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The impact of COVID-19 on the diffusion of machine learning amongst rural farms: A study of Algeria, Egypt, Morocco, Tunisia and the United Arab Emirates

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A R T I C L E I N F O

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A B S T R A C T

This study investigates the impact of the COVID-19 pandemic on the diffusion of Machine Learning (ML) among rural farms in Algeria, Egypt, Morocco, Tunisia, and the United Arab Emirates (UAE). Despite the proven benefits of ML in agricultural operations, rural farms in the MENA region have lagged in adoption due to barriers such as infrastructure deficits, costs, cultural factors, and limited knowledge/training. Through semi-structured interviews with 50 rural farm owners, this research explores shifts in attitudes towards ML adoption before and after the pandemic. The findings reveal a significant post-pandemic increase in ML awareness, confidence in technology usage, and recognition of ML's benefits, such as operational efficiency and cost reduction. Cultural resistance and knowledge gaps, once major barriers, have diminished, while infrastructure limitations and costs persist. The study introduces an empirically informed Machine Learning Adoption Framework version 3 (MLAFv3), highlighting changes in drivers and barriers pre- and post-COVID-19. It further proposes a practical ML-integrated crop management system to facilitate adoption among rural farmers. The findings contribute to addressing the digital divide in rural MENA agriculture and offer policy and practical recommendations to enhance ML adoption for rural economic resilience and cultural preservation.

1. Introduction

The COVID-19 pandemic era drove businesses to act more innovatively to survive the challenges of this period [21,38], which has been demonstrated in various industries like higher education [51]. This pandemic era saw limited opening hours, downsizing and closure of enterprises around the world [54]. In response to these challenges, businesses, especially small to medium enterprises (SMEs), leveraged the pandemic-era restrictions by adopting innovative practices like shifting their operations or processes to online services, which included online sale stores, online-based customer services and home delivery rather than customers going in-store for products [9]. Some enterprises strategically leveraged lockdown restrictions, shifting to online services and home delivery, proving cost-effective and advantageous [27]. The COVID-19 pandemic era saw a rise in the diffusion of Artificial Intelligence (AI) based applications like Machine Learning (ML), which transformed how businesses conducted daily operations through the integration of computer-based programs that have the capacity of self-learning without explicit instructions, which therefore leads to the automation of processes [50]. For example, ML has led to the automation of crop, cattle and inventory management as well as forecasting for crop yield in farms, which has led to minimised costs and improved time management for farmers [30,77].

Despite the demonstrated benefits of ML in farming, there still appears to be a deficit in ML diffusion between urban and rural areas, which is attributed to factors like culture, infrastructure and knowledge/

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training amongst farmers [31]. Therefore, a digital divide has been demonstrated for ML diffusion amongst farms between urban and rural areas. Shao [69] has highlighted the significance of the take-up of innovative technologies like ML by rural businesses like farms to ensure their survival and growth, which can lead to the revitalisation and survival of the rural economy and communities. For example, the downsizing or closure of rural businesses like farms can lead to increased unemployment, which then drives rural citizens to relocate to more urban areas for employment opportunities, which may then lead to the depopulation of rural areas and the extinction of ancient rural cultures and traditions [43,66]. Therefore, ML adoption by rural farms has a wider significance and impact on the wider population in terms of improved economy and preservation of rural identity and history.

Some studies investigate the role of ML in rural farms around the world (for example, Dixit et al. [25] in India; Zhang et al. [83] in Brazil but there appears to be a dearth in literature investigating ML diffusion amongst rural farms in the Middle East and North Africa (MENA) region, especially, in countries like Algeria, Egypt, Morrocco, Tunisia and the United Arab Emirates (UAE). The current available literature from MENA, like Al-Addous et al. [2], Ronaghi and Forouharfar [65] and Buchaillot et al. [13], explores ML diffusion amongst rural farms; however, these studies do not explore the direct impact of the COVID-19 pandemic on ML diffusion amongst rural farms. Therefore, to address this paucity in literature and to better understand how ML adoption amongst rural farms can be improved to ensure an improved level of survival of farms and ancient cultures in rural areas, the purpose of this study will be to investigate the factors influencing ML diffusion pre and post COVID-19 pandemic amongst rural farms located in the MENA countries of Algeria, Egypt, Morocco, Tunisia and the UAE. The selection of Algeria, Egypt, Morocco, Tunisia and the UAE for inclusion in this study over other MENA countries was attributed to these areas being highlighted (via initial scoping research done through Google Scholar inputting key terms like 'Machine Learning adoption amongst rural farms' plus the name of each MENA country) as the more under-researched regions in the area of ML adoption by rural farms.

The study will be underpinned by the following research objectives (ROs).

RO1 – To establish the parameters of remote-rural areas in the context of Algeria, Egypt, Morocco, Tunisia and the UAE.
RO2 – To develop a conceptual framework which explores the factors for ML diffusion amongst rural farms in Algeria, Egypt, Morocco, Tunisia and the UAE.
RO3 – To identify the drivers and barriers for ML adoption amongst rural farms in Algeria, Egypt, Morocco, Tunisia and the UAE.
RO4 – To identify whether there has been a shift in attitudes from before and after the COVID-19 pandemic era towards ML adoption amongst rural farms in Algeria, Egypt, Morocco, Tunisia and the UAE.

2. Background

2.1. Review of worldwide studies exploring ML diffusion among rural farms

Innovative technologies have proven to be effective for smaller and younger businesses to overcome the deficit in industries established by bigger and more resourceful rivals [22,60]. This was especially proven to be the case in the COVID-19 era for smaller businesses around the world that used the restrictions from the era as an opportunity to not just survive but to also thrive by adopting technologies like the internet for innovative practices like online stores, online/remote customer engagement, online communication with stakeholders and online banking which has allowed businesses to save time and money [1,44]. However, there appears to be a deficit in innovative technology adoption between urban and rural areas, which is especially the case for the diffusion of ML amongst rural farms lagging behind urban businesses [72]. The adoption of ML has proven to be significant in supporting the survival and growth of businesses by lowering costs and time from ML-powered operations, which has especially been the case for rural farms [35,64]. Therefore, ML related studies from around the world were reviewed to gain a greater insight into factors influencing ML diffusion amongst businesses to better inform strategies to improve ML adoption in rural farms to ensure the wellbeing of the rural economy to limit depopulation from rural areas and the preservation of ancient cultures and traditions exclusive to rural communities [57]. Additionally, the review has been conducted to further establish the paucity of literature related to ML diffusion amongst rural farms in the MENA region.

