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Savior or Distraction for Survival: Examining the Applicability of Machine Learning for Rural Family Farms in the United Arab Emirates

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Abstract: Machine learning (ML) has seen a substantial increase in its role in improving operations for staff and customers in different industries. However, there appears to be a somewhat limited adoption of ML by farm businesses, highlighted by a review of the literature investigating innovative behaviors by rural businesses. A review of the literature identified a dearth of studies investigating ML adoption by farm businesses in rural regions of the United Arab Emirates (UAE), especially in the context of family-owned farms. Therefore, this paper aims to investigate the drivers and barriers to ML adoption by family/non-family-owned farms in rural UAE. The key research questions are (1) what are the drivers and barriers for rural UAE farms adopting ML? As well as (2) is there a difference in the drivers and barriers between family and non-family-owned farms? Twenty semi-structured interviews were conducted with farm businesses across several rural regions in the UAE. Then, through a Template Analysis (TA), drivers and barriers for rural UAE-based farm owners adopting ML were identified. Interview findings highlighted that farms could benefit from adopting ML in daily operations to save costs and improve efficiency. However, 16 of 20 farms were unaware of the benefits related to ML due to access issues (highlighted by 12 farms) in incorporating ML operations, where they felt that incorporating ML into their operations was costly (identified by 8 farms). It was also identified that non-family-owned farms were more likely to take up ML, which was attributed to local culture influencing family farms (11 farms identified culture as a barrier). This study makes a theoretical contribution by proposing the Machine Learning Adoption Framework (MLAF). In terms of practical implications, this study proposes an ML program specifically targeting the needs of farm owners in rural UAE. Policy-based implications are addressed by the findings aligning with the United Nations' Sustainability Development Goals 9 (Industry, Innovation, and Infrastructure) and 11 (Sustainable Cities and Communities).

Keywords: machine learning; artificial intelligence; innovation; family businesses; farms; UAE; rural

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1. Introduction

Machine learning (ML) is a sub-field of artificial intelligence that is particularly focused on the utilization of available data to train machines to emulate human behavior [1]. The current technological advancements concerning Machine learning (ML) made it a popular discussion point amongst academic and industry professionals, especially regarding how it can be best applied in practice [1]. The ML application was initially developed by Donal Hebb in 1949, as part of a model aimed at investigating brain-cell interaction [2]. Machine learning involves a multi-step process that begins by collecting the data from which the machine intends to learn [1]. This is then pre-processed, before selecting and extracting the relevant features that will be used for training the machine learning model [1]. These features are then fed to a statistical-based model that trains itself to recognize patterns based on the unique characteristics of each feature class [1]. Overall, the term machine learning reflects its definite concept, which is training the machine to automatically make decisions according to set scenarios [1].

Automated decision making and predictions pose great potential benefits for farming applications. For example, [2] explains ML as a technology that benefits farm (an area of land that is mainly dedicated to generating food-based crops via agricultural processes) owners in minimizing losses related to farming by offering recommendations/solutions for how best to manage and nurture crops. Reference [3] adds to the points on machine learning (ML) [2] by identifying ML as a technology that provides insight into methods appropriate for analyzing data from large datasets retrieved from sensors installed within farms. A collective consensus from various authors (e.g., [4–6]) identified a positive impact of machine learning on the daily operations of farm businesses. However, this review of studies also highlighted no/limited research investigating the drivers and barriers for UAE (United Arab Emirates) based farm business owners in adopting machine learning for daily operations. Despite the growing popularity of ML, there appears to be a dearth of studies investigating the role of ML in businesses within the UAE. This is especially the case for family-owned businesses where a collective consensus from different authors have confirmed that culture and a lag in decision making appear to be heavily embedded barriers while taking up innovations amongst family-owned business than non-family-owned businesses ([7–10]). However, this notion has not been explored in the context of ML adoption by businesses in the UAE. It should be noted that over 90% of all private businesses in the UAE are family-owned [11]; therefore, there is an importance for the wider population related to researching technology-based solutions for family-owned businesses in the UAE. According to [12], sustainability consists of addressing the needs of current generations without neglecting the needs of future generations, while ensuring a consistent balance between the areas of economic growth, environmental care, and social and mental well-being. The review of studies investigating ML adoption by businesses also identified a dearth of studies investigating ML adoption by businesses in rural areas in the UAE. Based on the definition of sustainability [12], supporting the growth of rural and isolated communities by undertaking activities such as eliminating the digital divide between rural and urban areas is highly prioritized [13].

For this study, we examine the applicability of ML as an application that would aid decision making amongst farmers, in terms of how to best manage their resources to gain optimum results. Therefore, the purpose of this paper will be to investigate the drivers and barriers to the adoption/use of UAE-based family-owned farms. Additionally, the research questions for this paper are as follows:

(1) What are the drivers and barriers for rural UAE farms adopting ML?
(2) Is there a difference in the drivers and barriers between family and non-family-owned farms?

It is important to note that the scope of this work is limited to assessing the applicability and discussing potential applications and challenges of ML to farming and agriculture. Thus, building a deployable ML model in response to the findings of this work can be considered a future research direction, subject to the availability of agricultural data.

2. Literature Review

Various studies from around the world have identified the role of ML in improving business operations, especially in rural and farm business contexts (e.g., [4–6]). Authors have identified how ML can aid business owners such as farmers in assessing factors such as weather and soil conditions to determine optimum conditions for practices such as growing crops and managing livestock. Investigating the adoption of ML in farm businesses may be insightful for identifying solutions for improving the rural economy. Therefore, a review of worldwide studies investigating the role of innovative practices in rural businesses was conducted, which identified drivers and barriers to adopting innovative practices (including ML) by rural-based businesses.

A review of studies involving innovation adoption by rural area-based businesses led to the identification of drivers and barriers, which are presented in the below tables. For this study, drivers were identified as factors that promote innovation adoption, and barriers were identified as factors that limit or completely stop innovation adoption [14]. The identified drivers are presented in Table 1 in terms of the location of the study and the name of the authors.

Table 1. Summary of drivers for the innovation adoption by rural businesses.

Drivers	Location	Author(s)	Ref.
Access to business information	Asia	Srinivas et al., 2014 (India)	[15]
	Scotland, UK	Deakins et al., 2004; White et al., 2016	[16] [17]
Affordability (cost)	Africa	Masita-Mwangi et al., 2012 (Kenya)	[18]
	Europe	Doherty, 2012 (Ireland)	[19]
	New Zealand	Clark and Douglas, 2011	[20]
	North America	Kuhn et al., 2016 (USA)	[21]
Communication	Africa	Finbarr, 2015	[22]
	Asia	Bagchi, 2013 (India); Srinivas et al., 2014 (India)	[23] [15]
	Australia	Beacom and Nanere, 2010	[24]
	Scotland, UK	Townsend et al., 2014	[25]
	Wales, UK	Cardiff University, 2019; Groves-Phillips, 2013	[26] [27]
Confidence/training	Europe	Delalic and Oruc, 2014 (Bosnia–Herzegovina); Doherty, 2012 (Ireland)	[28] [19]
	MENA (Middle East and North Africa) and Gulf	Al Bar and Hoque, 2017 (Saudi Arabia); Alshebami, 2023b (Saudi Arabia); Bakar et al., 2019 (UAE); Elbeltagi et al., 2013 (UAE)	[29] [30] [31] [32]
Culture (growth-driven business)	Africa	Finbarr, 2015, Olaniyi, 2018	[22] [33]
	Asia	Srinivas et al., 2014 (India); Vakataki 'Ofa, 2018	[15] [34]
	England, UK	Bosworth and Salemink, 2014; Warren, 2004; Wilson et al., 2018	[35] [36] [37]
	Europe	Delalic and Oruc, 2014 (Bosnia–Herzegovina)	[28]
	MENA and Gulf	Al Bar and Hoque, 2017 (Saudi Arabia); Alshebami, 2023b (Saudi Arabia); Bakar et al., 2019 (UAE); Elbeltagi et al., 2013 (UAE)	[29] [30] [31] [32]
	New Zealand	Fabling and Grimes, 2016	[38]
	North America	Passerini et al., 2012 (USA)	[39]
	Scotland, UK	Townsend et al., 2014	[25]
	Wales, UK	Cardiff University, 2019	[26]

