M5	M6
$f \times j$	0.93	0.93	0.88	0.85	0.93	0.93
$f - j$	0.12	0.29	0.27	0.3	0.08	0.65

5. Results and Discussion

To rate the concept designs using the VIKOR methodology, all the options are arranged by the values S, R, and Q in ascending order as indicated in Table 18.

Table 18. Values of S, R, and Q for all alternatives:.

Concept				
	S	**R**	**Q**	**Rank**
T1	0.977911	0.488256	1	5
T2	0.520233	0.251757	0.513386	3
T3	0.630305	0.274644	0.594778	4
T4	0.40889	0.251757	0.455328	2
T5	0.01902	0.011374	0	1

We propose a compromise best solution according to the Q Value (min Q value) if the below two conditions are fulfilled:

A1. Acceptable advantage:

$$Q(X'') - Q(X') \geq DQ$$

where X'' shows the alternative ranked second according to Q value, and DQ is given by the equation $DQ = 1/(K - 1)$ where K denotes the number of other options we have. Here, we have K value 5.

A2. Acceptable stability in decision making:

The alternative (X') should also be ranked according to the other two parameters, R and S. We have found that the above result successfully fulfilled the above two conditions, which shows that our compromised solution is correct. According to [57] the second condition is more common when $\nu = 0.5$ and when calculating the two-parameter scores of S and R for each alternative.

From the fuzzy AHP, we determine the weightage of each criterion. We have found that the criteria robustness and comprehensiveness got a high weightage compared to others. After that, we employed the fuzzy VIKOR to rank the alternatives, and we found that.

The alternative T5, which stands for the unified theory of acceptance and use of technology, received the highest ranking of 1 in our methodology, making it the finest adoption model regarding our desired criteria. This demonstrates that the UTAUT acceptance model will yield a good and accurate outcome.

Prior researchers focused on two or three parameters in accordance with their model for technological adoption [60–62]. It can also be made more accurate by including other study-related parameters [63]. Therefore, we looked for an acceptance model that included all three-dimension parameters. Thus, it was discovered that UTAUT would be the appropriate theory for this research and it will provide a wide area for analyzing the technology adoption in the Agri-fresh supply chain.

Theoretical and Managerial Implications

Our primary purpose is to know the farmers' view concerning technology acceptance, why they are willing to take on or why they are reluctant to adopt new technology. So, we need to use a technology acceptance model, which helps us further research. This study helps us find a suitable model with a systematic approach without any pre-assumption, which comes out to be UTAUT. It shows that UTAUT consist of most of the factors that need to be considered in knowing farmers' intention to adopt the new technology. It also helps industry experts to focus on the areas which are essential for decision making for a farmer. The Agri-product organization should take care of those factors in its product design. Through this study, organizations will get a scope of product improvement, addressing the exact customer (farmer) need and helping organization's enhance their business. So, the more comprehensive a model is, the more reliable result it can produce.

6. Conclusions

The inclusion of new technology into agricultural practices is the need of the hour. In today's world, technology helps users in various ways: it can reduce the efforts, allow the user to reduce the resource, improve the output, and much more. In our work, we focus on selecting the best technology acceptance model, which can help in analyzing the factors in the adoption of Industry 4.0 technologies in agriculture. This article offers readers a methodical approach for choosing a technology adoption paradigm. The hypothesis that best fits a person's criteria can be determined by comparing them to potential alternatives. The first stage before analysing technology adoption is theory selection, which is the most important phase. If the wrong theory is chosen, there is a probability that we may not get accurate findings, squandering the time and effort invested by the researcher. This study offers an objective technique without any presumptions, which is its key addition. Previous researchers used subjective methods for selecting theories.

The selection was carried out by considering all potential driving factors responsible for Industry 4.0 technology adoption in agriculture. Farmers need to be involved with smart technologies, such as I4.0 Technology, in a big way since they face a lot of problems caused by several causes that are very unreliable and unpredictable. It is tough to tackle the challenges of agriculture practice with the conventional methods of agriculture, so the main aim is to find a model that incorporates every possible factor that a farmer considers while deciding. We employed fuzzy AHP and fuzzy VIKOR MCDM approaches for this selection. From the literature, we have found the essential criteria a model should incorporate to adopt technology in agriculture, because various researchers have mentioned different adoption models used in this context and their positive and negative aspects. We use three decision makers for our study, helping us build the comparison matrices. Fuzzy theory is employed in the study to handle the ambiguous nature of decision makers. Fuzzy AHP helps identify the weightage of criteria, followed by fuzzy VIKOR for ranking. Once we rank all the theories, then we justify which is our desired theory. According to our criteria and in fulfilment of our goals, we discovered that the theory UTAUT was a good match. This study is not specific to this agricultural context, as UTAUT can be applied well in other areas and produce efficient results. As our criteria are not very specific to the agricultural context, they can be a fit in other different contexts as well, so this study can have the same value for other areas. It is found from the literature also that the UTAUT model was very robust and comprehensive, and previous researchers applied it in their studies and yielded excellent results.

7. Limitations and Future Scope

This study also has certain limitations; firstly, we take the opinions of only three experts, which can be increased to five or six, which can then help to improve the accuracy and reduce the bias. Secondly, we limit our work by taking only six criteria, which can be increased in future work. By considering additional criteria making, our study is more focused and reliable, as more criteria covers more scope and leads to greater visibility. Here, we use fuzzy AHP with fuzzy VIKOR; in future, we can also compare our results by using other MCDM approaches, which create more trust in the results, and we can validate our results as well. Incorporating these points in future studies will make our analysis more reliable.

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