The literature review was based on studies that have involved ML adoption by rural farms. The inclusion of the studies for review was based on them being conducted post-2010, as 2010 saw the widespread rollout of deep learning within ML, which made the program more versatile and flexible to use for business operations, especially operations in rural farms [53,70]. The review of the studies was arranged in terms of geography and then in terms of the age of the study. The studies from the same geography and year were then arranged in terms of alphabetical order of the authors' surnames. The explanation for each of the identified factors (drivers/barriers) is provided in Table 1. It should be noted that for this study, drivers will represent factors which encourage ML adoption amongst farmers, and barriers will represent factors which prevent or discourage farm owners from adopting ML.

In the context of international and secondary research-based studies, Kumar et al. [40] indicated a perceived convenience from ML adoption as a driver, but the authors also indicated knowledge/training and infrastructure as significant factors which either drove or discouraged ML diffusion amongst rural farms. Thornber et al. [76] added to the findings from Kumar et al. [40] by indicating security as a barrier against ML adoption. Through a review of international studies, Sharma et al. [71] indicated an agreement with Kumar et al. [40] regarding perceived convenience but also indicated that an improved ability in marketing/promotion is a driver for ML diffusion amongst rural farms. Karbo et al. [37] indicated business research (business intelligence and forecasting from the analysis of old data) as being a driver for ML

Table 1
Explanation of Drivers/Barriers Identified in the Literature Review.

Factor (Driver/ Barrier)	Factor Codes	Explanation
Business research	BR	This involves business owners analysing archival data to inform future decisions.
Communication	COMM	Online engagement with all stakeholders.
Cost	CO	Any costs saved from using ML (driver)/any costs incurred from buying related equipment and a subscription (barrier).
Culture	CU	Organisational or local community culture which encourages (driver) or discourages (barrier) ML adoption
Government policy	GP	Government involvement which encourages (driver) or discourages (barrier) ML adoption
Infrastructure	I	The development in the infrastructure that will either allow (driver) or discourage (barrier) ML adoption
Knowledge/ training	K/T	A high level of knowledge/training amongst a population may act as a driver; however, a low level of knowledge and training will act as a barrier for ML adoption.
Marketing/ promotion	M/P	Online promotion of products or services through websites or social media.
Perceived convenience	PC	The farm owners' beliefs on the benefits related to ML adoption for everyday business operations.
Security	S	Security can either be improved via ML (driver), however, it can also be a risk for the confidentiality of business data (barrier).

adoption by rural farms. Gilani et al. [31] indicated an agreement with Thornber et al. [76] and Karbo et al. [37], but the authors also identify cost as a significant factor which either drives or acts as a barrier against ML adoption amongst rural farms. Singh et al. [73], Pandey et al. [59], and Priya et al. [61] indicate an agreement with authors Sharma et al. [71] and Gilani et al. [31] regarding the factors influencing ML adoption amongst rural farms.

In the context of the USA, Pruitt et al. [62] indicated that culture, infrastructure and knowledge/training played a role in either acting as a driver or a barrier for ML adoption amongst rural farms. Wang et al. [81] add to the findings from Pruitt et al. [62] by indicating infrastructure and government policy as significant factors which influence the adoption of ML amongst rural farms.

Dominguez et al. [26] in their Europe based study, indicate an agreement with the findings of Pruitt et al. [62] regarding the factors for ML adoption, however, the authors insist that infrastructure is more likely a driver than barrier towards ML adoption due to the significant advancements made in installing up to date infrastructure in rural regions in Europe.

Similar to the previously mentioned research, in the UK-based studies, Dominguez et al. [26] and Manning [49] identify the significant role of business research, infrastructure and government policy as drivers towards ensuring ML adoption amongst rural farms in the UK.

In a Canada-based study, Makinde et al. [47] indicate the significance of culture, knowledge/training and infrastructure as significant factors which drive ML adoption amongst rural farms. However, the authors mention that the interpretation of infrastructure as a driver or barrier may vary based on the demand for the infrastructure from the business operation itself.

In a Mexico-based study, Barrera-Perales and Burgos [7] add to the findings from Makinde et al. [47] by indicating culture, knowledge/training and infrastructure as barriers against ML adoption, where the authors also indicate cost as a significant barrier against ML adoption due to the perceived investment in acquiring ML-related equipment and subscription.

The findings from Zhang et al. [83] in their Brazil-based study align with the findings from Barrera-Perales and Burgos [7], but the authors indicate that cost can also be a driver for ML adoption due to saved costs from the remote completion of tasks like banking, meetings with stakeholders and improved efficiency in operations.

In an Africa-based study, Birhanu et al. [8] indicate a disagreement with Dominguez et al. [26] by highlighting infrastructure as a significant barrier against ML adoption, where the authors also identify knowledge/training, cost and culture as significant barriers against ML adoption by rural farms. Namirembe et al. [55] in their Uganda-based study and Olawale et al. [58] in their Nigeria-based study identify an agreement with the findings from Birhanu et al. [8]; however, they also indicate communication as a driver for ML adoption. Therefore, studies from the Africa region indicate knowledge/training, infrastructure, cost and culture as barriers against ML diffusion amongst rural farms.

In the context of South Asia, Subramanya et al. [75] (Nepal), Dixit et al. [25] (India), and Aslam and Li [4] (Pakistan) collectively agree that cost, knowledge/training, culture and infrastructure are significant barriers against ML adoption amongst rural farms. From the understanding of the authors, the findings from this region and the African region oppose findings from Western regions like Europe, the UK and the USA, which may be attributed to South Asian countries being classified as developing nations as opposed to Western nations, which are established as developed.

In China-based studies, Wang et al. [80], Zhang et al. [84] and Liu et al. [45] collectively agree on perceived convenience, marketing/promotion and knowledge/training as being drivers for ML adoption among rural farms, however, Ma et al. [46] in another China based study promote the importance of government policy as a driver to drive knowledge/training amongst rural farmers to improve awareness and offer support to farmers which can increase ML adoption amongst rural farms in China.

Lee et al. [42] in their Vietnam based study indicate an agreement with authors like Zhang et al. [84] for perceived convenience, marketing/promotion and knowledge/training as drivers for ML adoption amongst rural farms but they also add that for these to be drivers than government policy as well as infrastructure are required to be drivers for ML adoption as well.

In an Africa and Asia-based study, Hilmi [36] indicate that knowledge/training, infrastructure, and government policy are more likely to be drivers for ML adoption in the context of rural farms based in Asia in comparison to Africa, which may be attributed to cultural as well as economic factors between the regions. The findings from Hilmi [36] align with findings from authors like Liu et al. [45] and Olawale et al. [58].

In Algeria-based studies, Boudouda and Boukallel [11], Bouregaa [12] and Soum and Ayache [74] identify culture, infrastructure, government policy, cost and knowledge/training as barriers against ML adoption amongst rural farms. However, the authors also collectively agree with perceived convenience, business research and marketing/promotion as drivers for ML diffusion amongst rural farms.