Table 1. *Cont.*

Drivers	Location	Author(s)	Ref.
Environmentally friendly	MENA and Gulf	Alshebami, 2023a (Saudi Arabia); Alshebami, 2023b (Saudi Arabia)	[40] [30]
	Scotland, UK	Steiner and Atterton, 2014	[41]
Improved income for businesses	Asia	Novitasari et al., 2021 (Indonesia); Vakataki 'Ofa, 2018	[42] [34]
	England, UK	Wilson et al., 2018	[37]
	New Zealand	Fabling and Grimes, 2016	[38]
	Scotland, UK	Freathy and Calderwood, 2013; Lodwick, 2015	[43] [44]
	Wales, UK	Cardiff University, 2019	[26]
Infrastructure, e.g., satisfactory broadband quality and speed	Australia	Glance, 2017	[45]
	England, UK	Gerli and Whalley, 2018	[46]
	MENA and Gulf	Alshebami, 2023b (Saudi Arabia); Bakar et al., 2019 (UAE); Elbeltagi et al., 2013 (UAE)	[30] [31] [32]
	New Zealand	Fabling and Grimes, 2016	[38]
	Wales, UK	Davies, 2014	[47]
Marketing/promotion	Africa	Finbarr, 2015	[22]
	Asia	Kriechbaumer and Christodoulidou, 2014; Novitasari et al., 2021 (Indonesia)	[48] [42]
	Scotland, UK	Townsend et al., 2014	[25]
	Wales, UK	Cardiff University, 2019	[26]
Support towards daily operations (Planning)	Africa	Ojanji, 2013	[49]
	Asia	Vakataki 'Ofa, 2018	[34]
	England, UK	Wilson et al., 2018	[37]
	New Zealand	Clark and Douglas, 2011	[20]
	Scotland, UK	Galloway and Kapasi, 2014	[50]

Source: Authors.

As shown in Table 1, the main drivers for innovation adoption by rural businesses were identified as 'communication', 'culture' embedded in the organization, 'infrastructure', 'marketing', and 'planning'. The barriers are presented in Table 2 in terms of the location of the study and the name of the authors.

As shown in Table 2, the main barriers against innovation adoption for rural businesses were identified as 'lack of government support' and 'poor infrastructure'. These drivers and barriers have been identified as the main drivers and barriers to innovation adoption based on the number of reviewed studies referring to each driver and barrier. However, the rural classification (accessible-rural/remote-rural) of the business areas, along with their size (micro/small/medium/large sized business) and sector, were not clarified in the reviewed studies. The frequency of innovation adoption (e.g., daily, monthly, or annually) was not clarified by the participating rural businesses in the reviewed studies, where the only authors that addressed the frequency of innovation adoption were [16,43,50]. Additionally, the reviewed studies did not clarify whether the businesses were family or non-family-owned.

Table 2. Summary of innovation adoption barriers identified for rural businesses.

Barriers	Location	Author(s)	Ref.
Confidence/training	North America	Marlin and Bruce, 2006 (Canada)	[51]
	Scotland, UK	Philip et al., 2017; White et al., 2016	[52] [17]
	Wales, UK	Davies, 2014; Groves-Phillips, 2013	[47] [27]
Cost	North America	Marlin and Bruce, 2006 (Canada)	[51]
	Europe	Bourreau et al., 2017	[53]
	England, UK	Wilson et al., 2018	[37]
	Scotland, UK	Tookey et al., 2006; Townsend et al., 2014	[54] [25]
Culture	Asia	Olukayode et al., 2014 (Malaysia)	[55]
	North America	Marlin and Bruce, 2006 (Canada)	[51]
	New Zealand	Battisti et al., 2013	[56]
	Scotland, UK	Burnett and Danson, 2017; Townsend et al., 2014	[57] [25]
Lack of government support (awareness)	Asia	Srinivas et al., 2014 (India)	[15]
	Australia	Choudrie and Middleton, 2014	[58]
	North America	Marlin and Bruce, 2006 (Canada)	[51]
	England, UK	Wilson et al., 2018	[37]
	Europe	Znidarsic and Werber, 2012 (Slovenia)	[59]
	MENA and Gulf	Elbeltagi et al., 2013 (UAE)	[32]
	Scotland, UK	Hill et al., 2016	[60]
Poor Infrastructure	Africa	Finbarr, 2015; Olaniyi, 2018	[22] [33]
	Asia	Chuabsamai, 2016 (Thailand); Srinivas et al., 2014 (India); Vakataki 'Ofa, 2018	[61] [15] [34]
	Australia	Ameeta and Courvisanos, 2013	[62]
	North America	Marlin and Bruce, 2006 (Canada)	[51]
	England, UK	Cowie et al., 2013; Phillipson et al., 2011; Wilson et al., 2018	[63] [64] [37]
	Scotland, UK	Allardyce, 2017; Burnett and Danson, 2017; Ogston, 2017; Philip and Williams, 2019	[65] [57] [66] [67]
	Wales, UK	Cardiff University, 2019	[26]
Security/level of trust	Scotland, UK	Townsend et al., 2014	[25]

Source: Authors.

In terms of studies related to innovation/technology adoption by family-owned businesses, [68] identified communication as a prominent driver for family businesses in reaching their customers through social media platforms for securing sales and after-sales services. Other drivers for adoption by family-owned businesses were highlighted as improving/establishing brand awareness, reducing costs, and improving sales, which improved opportunities for business collaborations via business/social networks established on sites such as LinkedIn [68]. However, [68] also refers to challenges/barriers against technology adoption for family businesses, which are negative online feedback adversely impacting the business and keeping up to date with regular changes in online consumer trends/behaviors. Additionally, the adoption of technology by family-owned businesses may be influenced by family-centered emotions/feelings (culture) towards innovation/technology, which may act as a barrier or driver for technology adoption ([7–10]).

Ref. [69] agrees with the findings from [68] on reduced costs and improved revenue acting as drivers for technology adoption by family-owned businesses. The authors also identify immediate exposure to a larger customer base as a driver for family businesses adopting technology. However, [69] refers to employees' resistance to technology adoption (culture) as a barrier which aligns with the findings from [10].

Ref. [70] identifies that family-owned businesses are less likely inclined towards innovation/technology adoption in comparison to non-family-owned businesses, which highlights an anti-innovation culture amongst family-owned businesses. Ref. [71] adds to the findings of [70] related to culture in family-owned businesses being a barrier against technology adoption by explaining factors such as protecting heritage, nostalgia, and legacy as deterrents against adoption. Ref. [72] agrees with the points from other authors on culture within family businesses playing an influential role in innovation/technology adoption; however, they also add that the higher probability of conflict (i.e., problems at work can easily be brought back home due to family co-ownership/colleagues) in family businesses may act as a barrier against adoption.

After reviewing worldwide studies related to technology/innovation adoption by rural businesses, there appears to be limited literature investigating technology adoption by family businesses in the UAE. This is especially the case for family businesses based in rural areas within the UAE. Additionally, there appear to be no studies that investigate the difference between family and non-family businesses for machine learning adoption that are based in rural areas. Therefore, there is a need for research investigating ML adoption by family and non-family businesses in rural UAE. Additionally, this section has also identified that there is a lack of clarification on the rural area classification of the researched businesses included in the reviewed studies.

Conceptual Framework

Ref. [73] explains a theoretical perspective as a framework or model which is based on a set of assumptions about reality, which inform questions researchers pose and the type of answers they achieve resulting from these posed questions. Theories are formulated to clarify, predict, as well as understand phenomena [73]. Additionally, a theoretical framework or model is explained by authors as a structure that can hold as well as support theory in each research study ([74,75]).