Sayed et al. [67] and Alhendawya et al. [3] in their Egypt-based studies highlight an agreement with authors like Bouregaa [12] in relation to drivers and barriers for ML diffusion amongst rural farms. While agreeing with the findings from Sayed et al. [67] and Alhendawya et al. [3], another Egypt-based study conducted by Barakat et al. [6] indicates that culture may alternate between driver and barrier based on each rural community in Egypt.

Bonzanigo et al. [10], Mana et al. [48], and En-Nia et al. [28] are Morocco-based studies which highlighted culture, infrastructure and knowledge/training as barriers and communication as a driver for ML diffusion amongst rural farms based in Morocco. These findings also align with findings from Boudouda and Boukallel [11].

In Tunisia-based studies, Dhraief et al. [24] indicate culture and infrastructure as barriers against ML adoption. However, Dhehibi et al. [23] identify culture as a driver as well as a barrier for ML adoption, which aligns with Barakat et al. [6]. Additionally, Khader [39] further expands on the findings from Dhraief et al. [24] by highlighting infrastructure as a driver as well as a barrier based on rural regions in Tunisia.

In a study based in the UAE and Taiwan, Chen [14] highlights cost, culture, security and knowledge/training as barriers against ML adoption by rural farms. Gilani et al. [30] in their UAE-based study add to the findings from Chen [14] by indicating underdeveloped infrastructure in rural areas as a barrier for ML adoption by rural farms. However, Gilani et al. [30] highlight that there is a significant drive by the UAE government to upgrade rural infrastructure to eliminate the digital divide between and social exclusion between businesses and communities. In studies conducted in the Gulf Cooperation Council (GCC) context, Lakhouit et al. [41] and Ramadan et al. [63] highlighted knowledge/training and culture as significant barriers for ML adoption by rural farms in the GCC.

In a cross-country study involving Egypt, Tunisia, Italy, and Spain, Gonzales-Gemio and Sanz-Martin [34] indicate knowledge/training, cost, infrastructure and culture as barriers for ML adoption amongst rural farms in Egypt and Tunisia, which aligns with authors like Khader [39] and Barakat et al. [6]. However, the study also indicated knowledge/training, cost, infrastructure and culture as drivers for ML adoption amongst rural farms in Italy and Spain, which aligns with studies like Dominguez et al. [26]. Additionally, communication is identified in the study as a driver for ML adoption amongst rural farms.

In MENA-based research, Awaad et al. [5] identified culture, knowledge/training and infrastructure as factors that were consistently indicated as barriers for ML adoption for rural farms. While agreeing with the findings from previous MENA studies, Ronaghi and Forouharfar [65] and Ficarra et al. [29] indicate cost and government policy as influential factors which may drive or limit ML adoption amongst rural farms. Additionally, Al-Addous et al. [2] and Buchaillot et al. [13] in their MENA-based studies highlighted security and marketing/promotion as drivers for ML adoption amongst rural farms, which aligns with the findings of authors like Dominguez et al. [26]. In another MENA-based study, Lakhouit et al. [41] identified culture, knowledge/training, cost, government policy and infrastructure as barriers for ML diffusion amongst rural farms, which aligns with authors like Awaad et al. [5] and Ficarra et al. [29].

The findings for each of the reviewed studies are provided in Table 2 and are arranged in terms of year, alphabetical order for authors' names, geography, drivers and barriers.

As shown in Table 2, business research, communication, marketing/promotion, and perceived convenience were identified as the most prominent drivers for ML adoption amongst rural farms. However, costs, culture, government policy, infrastructure, knowledge/training and security were identified as drivers as well as barriers for ML adoption amongst rural farms.

The review of worldwide ML adoption related studies has highlighted findings related to the drivers and barriers for ML diffusion amongst rural farms in the contexts of Algeria, Egypt, Morocco, Tunisia, the UAE and the MENA region, however, there appears to be a dearth in literature exploring the pre and post COVID-19 attitudes of rural farm owners in the MENA region regarding ML adoption amongst rural farms, especially, in Algeria, Egypt, Morocco, Tunisia and the UAE.

Additionally, the review of the literature has identified a dearth in primary research-based studies in the context of Algeria, Egypt, Morocco, Tunisia and the UAE (these countries are pinpointed via circles on a map in Fig. 1) individually (studies based on each mentioned country) as well as collectively (research that focuses on the mentioned countries collectively) which indicates the scope for future primary research in the mentioned countries.

Primary research exploring ML adoption amongst rural farms in Algeria, Egypt, Morocco, Tunisia and the UAE is not only important for addressing an identified paucity in the literature, but primary research will also provide rich insight into the emotions and social constructs in addition to drivers and barriers influencing the decision of rural farmers in adopting ML. Additionally, these countries have a global significance as they contain precious and sought after natural resources or commodoties like petroleum, phosphates, gold, iron ore and uranium which are a challenge to locate elsewhere [52], hence, research into strategies improving the rural economy (exploring how ML adoption can be improved amongst rural farms in these countries) in these countries to ensure the resilience and growth of their respective national economies is significant for the global economy. Therefore, there is a need for further research investigating the pre- and post-COVID-19 drivers and barriers for ML adoption amongst rural farms in Algeria, Egypt, Morocco, Tunisia and the UAE.

2.2. Conceptual framework

The conceptual framework for this research has been informed by the Machine Learning Adoption Framework (MLAF) from Gilani et al. [30] and the factors for ML adoption highlighted in the literature review indicated as drivers or barriers or both (please refer to Table 3 for the coded factors in terms of being identified as drivers/barriers/drivers barriers).

As shown in Fig. 2, the MLAFv2 consists of the technological, organisational and environmental perspectives from the Technological Organisational Environmental (TOE) framework. Each perspective consists of the factors for ML adoption identified from the review of studies, where each factor is coded and labelled as drivers/barriers/drivers barriers (please refer to Table 3). In Fig. 1, like the original MLAF (from Gilani et al. [30]), 'K' represents Knowledge, 'P' represents Persuasion, 'D' represents Decision, 'I' represents Implementation, and 'C' represents Confirmation. The inclusion of K, P, D, I and C has been informed by the Diffusion of Innovations (DoI) theory. The ML adopters are classified into the different adopter groups of Innovators, Early

Table 2
Summary of drivers and barriers for ML adoption.

Year	Author(s)	Geography	Drivers	Barriers
2012	Pruitt et al.	USA	Culture, infrastructure and knowledge/ training	Culture, infrastructure and knowledge/ training
2016	Bonzanigo et al.	Morocco	Communication	Culture, infrastructure and knowledge/ training
2019	Dhraief et al.	Tunisia		culture and infrastructure
2020	Awaad et al.	MENA		culture, knowledge/ training and infrastructure
2020	Ronaghi and Forouharfar	MENA		Cost and government policy
2021	Kumar et al.	International		knowledge/ training and infrastructure
2021	Subramanya et al.	Nepal		cost, knowledge/ training, culture and infrastructure
2021	Wang et al.	China	perceived convenience, marketing/ promotion and knowledge/ training	
2022	Birhanu et al.	Africa		Infrastructure, knowledge/ training, cost and culture
2022	Ficarra et al.	MENA	Cost and government policy	Cost and government policy
2022	Makinde et al.	Canada	culture, knowledge/ training and infrastructure	
2022	Mana et al.	Morocco	Communication	culture, infrastructure and knowledge/ training
2022	Sayed et al.	Egypt	Culture	Culture
2022	Thornber et al.	International		security
2022	Wang et al.	USA	infrastructure and government policy	infrastructure and government policy
2022	Zhang et al.	Brazil	Cost	
2023	Alhendawya et al.	Egypt	Culture	culture
2023	Barrera-Perales and Burgos	Mexico		culture, knowledge/ training and infrastructure
2023	Chen	UAE and Taiwan		cost, culture, security and knowledge/ training
2023	Dhehibi et al.	Tunisia	Culture	culture
2023	Dixit et al.	India		cost, knowledge/ training, culture and infrastructure
2023	Gilani et al.	UAE		infrastructure
2023	Hilmi	Africa and Asia	knowledge/ training, infrastructure, and	knowledge/ training, infrastructure, and government

(continued on next page)

Table 2 (*continued*)

Year	Author(s)	Geography	Drivers	Barriers
			government policy (for Asia)	policy (for Africa)
2023	Sharma et al.	International	perceived convenience and marketing/ promotion	
2023	Zhang et al.	China	perceived convenience, marketing/ promotion and knowledge/ training	
2024	Aslam and Li	Pakistan	cost, knowledge/ training, culture and infrastructure	
2024	Domínguez et al.	UK	business research, infrastructure and government policy	
2024a	Gilani et al.	International	Cost	cost
2024	Karbo et al.	International	business research	
2024	Khader	Tunisia	infrastructure	infrastructure
2024	Lee et al.	Vietnam	perceived convenience, marketing/ promotion, government policy, infrastructure and knowledge/ training	
2024	Liu et al	China	perceived convenience, marketing/ promotion and knowledge/ training	
2024	Manning	UK	business research, infrastructure and government policy	
2024	Namirembe et al.	Uganda	Communication	Infrastructure, knowledge/ training, cost and culture
2024	Singh et al.	International	perceived convenience, marketing/ promotion, knowledge/ training and infrastructure	knowledge/ training and infrastructure
2025	Barakat et al.	Egypt	Culture	culture
2025	Boudouda and Boukallel	Algeria	perceived convenience, business research and marketing/ promotion	culture, infrastructure, government policy, cost and knowledge/ training
2025	Bouregaa	Algeria	perceived convenience, business research and marketing/ promotion	culture, infrastructure, government policy, cost and knowledge/ training
2025	En-Nia et al.	Morocco	Communication	culture, infrastructure and knowledge/ training
2025	Gonzales-Gemio and Sanz-Martín	Egypt, Tunisia, Italy and Spain	knowledge/ training, cost, infrastructure and culture (for Italy and Spain) Communication	knowledge/ training, cost, infrastructure and culture (for Egypt and Tunisia)

Table 2 (*continued*)

Year	Author(s)	Geography	Drivers	Barriers
			(for all involved countries)	
2025	Lakhouit et al.	GCC		knowledge/ training and culture
2025	Ma et al.	China	government policy	
2025	Pandey et al.	International	Cost, perceived convenience, knowledge/ training and infrastructure	Cost, knowledge/ training and infrastructure
2025	Priya et al.	International	Cost, perceived convenience, knowledge/ training and infrastructure	Cost, knowledge/ training and infrastructure
2025	Olawale et al.	Nigeria	Communication	Infrastructure, knowledge/ training, cost and culture
2025	Ramadan et al.	GCC		knowledge/ training and culture
2025	Soum and Ayache	Algeria	perceived convenience, business research and marketing/ promotion	culture, infrastructure, government policy, cost and knowledge/ training

Adopters, Early Majority, Late Majority and Laggards. The inclusion of these adopter groups in the framework has been informed by the DoI theory.

2.3. Research questions

The findings from the review of worldwide literature related to ML adoption amongst rural farms and the MLAFv2 have informed the following Research Questions (RQs).

RQ1 – What were the drivers and barriers for ML adoption amongst rural farms in Algeria, Egypt, Morocco, Tunisia and the UAE before the COVID-19 pandemic era?
RQ2 – What were the drivers and barriers for ML adoption amongst rural farms in Algeria, Egypt, Morocco, Tunisia and the UAE after the COVID-19 pandemic era?
RQ3 – Has there been a change in rural farm owners' attitudes to ML adoption between the pre- and post-COVID-19 pandemic eras (which will be indicated by the variation of drivers and barriers for ML adoption between the 2 eras)?

3. Methodology

As mentioned earlier, Algeria, Egypt, Morocco, Tunisia and the UAE were selected as the target countries in this study as an initial scoping study indicated these regions to be the most under-researched in the area of ML adoption by rural farms amongst all MENA countries. Additionally, the review of worldwide literature also indicated the same disparity in ML adoption research in the context of Algeria, Egypt, Morocco, Tunisia and the UAE amongst all MENA regions.

Review of sources like Gilani et al. [32], Nazarczuk et al. [56], Woods [82] and the Scottish Government [68] identified proximity, population density, development and social/cultural values as parameters that differentiated rural areas from urban areas. However, for this study, the Scottish Government's [68] definition of rural was adopted as it was more quantifiable in terms of distance and population size. As per the Scottish Government [68], the interpretation of a rural area is an

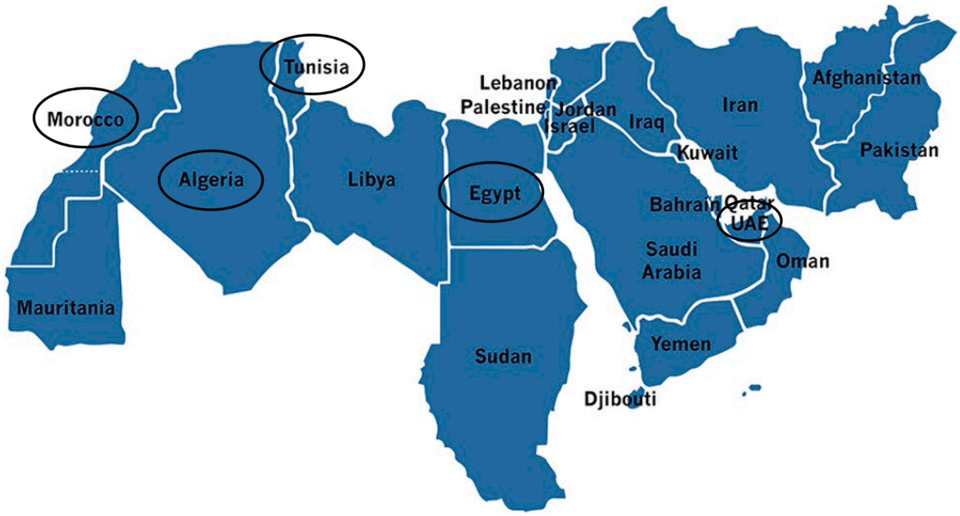

Fig. 1. Algeria, Egypt, Morocco, Tunisia and the UAE on the worldwide map.
Source: The image has been adapted from Creative Unites Newsroom [15].