Various technology adoption theoretical frameworks/models were selected and reviewed by [13] based on their inclusion in previous technology adoption-related studies. The Bass Diffusion Model, Technological Acceptance Model (TAM), Diffusion of Innovations (DOI) theory, and the Technological Organizational and Environmental (TOE) framework were the frameworks/models reviewed by [13] to inform the development of the Broadband Adoption Framework (BAF), which could investigate broadband adoption/use by rural businesses. After a review of several technology adoption-related theories, the authors noted that the DOI theory has the features to investigate technology adoption by a family as it focuses on innovation adoption by populations/groups of people, whereas the TOE framework was found to be the most appropriate to investigate innovation adoption by businesses [76]. Therefore, a combination of the DOI and TOE may lead to a framework that can effectively investigate innovation/technology adoption by family-owned businesses. The creation of the BAF was informed by elements from the TOE and DOI theories [76]. The BAF is illustrated in Figure 1.

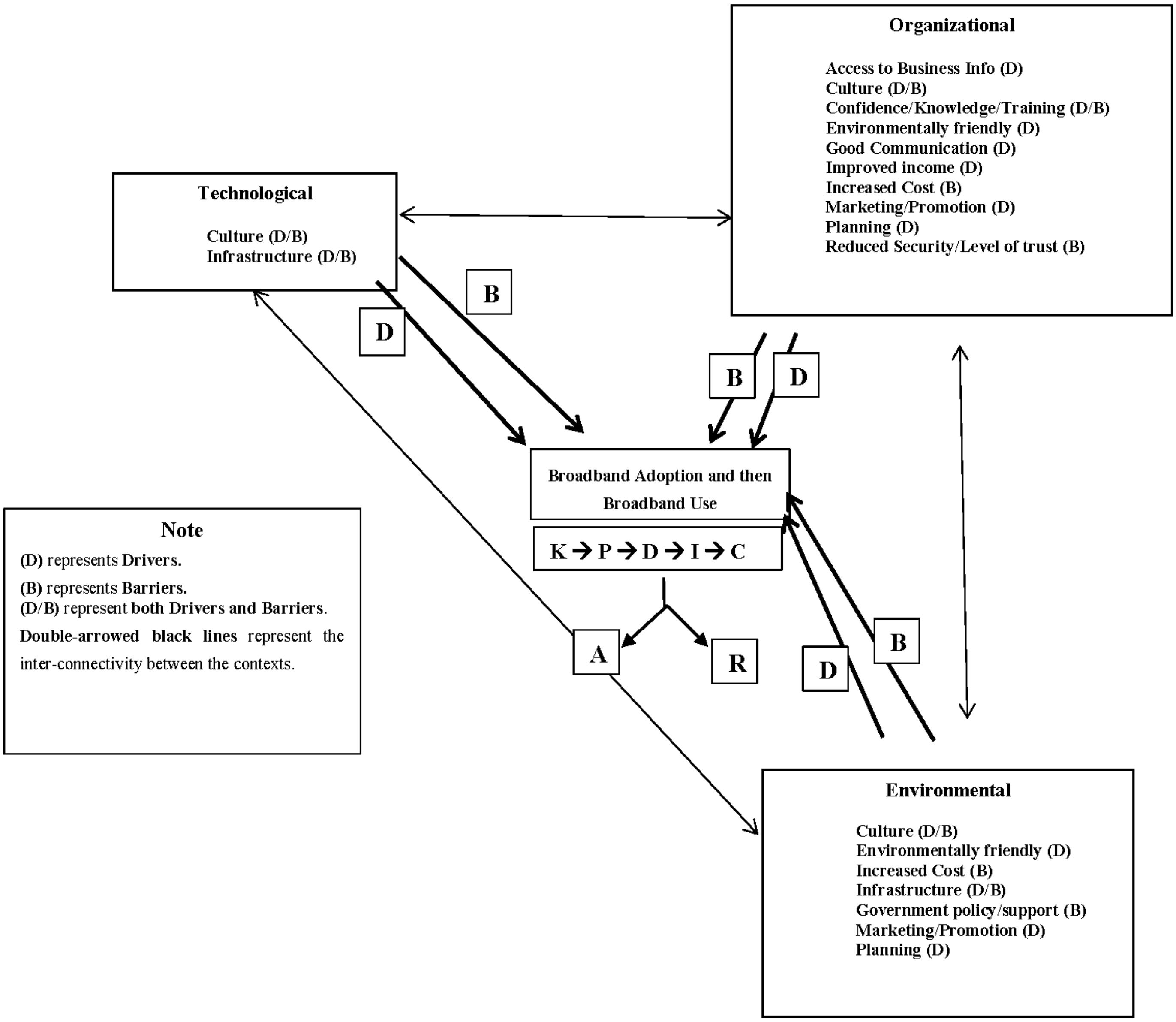

Figure 1. Broadband Adoption Framework. Source: Gilani (2021) [76].

As shown in Figure 1, the drivers and barriers to broadband adoption/use are presented under the technological, organizational, and environmental contexts of the TOE. The words and lines in Figure 1 labeled with 'D' represent drivers; words and lines labeled with 'B' represent barriers; words labeled 'D/B' represent both drivers and barriers. Additionally, the single arrows in the lines labeled with 'D' and 'B' in Figure 1 represent, respectively, drivers leading to broadband adoption/use and barriers leading to non-broadband adoption/use; the inter-connectivity between the contexts of technology, organization, and environment are represented by the double-arrowed black lines. Knowledge is represented by 'K', persuasion is represented by 'P', decision is represented by 'D', implementation is represented by 'I', and confirmation is represented by 'C'. Additionally, adoption is represented by 'A', and rejection is represented by 'R' [76]. However, for this research linked to the adoption of machine learning by family/non-family-owned farms based in rural UAE, the BAF has been slightly amended to the Innovation Adoption Framework (IAF), which is shown in Figure 2.