Table 3
The identified drivers and barriers from the literature review and associated codes.

Factor (Driver(D)/Barrier(B))	Code
Business research (BR)	BR(D)
Communication (D)	COMM(D)
Cost (D/B)	CO(D/B)
Culture (CU)	CU(D/B)
Government policy (GP)	GP(D/B)
Infrastructure (I)	I(D/B)
Knowledge/training (K/T)	K/T(D/B)
Marketing/promotion (M/P)	M/P(D)
Perceived convenience (PC)	PC(D/B)
Security (S)	S(D/B)

The adapted MLAF, which has been labelled as the MLAF version 2 (MLAFv2), is illustrated in Fig. 2.

area with under 3000 residents and over a 30-minute drive from the nearest 10,000-plus population area. The use of the Scottish Government [68] definition for rural areas in the farm databases of Datantify [16–20] for Algeria, Egypt, Morocco, Tunisia, and the UAE identified an initial sample of 653 farms. A contact number or email address was identified as a method of communication for 113 of the farm businesses across the 5 countries. These businesses were either contacted via phone call or email with verbal (phone) or written (email) forms of participant information for the research shared, and participants' consent was gained.

The final sample was established as 50 farmers, from which 10 represented each of Algeria, Egypt, Morocco, Tunisia and the UAE. This sample was informed by the initially contacted farmers agreeing via email or phone to participate in this study. Semi-structured interviews were conducted via platforms like Microsoft Teams and Zoom with farmers during the period from the 2nd to the 30th of October 2019 and 2nd to the 30th of January 2023. The participants are labelled in terms of their country and region in Table 4.

To increase the likelihood of capturing responses from all participants, the researchers offered farmers the opportunity to receive questions and provide responses in Arabic as well as in English. The interview questions are provided in Table 5. It should be noted that the development of the interview questions was informed by the MLAFv2.

The duration of each interview was 10 – 60 min. Subject to participants' consent, farmers' responses to interview questions were captured via audio recordings; otherwise, the responses were captured via pen and notebook. The captured interview findings were then transcribed, but also translated into English if the initial captured data was in Arabic. The raw data from the interviews was organised in terms of the ML adoption drivers/barriers/drivers' barriers related codes in Table 3. Content Analysis and Thematic Analysis were the methods adopted to analyse the captured interviews data to identify emerging themes from the highlighted drivers and barriers for ML adoption amongst rural farms before and after the COVID-19 pandemic era.

Participants' identities were anonymised via pseudonyms, and the confidentiality of the interview data was ensured by storing the data in a password-protected Birmingham City University OneDrive. Participants' consent was ensured via a written and verbal format before each interview. This research study was informed by Glasgow Caledonian University (GCU) research guidelines and the Data Protection Act 2018 [[33] 2025; [78]].

4. Findings and analysis

The findings from the interviews conducted before the COVID-19 pandemic era (2nd to 30th of October 2019) are in Table A, and interviews conducted after the pandemic era (2nd to 30th of January 2023) are in Table B within the Appendix section.

As shown in Tables A and B, a significant increase in awareness of ML is visible. 19 farmers now indicate that they are aware of ML – a sizeable jump compared to the period before COVID-19. Unexpectedly, none of the interviewees indicated that they believe they have the skills required to use technology for their farm operations. 27 of the participating farmers indicated that they make use of mobile/smartphone technology. However, only 2 farmers were willing to use ML in their business operations.

In terms of infrastructure, 3 farmers indicated that they have the infrastructure that would allow them to effectively adopt ML. 47 owner-managers either indicated a level of scepticism about the adequacy of infrastructure or were unsure. 33 participants indicated that they were unsure of the benefits of ML. The remaining participants stated that reduced costs and improved products drove the adoption of ML in their business operations.

The most common types of barriers indicated by interviewees when asked the open-ended question were knowledge/training, costs and cultural. Of note is that all farmers either did not believe the government would play a supportive role in the adoption of ML or were unsure about the government's position in supporting ML adoption.