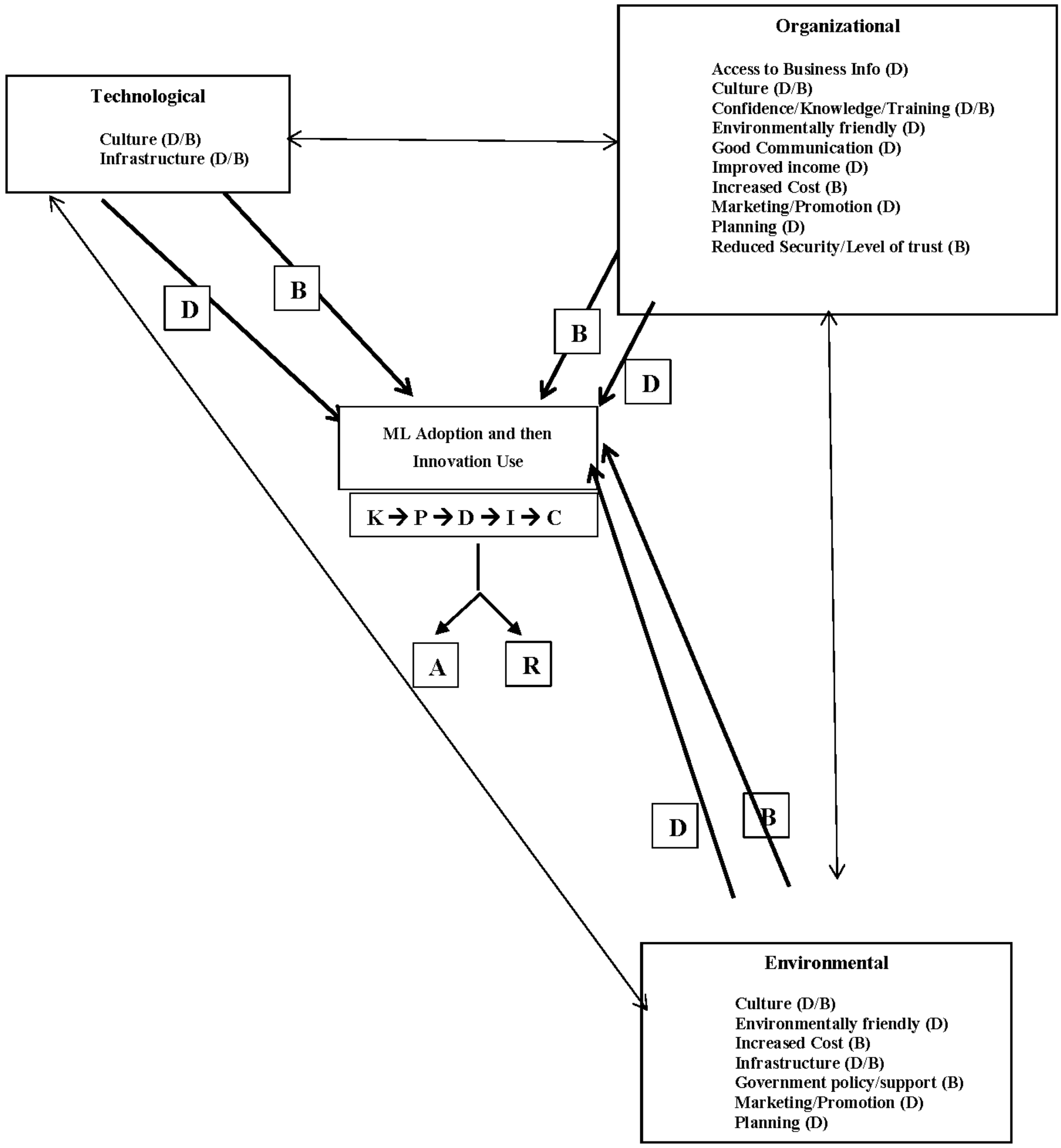

Figure 2. Innovation Adoption Framework (IAF). Source: Authors.

All the elements within the IAF in this research will be interpreted in the same manner as in the original BAF in Figure 1. Additionally, this framework will be adopted in the research to investigate the drivers and barriers for rural-based United Arab Emirates (UAE) families and non-family-owned farms in adopting ML.

3. Research Methodology

Considering the drivers and barriers identified in Section 2, this section examines relevant areas in agriculture and farming, particularly within the rural areas of the UAE, that can benefit from the automation feature offered by machine learning.

To measure the applicability and benefits of ML, several important factors need to be considered. This includes the ability and confidence of farmers towards the use and benefits of technology, the extent to which technology will be implemented, and the areas in which it could be utilized.

Machine learning algorithms have extensively been used in various areas, including education, healthcare, sustainability, and entertainment. The versatility of the overall method allows the flexibility to extend this to agricultural applications as well. A survey conducted by [77] concentrates on the automation benefits of machine learning in various stages of farming, including pre-harvesting, harvesting, and post-harvesting tasks. Pre-harvesting tasks can include the examination of the soil, as well as the suitability of the land for the intended purpose. Harvesting applications can involve the detection and classification of ripe goods. Finally, post-harvesting applications can help assess the shelf life and quality of the goods harvested [77]. Additionally, machine learning can also be used to assess the suitability of the price by which the products are being sold, depending on factors such as competitor pricing, area pricing, as well as the quality and quantity of the goods.

Overall, the automation advantages coupled with machine learning could aid farmers in developing a more systematic way of harvesting. The art of farming can be challenging, as learning the right strategies to mitigate problematic situations require years of experience. The ability of machine learning to utilize previously available data and patterns provides farmers with the advantage of alleviating problems that they may face before, during, or even after farming. Applications of machine learning allow for more efficient farming, which requires less human intervention in producing quality goods.

Provided the applicability and suitability of machine learning for different stages of the agricultural process, this section provides an overview of the ML methodology. The methodology explains the process for three relevant examples, including providing an assessment score for the soil to aid in planting crops using regression (pre-harvesting), the classification of ripe and raw fruits (harvesting), and determining the shelf life of crops (post-harvesting).

Before discussing the methods, two major areas of supervised learning, which involve the use of pre-categorized data, must be introduced. Classification corresponds to a branch of supervised learning that deals with discrete, independent labels. For example, the case of categorizing ripe fruits only consists of two distinct categories: ripe and unripe. Regression, on the other hand, refers to a type of supervised learning that involves continuous labels. For example, price and scores are continuous labels that may change with time. Considering these, the following points summarize the entire machine learning process. Several examples are discussed in line with these steps in Table 3.

Table 3. Machine learning application examples.

Application	Data	Features	Supervised Learning
Providing an assessment score for the soil to aid in planting crops	Database of previous information	Climatic variables (weather, temperature, humidity, outlook), agronomical parameters (soil quality, sun direction), state attributes	Regression (provides an assessment score from 0.00 to 100.00)
Classification of ripe and raw fruits	Images of ripe and raw fruits organized into folders	Color, size, shape, entropy, etc.	Classification (labels of 'ripe' or 'raw')
Determining the shelf life of crops	Images of crops organized into folders based on the shelf life of previous examples	Color, size, shape, entropy, etc.	Classification or regression (depends on whether a distinct number will be provided (e.g., 3 months), in which case it will be a classification problem, or a variable rating score (e.g., 10.467), by which it will be regression

Source: Authors.

1. Data collection: the process of gathering the data that will be used to train the model;
2. Data pre-processing: cleaning and uniformization of data;
3. Feature selection and extraction: selecting and extracting the required features for training;
4. Model training: training the model based on the features extracted;
5. Testing and deployment: testing the model against unseen data, and deploying the trained model once it exhibits satisfactory results.

Throughout the machine learning process, a higher percentage is usually utilized for training the model. A smaller sample set is then used for testing, often in several batches, to avoid potential overfitting. Once the model is generalized well, it is then exported and deployed for use. This is carried out using a simple website, or an application with an easy-to-use user interface, such as the example provided in Figure 3, which was designed through the Matlab app designer for visualization purposes. Nonetheless, the development of such ML models is subject to the availability of extensive agricultural data. The concept can also be further explored through simulation models such as digital twins.

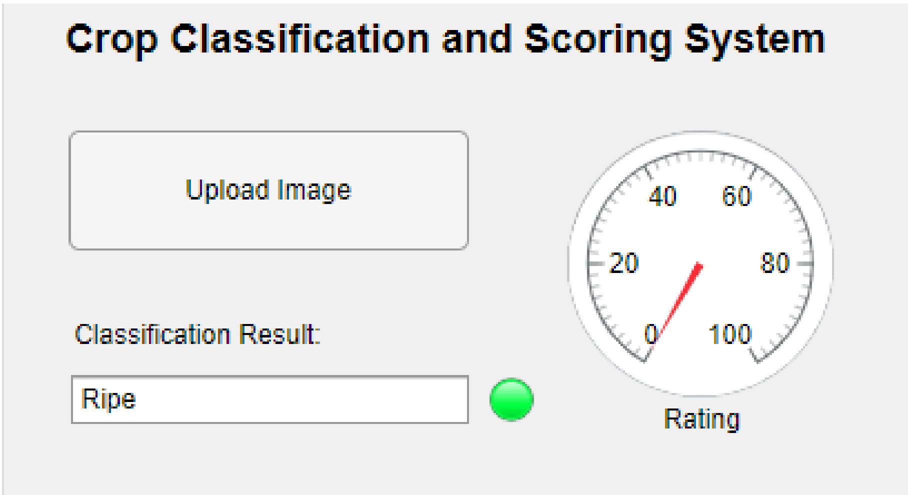

Figure 3. Example of a machine learning-powered application. Source: Authors.

The content in Table 4 and Figure 3 has informed the questions in the research interviews, where the details related to the research sample are provided in the next section.

Table 4. Dimensions for defining rural areas.