As shown in Table B, 41 farmers reported knowing ML. Most notably,

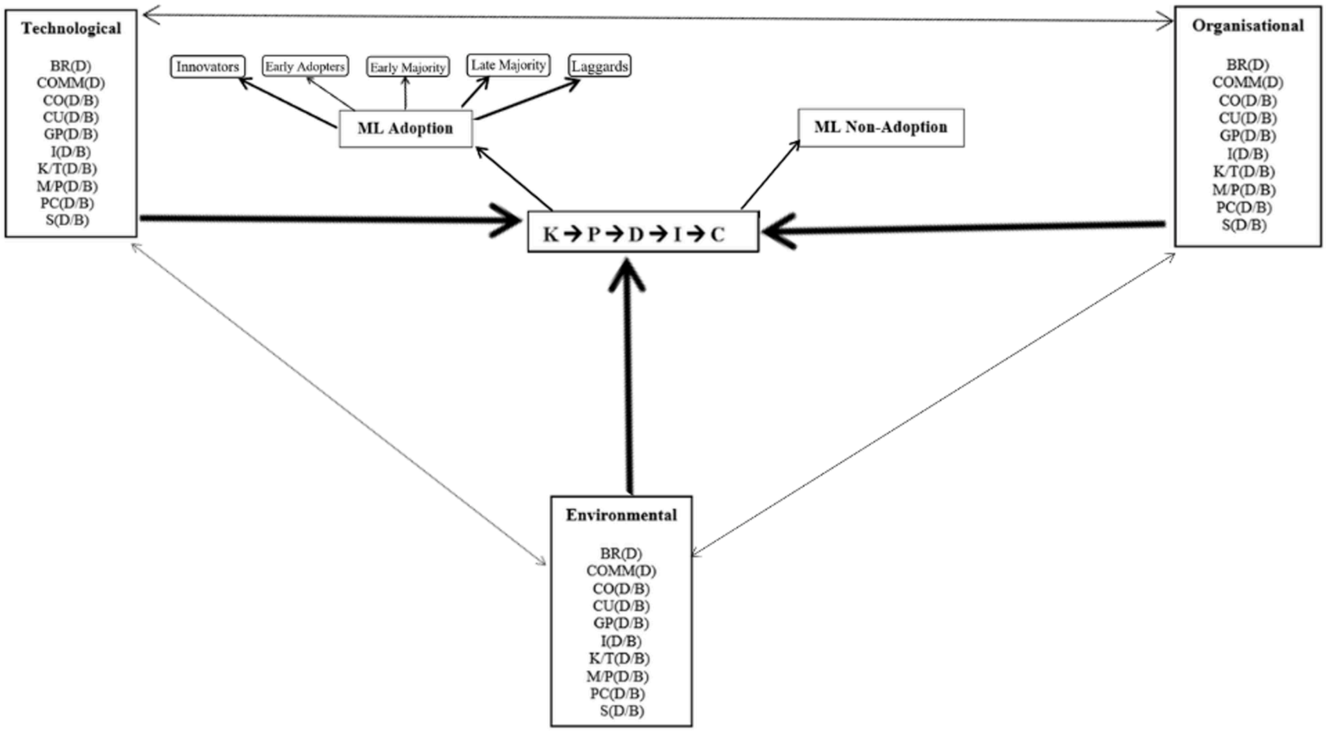

Fig. 2. The MLAFv2.

Table 4
The labelling of participants in terms of country and region.
Ah = Ahl El Koudia, ***F*** = Fekhara, ***G*** = Gueddara, **Hi** = Hini, ***Z*** = Zaatra, **Am** = Amrit, **Asy** = Asyut, **Ba** = Balat, **Bal** = Baltim, **Da** = Damas, **Asi** = Asilah, **Bha** = Bhalil, **El *J*** = El Jebha, **Mir** = Mirleft, **Ris** = Rissani, **Car** = Carthage, **Ham** = Hammamet, **Kai** = Kairouan, **Sf** = Sfax, **Sou** = Sousse, **Al *A*** = Al Ain, **Al *B*** = Al Bateen, **Al *D*** = Al Dhafra, **Al *F*** = Al Foah and **Al *K*** = Al Khazna (Same meanings are adopted in Tables A and B).

Algeria	Egypt	Morocco	Tunisia	UAE
Ah 1	Am 1	Asi 1	Car 1	Al A 1
Ah 2	Am 2	Asi 2	Car 2	Al A 2
F 1	Asy 1	Bha 1	Ham 1	Al B 1
F 2	Asy 2	Bha 2	Ham 2	Al B 2
G 1	Ba 1	El J 1	Kai 1	Al D 1
G 2	Ba 2	El J 2	Kai 2	Al D 2
Hi 1	Bal 1	Mir 1	Sf 1	Al F1
Hi 2	Bal 2	Mir 2	Sf 2	Al F2
Z 1	Da 1	Ris 1	Sou 1	Al K 1
Z 2	Da 2	Ris 2	Sou 2	Al K 2

9 interviewees reported believing that they could effectively use technology to operate their farm. This is an improvement over the responses collected before the start of COVID-19. A more drastic improvement is seen in the use of mobile/smartphone technology; 42 owner-managers reported the use of technology on their farms, which is an obvious improvement over the pre-COVID-19 responses. A surprising result is that only 6 farmers reported not being willing to adopt ML to operate their business. This is in direct opposition to the pre-pandemic responses, which were more likely to be unwilling.

44 farmers reported that they had the required infrastructure for an effective ML adoption. However, some owner-managers reported not believing they had effective infrastructure or were unsure. This suggests that there is a greater awareness on the part of farmers in terms of the available infrastructure as compared to the responses pre-COVID-19. In terms of the benefits of ML, only one participant reported being unsure, and the remaining 49 participants reported improved overall efficiency, reduced costs, and improved products as main reasons to adopt ML. This is an improvement over the pre-COVID-19 responses in terms of farmers' awareness of the benefits of ML.

The majority of the farmers listed costs and infrastructure as barriers to ML adoption for use on their farm. Culture and knowledge/training, two main barriers listed in the pre-COVID-19 results, were not listed as often post-COVID-19. This suggests a cultural shift, and that it is now more favourable among farmers for the adoption of innovations. As with the responses collected pre-COVID-19, most interviewees did not report believing that the government had a hand in their ML adoption. However, there are a few unsure responses and a few farmers who reported that their ML adoption was aided by the government post-COVID-19.

Table 5
Interview questions.

Questions
1. Are you aware of ML?
2. Are you comfortable using technology for tasks on the farm?
3. Do you use any technologies like mobile phones, tablets and laptops on the farm?
4. Would you consider adopting ML for undertaking tasks on your farm?
5. Would the level of local infrastructure influence your adoption of technology on the farm?
6. What are the drivers for you to adopt ML on the farm?
7. What are the barriers to your adopting ML on the farm?
8. In your opinion, what is the role of the government in encouraging ML adoption amongst businesses in your local area?

5. Discussion

The review of studies exploring factors influencing ML diffusion amongst rural farms in Section 2.1 indicated a dearth in research in the context of Algeria, Egypt, Morocco, Tunisia and the UAE, especially, studies exploring the impact of the COVID-19 pandemic on the attitudes of rural farmers for ML adoption. Therefore, a need for research investigating the drivers and barriers for ML adoption amongst rural farms before and after the COVID-19 pandemic era in Algeria, Egypt, Morocco, Tunisia and the UAE was established at the end of Section 2.1.

The findings from the pre- and post-COVID-19 era semi-structured interviews with 50 farmers in this research indicated a substantial increase in the awareness of ML amongst the farm owners. There was also an improved level of confidence indicated amongst farm owners for adopting ML in farm-based operations. These findings related to awareness and confidence also highlight an improved level of knowledge/training (K/T) amongst the interviewed rural farm owners, which also aligns with studies like Liu et al. [45] and Singh et al. [73]. The findings also indicated a significant increase in the diffusion of innovative technologies like mobile phones, laptops and tablets for farm operations from before COVID-19 to after the pandemic era. The findings also indicated that farmers were more willing to adopt ML for business purposes in the post-pandemic era as opposed to the pre-COVID-19 era. In the findings from after the pandemic era, the farmers indicated an improved level of access to the required infrastructure than before the pandemic era.