Dimension	Focus
Dimension 1	Population and population density
Dimension 2	Proximity to urban areas
Dimension 3	Development
Dimension 4	Culture
Dimension 5	Social Perception

Source: Gilani et al. (2022) [13].

Convenience sampling was implemented by accessing the [78] database to identify 553 farm businesses in the UAE. Then, 115 potential interviewees (rural farms) for this research were identified through the dimensions of rurality [76]. After initial contact via email/phone to confirm farm owners' participation, a sample of 23 farms from the 10 rural areas were identified as willing participants for this research. However, to ensure better representativeness of the sample, the researchers opted for a final sample of 20 farms, whereas in this sample, 2 farms represented each of the 10 rural UAE regions. The 10 rural regions in the UAE as per the dimensions of [76] (Table 4) were identified as Al Ain, Al Bateen, Al Dhafra, Al Foah, Al Khazna, Al Madam, Al Qattara, Al Remah, Masafi, and Sweihan.

A profile for each of the interviewees is presented in Table 5 in terms of farm location; interviewees' age, gender, and nationality; whether the farm was a family/non-family business; and what was the nature of the farm.

Table 5. Location, age, gender, nationality, and type of farm.

Location	Age	Gender	Nationality	Family Business	Nature of Farm
Al Ain 1	40	Male	Non-Emirati	Yes	Farming
Al Ain 2	38	Male	Emirati	Yes	Farming
Al Bateen 1	60	Male	Emirati	Yes	Farming
Al Bateen 2	42	Female	Emirati	Yes	Livestock
Al Dhafra 1	51	Male	Emirati	Yes	Farming
Al Dhafra 2	54	Female	Emirati	Yes	Farming
Al Foah 1	27	Male	Emirati	No	Farming
Al Foah 2	37	Male	Emirati	Yes	Livestock
Al Khazna 1	37	Male	Non-Emirati	No	Livestock
Al Khazna 2	57	Male	Emirati	Yes	Livestock and farming
Al Madam 1	33	Male	Emirati	Yes	Agricultural farm
Al Madam 2	48	Female	Emirati	Yes	Greenhouse
Al Qattara 1	45	Male	Emirati	No	Farming
Al Qattara 2	41	Male	Non-Emirati	Yes	Agricultural farm
Al Remah 1	32	Female	Emirati	Yes	Farming
Al Remah 2	42	Female	Emirati	Yes	Livestock
Masafi 1	28	Male	Non-Emirati	Yes	Agricultural farm
Masafi 2	66	Male	Emirati	No	Farming
Sweihan 1	49	Male	Emirati	Yes	Greenhouse
Sweihan 2	55	Female	Emirati	Yes	Farming

Source: Authors.

The interviews were conducted via telephone and face-to-face conversation between a member of the research team and farm owners during the period of 15–31 March 2022. The interviews were conducted using Arabic-translated questions to reach out to non-English speakers. The interviews ranged from approximately 10 to 45 min in length. The interview was audio recorded and later transcribed using Arabic as a medium of conversation. Ref. [79] proposed constant comparative analysis as a technique for developing 'categories, themes, or other taxonomic classes that interpret the meaning of the data' (p. 192). The team, through Thematic Analysis (TA), looked specifically for emergent themes related to the ability and confidence of farmers towards the use and benefits of ML, the extent to which ML will be implemented, and the areas in which it could be utilized. Following the initial data analysis, our research team held an internal debriefing to discuss the findings and develop the final interpretation [80]. The research interview questions are provided in Table 6.

Table 6. Interview questions.

Questions
1. Do you know what machine learning is?
2. Are you confident in using technology for the farm?
3. Do you use mobile/smartphone technologies?
4. Would you use ML for business operations?
5. Does the local infrastructure allow you to use technology for the farm?
6. Is there something that would prevent you from using ML?
7. Does the government support you in using technology for the farm?

Source: Authors.

In terms of ethical considerations, the researchers ensured that consent was gained from all interviewees before that data were used in the research, and the identity of all participants was anonymized by using the name of areas and numbers to represent findings from different businesses in each area. The confidentiality of the interview data was ensured by storing interview findings on password-protected technologies. A flowchart for the methodology is illustrated in Figure 4.

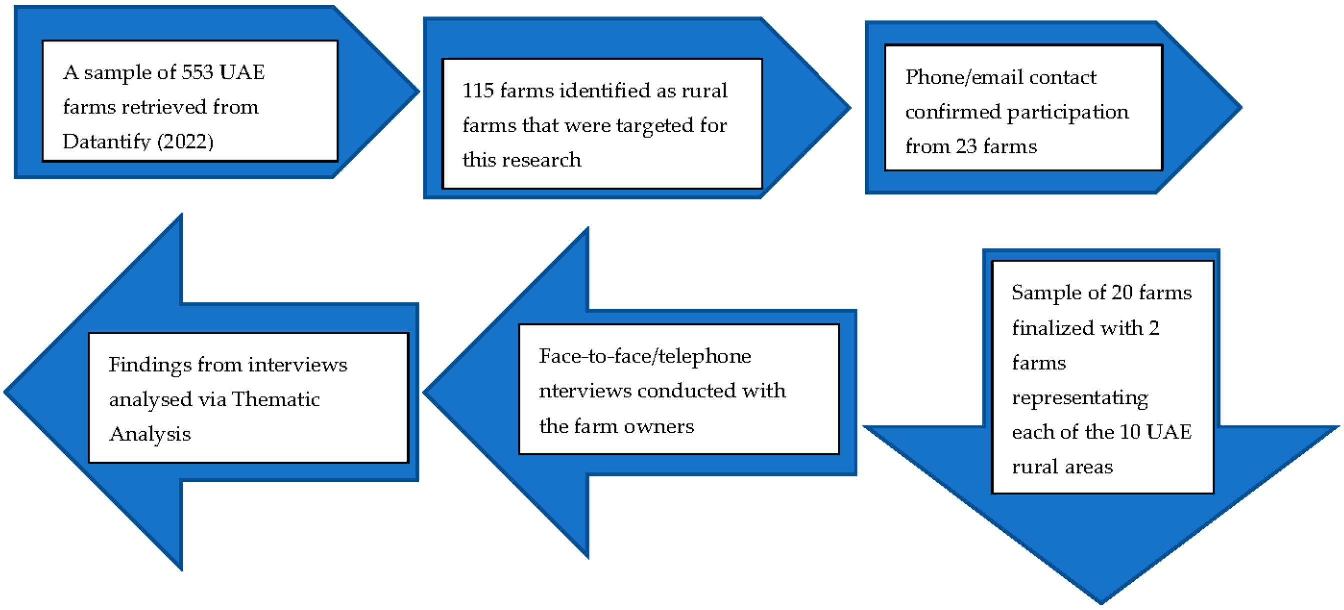

Figure 4. Flow chart of the research methodology. Source: Authors.

4. Findings

The findings from the 20 interviewees are summarized in Table 7 in terms of location, interviewees' age, gender, nationality, nature of the farm, and the issues encountered by interviewees while running their business.

As shown in Table 7, the majority of the interviewed farm owners are male and of Emirati nationality. Most of the businesses interviewed are family-owned businesses that are general farm businesses covering operations such as livestock and harvesting of crops rather than being exclusively focused on one operation/product line. The prominent issues encountered by all farm business owners were irrigation and water access/salinity issues, increased operational costs, decreased profit, increased foreign competition, and unstable weather conditions. Interviewees' responses related to their understanding and adoption of machine learning are provided in Table 8.

As shown in Table 8, the main findings from the interviews are highlighted as UAE farm owners benefitting from adopting ML in daily operations to save costs and improve operational efficiency. However, 16 out of 20 farm owners were unaware of the benefits related to ML as well as had access issues against incorporating ML-based operations (12 mentioned access issues, however, other farms were unsure) where they felt that incorporating ML into their operations may be costly (8 out of 20 farms).

A common barrier against adopting ML identified by a majority of the family farms (11 out of 16 family farms) was a culture which, in other words, was their heritage, traditions, and norms not allowing them to readily adopt ML in the farms. The culture was not identified as a prominent barrier for non-family farms. The adverse impact of culture in the case of family farms may be attributed to a reluctance amongst these businesses to adopt innovations due to an established culture embedded in the business and related households, where any change may be a major upheaval for such businesses. It should be noted that there may be more at stake from adopting ML in the family business context, as a decision leading to failure may lead to severed family ties which is not the case in a non-family farm context.

Table 7. Location, age, gender, nationality, type of farm, and issues encountered by research interviewees.

Location	Age	Gender	Nationality	Family Business	Nature of Farm	Issues Encountered by Interviewees
Al Ain 1	40	Male	Non-Emirati	Yes	Farming	>Issues related to the irrigation and desalination of water. >The costs of running the farm and producing products are higher than the returns.
Al Ain 2	38	Male	Emirati	Yes	Farming	>Lack of government support. >Lack of solutions to livestock losses. >Unstable weather conditions.
Al Bateen 1	60	Male	Emirati	Yes	Farming	>The salinity of the water is a big challenge. >Cannot use wastewater for agriculture as it will harm health.
Al Bateen 2	42	Female	Emirati	Yes	Livestock	>High overheads and low profits. >Unstable weather conditions. >Salinity of water.
Al Dhafra 1	51	Male	Emirati	Yes	Farming	>Foreign competitors. >Low profits. >Increasing running costs.
Al Dhafra 2	54	Female	Emirati	Yes	Farming	>High costs of running a farm. >Lack of knowledge. >Motivation due to limited incentives.
Al Foah 1	27	Male	Emirati	No	Farming	>Inability of their products to compete with established food brands and crops imported from abroad at lower prices where some of these imported products are of lower quality than local products.
Al Foah 2	37	Male	Emirati	Yes	Livestock	>Pests. >Unstable weather. >Expensive electricity. >High production costs. >Post-harvest losses.
Al Khazna 1	37	Male	Non-Emirati	No	Livestock	>Vulnerability of the animals during the summer and winter. >Losses attributed to extreme weather conditions.
Al Khazna 2	57	Male	Emirati	Yes	Livestock and farming	>Unstable weather conditions. >High electricity costs. >Low return on investment (ROI). >Scarcity of fresh water has become a challenge in many regions.
Al Madam 1	33	Male	Emirati	Yes	Agricultural farm	Substantial costs related to >Electricity. >Water. >Labor.

Table 7. *Cont.*

Location	Age	Gender	Nationality	Family Business	Nature of Farm	Issues Encountered by Interviewees
Al Madam 2	48	Female	Emirati	Yes	Greenhouse	>Lack of arable land. >Scarcity of water. >Hot climate. >Insufficient investment in agricultural research. >Reliance on fossil fuels. >Lack of plotting of high-valued crops. >Limited technical know-how in production. >Overreliance on desalination.
Al Qattara 1	45	Male	Emirati	No	Farming	>The Falaj (irrigation) does not supply fresh water like before. >Salinity is a big challenge.
Al Qattara 2	41	Male	Non-Emirati	Yes	Agricultural farm	>Increase in water costs. >Water salinity. >Irrigation issues. >Unstable weather conditions.
Al Remah 1	32	Female	Emirati	Yes	Farming	>The owner is looking to rent the farm out as there is no profit generated due to high overhead costs.
Al Remah 2	42	Female	Emirati	Yes	Livestock	>Low ROI. >Increasing costs. >Increased foreign competitors.
Masafi 1	28	Male	Non-Emirati	Yes	Agricultural farm	>Scarcity of groundwater. >Scarcity of arable land. >Inefficient irrigation techniques.
Masafi 2	66	Male	Emirati	No	Farming	>The ROI for farming is less in comparison to the importation of food supply from neighboring countries. >Have to close farms rather than incur high costs from overheads.
Sweihan 1	49	Male	Emirati	Yes	Greenhouse	Negative income attributed to revenue not overcoming overheads of >Municipal water. >Fertilizers. >Other operational costs.
Sweihan 2	55	Female	Emirati	Yes	Farming	>Limited understanding of farming. >Increase in regular monetary losses. >Irrigation issues. >Water salinity issues.

Source: Authors.

Table 8. Responses to ML-based questions.

	1. Do you know what machine learning is?	2. Are you confident in using technology for the farm?	3. Do you use mobile/smartphone technologies?	4. Would you use ML for business operations?	5. Does the local infrastructure allow you to use technology for the farm?	6. Is there something that would prevent you from using ML?	7. Does the government support you in using technology for the farm?
Al Ain 1	No	No	No	Yes	Unsure	Costs	Not sure
Al Ain 2	No	No	No	No	Unsure	Skills and culture	Not sure
Al Bateen 1	No	No	No	No	Unsure	Skills and culture	Not sure
Al Bateen 2	Yes	No	Yes	Yes	Unsure	Costs and culture	Yes
Al Dhafra 1	No	No	No	No	Unsure	Skills and culture	Not sure
Al Dhafra 2	Yes	Yes	Yes	No	No	Skills and costs	Yes
Al Foah 1	No	No	No	No	No	Skills and costs	No
Al Foah 2	No	No	No	No	No	Costs	Not sure
Al Khazna 1	No	No	Yes	Not sure	Unsure	Access	Not sure
Al Khazna 2	No	No	Yes	No	No	Costs and access	Not sure
Al Madam 1	No	No	No	No	No	Costs, culture, and skills	Not sure
Al Madam 2	No	No	No	No	No	Costs, culture, and access	No
Al Qattara 1	No	No	No	No	No	Access and skills	Yes
Al Qattara 2	No	No	No	Yes	No	Costs and culture	Not sure
Al Remah 1	No	No	No	No	Not sure	Access and culture	Not sure
Al Remah 2	Yes	No	No	No	No	Skills	Not sure
Masafi 1	No	Yes	No	Not sure	No	Costs, culture, access, and skills	Not sure
Masafi 2	No	No	No	No	No	Skills	Not sure
Sweihan 1	Yes	No	No	No	Not sure	Skills and culture	Yes
Sweihan 2	No	Yes	No	Not sure	No	Access, culture, and costs	Not sure

Source: Authors.

As most of the interviewed family businesses are Emirati-owned (13 out of 16 family farms), it should be noted that there is a higher level of general protectionism when it comes to preserving family unity; therefore, a dangerous/high-risk business decision may be less likely explored by such businesses due to its detrimental implications on the significantly regarded family structure preservation. Therefore, the findings signifying the difference between family and non-family-owned farms in rural UAE are representative of the culture and attitudes of family farm businesses through the context of the Emirati ethnicity.

Based on the findings from this research, the IAF has been updated to the Machine Learning Adoption Framework, which is illustrated in Figure 5.

The meaning of the arrows, terms, and symbols in Figure 5 is the same as the explanations related to Figure 1. Based on the findings from Table 8, the authors propose two ML program solutions to address the issues highlighted by farm owners based in rural parts of the UAE. The first solution (Solution A) involves a Water Predictive Recommendation System, which provides recommendations on a water cleaning schedule, chemical dosing, and cleanliness recovery to ensure the availability of access to saline water. Recommendations will be carried out based on the relevant information regarding the bodies of water, such as the required and current pH level, C-N-P ratio, and many others. Another solution (Solution B) is the Farming Activity Suitability Assessment Tool based on weather forecasts. This requires input data that provide suitable weather conditions for certain farming activities, as well as the required moisture, temperature, and other considerations. Based on this and the weather forecast, it automatically advises users regarding the suitability of certain farming activities based on the weather. This will allow farmers to plan their schedule, paving the way for a smoother farming process. Figure 6 provides the ML template for Solution A.