Regarding ML adoption drivers, a significantly higher number of farmers than before the pandemic era indicated that improved efficiency in farm operations acted as a drive for ML which aligns with the perceived convenience (PC) that was also indicated as a driver for ML adoption in studies like Soum and Ayache [74], Pandey et al. [59] and Priya et al. [61]. Lowered costs (CO) were another prominent driver for ML adoption indicated amongst the farmers, where lowered costs increased as a driver for ML amongst farmers than before the pandemic era, which aligns with the findings from authors like Gonzales-Gemio and Sanz-Martín [34], Pandey et al. [59] and Gilani et al. [31].

Unlike before the pandemic era, culture and knowledge/training were not indicated as major barriers for ML adoption amongst farmers interviewed after the pandemic, where culture as a driver for ML adoption aligns with findings from authors like Barakat et al. [6] and Gonzales-Gemio and Sanz-Martín [34]. Therefore, the findings indicated a transition to a culture amongst the farmers that encouraged ML adoption for farm-based operations.

Findings from both pre- and post-COVID-19 era-based interviews indicated costs (C) and infrastructure (I) amongst farmers as barriers to adopting ML for farm-based operations. The findings from this research in regard to infrastructure as a barrier to ML adoption align with findings from studies like Birhanu et al. [8], Olawale et al. [58] and Pandey et al. [59]. The findings from this research identifying cost as a barrier align with findings from authors like Birhanu et al. [8], Olawale et al. [58] and Chen [14].

Like the interview responses from before the pandemic era, findings from interviews after the pandemic indicated a collective consensus amongst farmers that the government (Government Policy (GP)) could play a bigger role in supporting ML adoption amongst rural farmers. The findings from this research indicate that government policy as a barrier to ML adoption aligns with studies like Soum and Ayache [74], Bouregaa [12] and Wang et al. [81].

The identification of drivers and barriers for ML adoption amongst rural farmers interviewed before and after the COVID-19 pandemic has fulfilled RQ1 and RQ2 outlined in Section 2.3. The highlighted change in rural farmers' attitudes to ML from before and after the pandemic, regarding culture, knowledge/training, and perceived convenience from barriers to drivers, addresses the requirements of RQ3 (from Section 2.3). Therefore, the interview findings were not only underpinned by the MLAFv2 developed in Section 2.2. While addressing RQ1, RQ2 and RQ3, the findings from the farmers have also informed further developments in the MLAFv2 in terms of the factors (identified in Table 1) being classified as drivers/barriers/drivers' barriers. The empirically informed MLAFv3 (MLAF version 3) in the context of ML adoption amongst rural farms in Algeria, Egypt, Morocco, Tunisia and the UAE is illustrated in Fig. 3.

In Fig. 3, the term 'pre-COV-19′ represents the pre-COVID-19 pandemic era and the term 'post-COV-19′ represents the post-COVID-19 pandemic era. The terms BR, COMM, CO, CU, GP, I, K/T, M/P, PC and S represent the same meanings as depicted in the MLAFv2. Any changes to the allocation of drivers (D) and barriers (B) for each of the factors have been informed by the changes in the farmers' interview responses on ML adoption from before the COVID-19 era and after the pandemic era.

The findings from this research from the interviews and the MLAFv3 have informed the development of a practical solution to improve ML adoption amongst rural farmers, especially in MENA-based countries like Algeria, Morocco, Egypt, Tunisia and the UAE. The proposed practical solution is a crop management system which can provide valuable insights to rural farm owners in selecting appropriate crops based on the available local infrastructure and resource availability, which may therefore benefit the wider population and society. The proposed application's interface is illustrated in Fig. 4. This interface may have the ability to support farm owners in efficiently managing their farm-based tasks to ensure optimal results and output. To better manage the identified ML adoption barriers of infrastructure and costs, the proposed application can be integrated into a user-friendly application which is cost-effective and not reliant on local infrastructure, and is accessible on smartphones, laptops and tablets. Such an application can be especially effective for rural farmers in developing countries like Algeria, Egypt, Morocco, Tunisia and the UAE, where knowledge/training, cost and infrastructure have already been identified as challenges against ML adoption.

Fig. 4 shows the simple operational requirements of the proposed application. The proposed interface is very much like a regular mobile application, where we have buttons and dropdown menus to select, which in turn is easy to operate and has the potential to increase the user-friendliness, thereby enticing the farmers to adopt such a system. The input provided by the users, along with the available datasets, will help the ML models to generate precise and personalised recommendations for each farmer.

6. Conclusion

The paper demonstrated that despite the significance of ML adoption in helping businesses overcome the challenges of the COVID-19 pandemic, especially for smaller or more geographically isolated businesses, which benefited from lowered costs and convenience through the use of ML in business operations. However, a deficit in ML adoption was highlighted between businesses in rural regions and urban businesses, where ML adoption by rural businesses was lower. This was found to be especially the case for rural farms. A scoping review of the literature related to ML adoption by rural farms highlighted a dearth of literature based in the MENA region, especially in countries like Algeria, Egypt, Morocco, Tunisia and the UAE. Therefore, this led to this research investigating the drivers and barriers for ML adoption amongst rural farms in Algeria, Egypt, Morocco, Tunisia and the UAE. The fulfilment of the ROs is explained below.

6.1. Realisation of research objectives (ROs)

RO1 – To establish the parameters of remote-rural areas in the context of Algeria, Egypt, Morocco, Tunisia and the UAE.

The review of different sources related to defining rural areas informed this research in adopting the definition of rural areas from the Scottish Government [68], of rural areas being classified as areas with a