It is important to note that the same template is used for Solution B. Nonetheless, the input data and extracted features will be adjusted accordingly. As observed, ML models require a large level of data to train the model. Hence, 80% of the available data is planned to be used for training, with the remaining 20% serving as the unseen test data, for which the generalization properties of the model will be tested. It is important to note that the test data should not be included in the training; otherwise, this can potentially overfit the ML model. The relevant features are then extracted from the data. Features can be extracted through algorithms such as the bag-of-visual-words, computed through mathematical equations, or extracted manually. Once the features are extracted, the training features are sent into the selected ML model for training. Several ML models currently exist, such as Decision Trees, Support Vector Machines, Clustering, Neural Networks, Naïve-Bayes, and many more. The optimum model to use can be found through comparisons of the results. In some cases, the combination of two or more ML models also improves the overall result. Once trained, the model is deployed and is used to automatically predict the results for the unseen test data. To promote ease of use, this will be packaged into a mobile application that can be downloaded to smartphones.

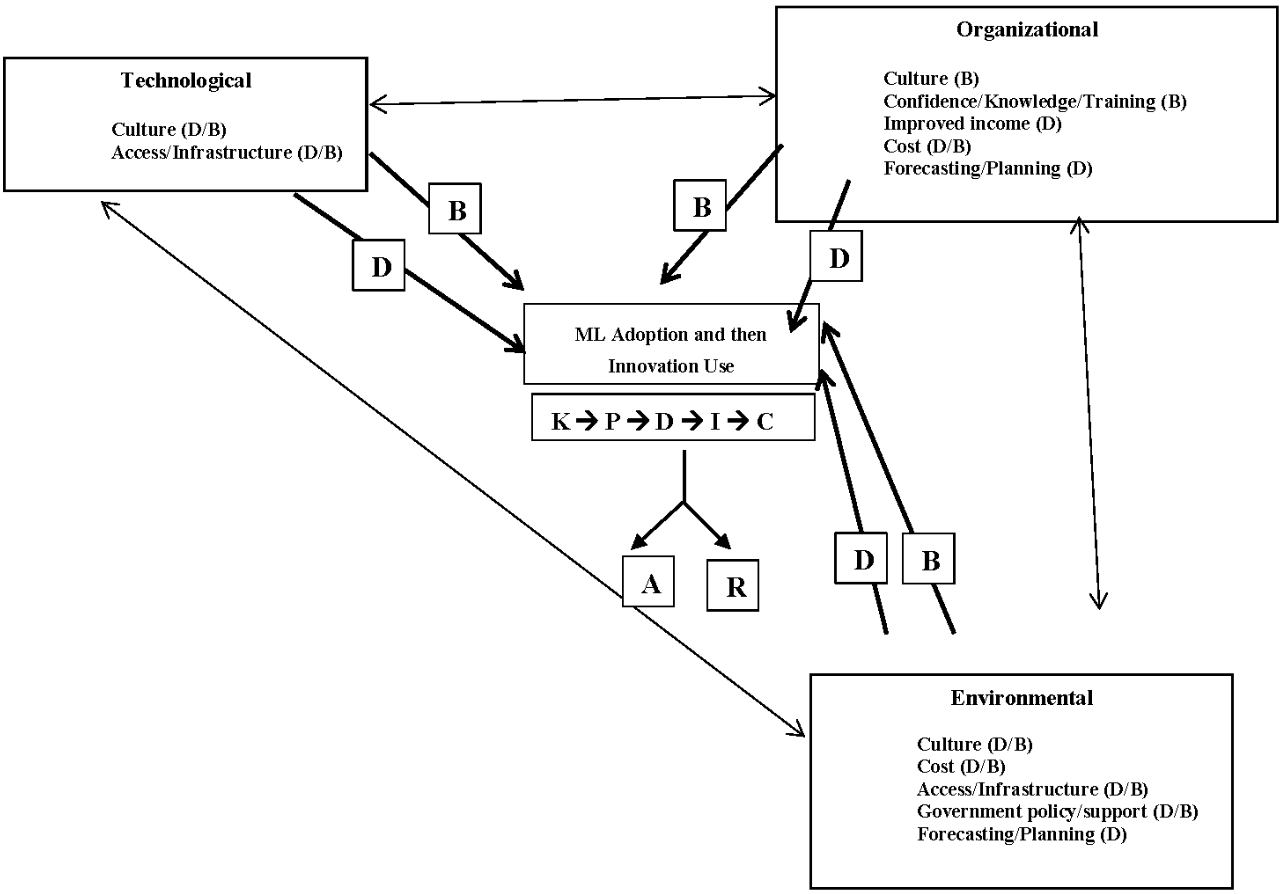

Figure 5. Machine Learning Adoption Framework (MLAF). Source: Authors.

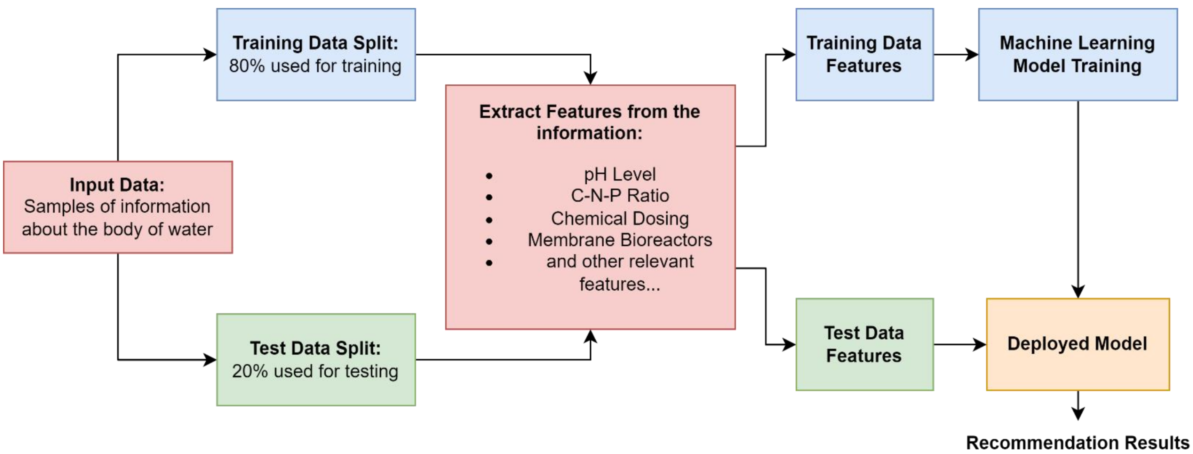

Figure 6. Machine learning program template for rural UAE farm owners (shown above for Solution A—Water Predictive Recommendation System). Source: Authors.

5. Discussion

A review of the worldwide literature related to investigating the role of ICT adoption by rural businesses identified 'communication', 'culture' embedded in the organization, 'infrastructure', 'marketing', and 'planning' as the main drivers for ICT adoption/use. The literature review also identified 'lack of government support' and 'poor infrastructure as the main barriers against ICT/innovation adoption/use by rural businesses. However, the rural classification (accessible-rural/remote-rural) of the business areas, along with their size (micro/small/medium/large-sized business) and sector, were not clarified in the reviewed studies. The frequency of innovation adoption (i.e., daily, monthly, or annually) was not clarified by the participating rural businesses in the reviewed studies outside of [16,43,50]. Additionally, the reviewed studies did not clarify whether the businesses included were family or non-family businesses.

In terms of machine learning, various authors have identified a positive impact of the adoption of ML by farm owners in their daily operations. However, the review of studies related to ML also highlighted that there was no/limited research investigating the drivers and barriers for farm business owners in adopting machine learning for daily operations related to their businesses (e.g., [3,4,81,82]). Therefore, the paucity identified from the review of the literature informed the need for further research in the context of the UAE.

The dimensions of rurality from [76] and the [78] database led to the identification of 20 farm businesses that were willing to participate in interviews. The 20 interviewees were based in the areas of Al Ain, Al Bateen, Al Dhafra, Al Foah, Al Khazna, Al Madam, Al Qattara, Al Remah, Masafi, and Sweihan. As shown in Table 7, the majority of the interviewed farm owners were male (16 out of 20) and of Emirati nationality (14 out of 20). Most of the businesses interviewed were family-owned businesses (16/20) that were general farm businesses covering operations such as livestock and harvesting of crops rather than being exclusively focused on one operation/product line. The prominent issues encountered by all farm business owners were related to irrigation and water access/salinity issues, increased operational costs, decreased profit, increased foreign competition, and unstable weather conditions (Table 7).

In terms of ML, the findings in Table 8 highlight that most of the farm owners are unaware of what ML is; a majority confirmed that they were not comfortable in using technologies/innovations for farm operations (17 out of 20); a majority confirmed that they did not generally use smart/mobile technologies (16 out of 20). In terms of adopting ML for farm operations, most of the interviewees confirmed that they would not be comfortable using ML (17 out of 20 farms). Most of the farm owners were unaware of whether local infrastructure allowed them access to using ML (7 out of 20 farms). Most of the respondents confirmed that the required skills (11 out of 20), related costs, as well as access might be barriers to them using ML for farm operations. In terms of government involvement, most of the farm owners (16 out of 20 farms) were unaware of whether there was scope for more government support towards ensuring that they benefit from technologies in improving their daily farm-based operations.

The interview findings presented in Table 7 presented a context where the farm owners encountered issues in running their farms due to unstable weather conditions. This finding relates to findings from the existing literature, where authors such as [4,83] propose ML as a solution for farm owners to overcome unstable weather conditions while running their businesses, as ML can forecast future weather conditions.

In the existing literature, authors such as [3,5,82,83] identified that ML is good for analyzing production and identifying more efficient solutions for production via sensors on farms which may lower overall production costs. This finding of lowered costs through the adoption of ML links to the interview findings in Table 7, where farm owners identified increased costs related to production as an issue towards the survival or growth of the business, where ML may aid in lowering operating overheads.

A comparison between the interview findings and literature review findings also highlights additional issues for UAE farms that can be overcome by ML, which are related to irrigation, water access/salinity issues, and increased foreign competition. The identified role of ML in supporting these additional issues is exclusive to the findings of this research. The findings related to UAE farm owners in Table 7 and their understanding/use of ML in Table 8 have informed developments in the IAF, which are illustrated below.

The finding of reluctance to adopt ML was highlighted for most family farms in this study, where culture was identified as a common barrier against ML adoption by these businesses (11 out of 20 businesses). This aligns with findings from studies such as [8,9] and [10] on culture. This study specifically highlighted a differentiation between family and non-family-owned businesses regarding culture playing a role against ML adoption for family farms, which aligns with the findings from [70] study, which also found the culture to be a more prevalent deterrent against innovation adoption in family businesses over non-family businesses. Additionally, from the themes identified from the findings, the authors believe that conflict caused in the home and at work caused by a possibly inaccurate decision may also act as a barrier for family-owned farms against ML adoption, which aligns with the findings from [72] related to family businesses avoiding innovation adoption to minimize the possibility of conflict within a family.

The relation and connection between these proposed ML solutions and the problems highlighted by the survey participants are also summarized in Table 9. Although a majority of the respondents mentioned their lack of technical skills in using smartphones, other research surveys state otherwise. According to the 2017 Farm Journal Media mobile research survey, 94% of farmers are cell phone or smartphone users. With the rise of technology nowadays, and with the similarity of the operability of most applications, adjustment to the use of mobile applications can be expected.

Table 9. Justifications on ML solutions.

Category	Issue	ML Solution
Application Issues	Irrigation/water salinity	Solution A: Water predictive recommendation system
	Unstable weather conditions	Solution B: Automated classification on assessing the suitability of farming activities based on weather forecasts
	Increased foreign competition	Application of Solutions A and B will automate certain farming processes. In turn, this encourages fast and high-quality production with higher accessibility, providing an edge over foreign competitors.
	Increased operational costs	Application of Solutions A and B will automate certain farming processes. In turn, this decreases staff and time allocation requirements.
Usage	Technical skills	The utilization of Solutions A and B does not require an advanced technical understanding of the methods used, provided that it will be packaged in a simple interface with a few buttons. Refer to Figure 4 for a sample interface.
	Confidence	
	Costs and accessibility	The AI solutions will be packaged as a mobile application, which can easily be accessed.

Source: Authors.

One of the main problems/limitations encountered during the research was the researchers' inability to visit all business premises due to the COVID-19 restrictions; in such circumstances, the interviews were conducted remotely via Teams, Zoom, and telephone conversations. The authors believe that through the inability to visit farms to conduct interviews, the researchers have not been able to capture the actual settings and environment that farmers operate within, which would have provided additional insight into the research study.

Another prominent problem/limitation experienced by the researchers was some participants' inability to communicate in English, which led to the requirement of Arabic translation to English, which led to more time being consumed during the data collection/analysis process.

The sample of 20 farm owners was not quite representative of the whole of the UAE due to no response from farm owners in under-represented regions. Lastly, limited access to government policy documents focusing on the development of digital infrastructure in rural areas of the UAE was another limitation encountered during the research, which acted as a barrier to understanding the role of government in supporting farmers in taking up ML for their business.

6. Conclusions and Recommendations

6.1. Conclusions

As identified in Section 1, the purpose of this paper was to investigate the drivers and barriers to the adoption/use of UAE-based family-owned farms. Additionally, the research questions for this paper were as follows:

(1) What are the drivers and barriers for rural UAE farms adopting ML?
(2) Is there a difference in the drivers and barriers between family and non-family-owned farms?

The purpose of this paper and the research questions were addressed from the research identifying drivers and barriers for ML adoption by family farms in the UAE through conducting semi-structured interviews with 20 farm owners from 10 rural regions in the UAE (Table 8). Findings from the interviews highlighted that rural UAE farm owners can benefit from adopting ML in daily operations to save costs and improve operational efficiency. However, 16 out of 20 farm owners were unaware of the benefits related to ML as well as had access issues against incorporating ML-based operations (12 mentioned access issues; however, other farms were unsure) where they felt that incorporating ML into their operations may be costly (8 out of 20 farms). Additionally, the findings highlighted that non-family-owned farms were more likely to take up ML compared to family farms, which was attributed to local culture (11 out of 16 family farms identified culture as a barrier).

6.2. Theoretical Implications

The development of the MLAF demonstrates theoretical implications from this paper, where a change in geographic context in future research may lead to further changes in the MLAF.

6.3. Policy Implications

The findings from this research may inform government policy on an international and national level, as in terms of sustainability, the focus of this research was aligned with the United Nations' Sustainability Development Goals 9 (Industry, Innovation, and Infrastructure) and 11 (Sustainable Cities and Communities) (UN, 2023) [84].

6.4. Practical Implications

In terms of practice, this paper proposed an ML program (Figure 6) which was informed by the empirical and theoretical findings in this paper. In terms of policy, the research identified that the participant farm owners were unaware of the support and infrastructure for ML offered by the UAE government, where the authors believe that having an awareness of the role of government in informing the population and infrastructure may encourage farmers to consider ML for their daily operations. Additionally, the authors believe that the adoption of ML by UAE farm owners may improve the rural economy and may lead to an improvement in job creation within rural regions in the UAE.

6.5. Research Implications

The findings from this research may have also informed government policy related to improving infrastructure, funding, and awareness related to ML adoption by businesses based in rural UAE.

6.6. Recommendations

The inclusion of the survey strategy may perhaps lead to a more comprehensive research sample. Conducting research in the same contextual settings outside of the COVID-19 era may lead to a variation in the findings related to ML adoption by family and non-family farm businesses. Including government officials/policymakers may provide insight from a different perspective in terms of the role of ML for UAE farms in rural areas.

Future researchers can test a developed ML program on participants to assess the role of ML in improving farm practices amongst the research participant sample. The MLAF may act as a guide for future policymakers or researchers focusing on assessing the role of ML in UAE farms, where further developments in the MLAF may be informed by the research findings.

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