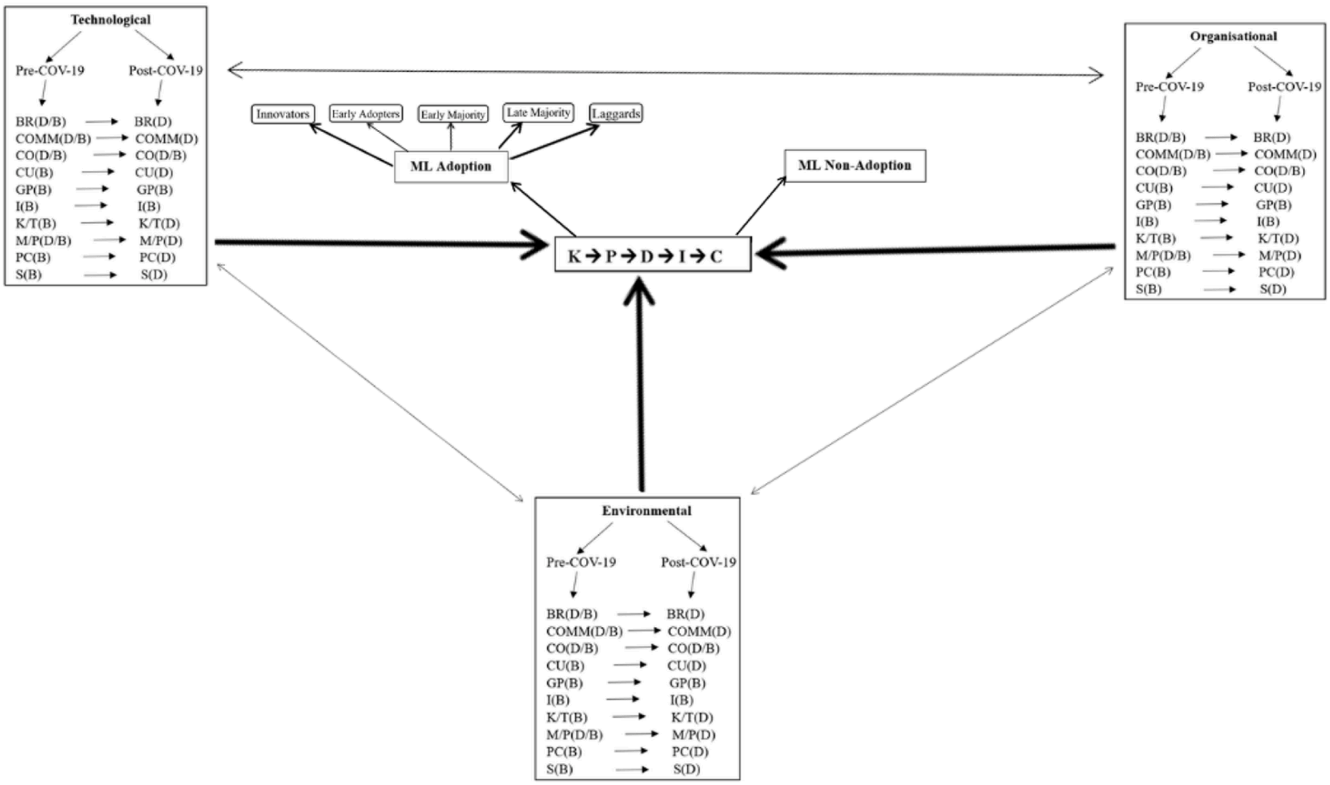

Fig. 3. The MLAFv3.

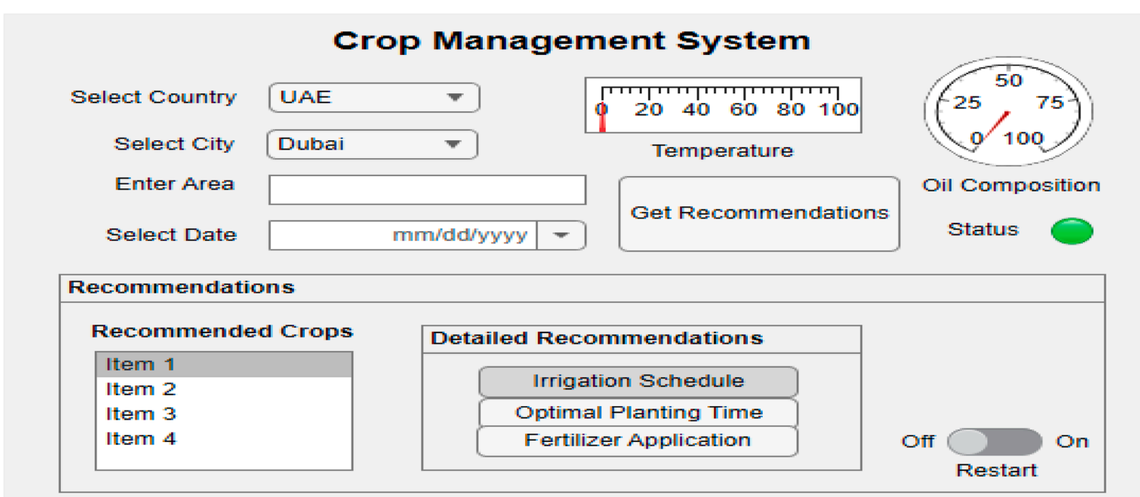

Fig. 4. Proposed Interface to host the MLAFv3 for a Crop Management System.

population of <3000, with over a 30-minute drive away from areas with a 10,000-plus population. The authors selected this definition over other options as, unlike other options, it was quantifiable and it also considered parameters like population size, proximity to urban areas, population density and development, which proved to be a multi-faceted approach in understanding the rurality of an area.

RO2 – To develop a conceptual framework which explores the factors for ML diffusion amongst rural farms in Algeria, Egypt, Morocco, Tunisia and the UAE.

The findings from the literature review in Section 2.1 and the original MLAF from Gilani et al. [30] informed the development of the MLAFv2. The empirical findings then informed the MLAFv3, which represented drivers and barriers for ML adoption before and after the COVID-19 pandemic era amongst rural farms in Algeria, Egypt, Morocco, Tunisia and the UAE.

RO3 – To identify the drivers and barriers for ML adoption amongst rural farms in Algeria, Egypt, Morocco, Tunisia and the UAE.

The key findings from the semi-structured interviews before the pandemic with 50 farms from rural areas in Algeria, Egypt, Morocco, Tunisia and the UAE identified cost, culture, infrastructure and knowledge/training as barriers against ML adoption; however, cost, culture and knowledge/training were identified as drivers for ML adoption after the pandemic.

RO4 – To identify whether there has been a shift in attitudes from before and after the COVID-19 pandemic era towards ML adoption amongst rural farms in Algeria, Egypt, Morocco, Tunisia and the UAE.

The findings from the interviews before and after the pandemic indicated a shift in farmers' attitudes towards ML adoption, where, after the pandemic era, factors like culture, cost and knowledge/training were identified as drivers for ML adoption, which was not the case for the findings in the interviews before the pandemic.

The key findings in this research addressing the realisation of the ROs in addition to the RQs have not only addressed the purpose of this paper to investigate the drivers and barriers for ML adoption before and after the pandemic era amongst rural farms, but they have also significantly contributed to the body of knowledge available on ML adoption amongst rural farms. This study has not only addressed a paucity in literature, but it has also introduced a new theory in the form of MLAFv2/MLAFv3. Therefore, contributions to knowledge have been made from this study, which included addressing a gap in the literature for ML adoption amongst rural farms in MENA, introducing a new framework in the form of adapted versions of MLAF (Figs. 2 and 3) and proposing an interface (Fig. 4) for businesses to integrate ML into their operations.

6.2. Policy-based implications

The findings from this research may inform policymakers in developing policy to ensure the digital divide and social exclusion between urban and rural businesses and communities is minimised through integrating the Sustainable Development Goals (SDGs) of SDG 9 (Industry, Innovation and Infrastructure), SDG 10 (Reduced Inequalities) and SDG 11 (Sustainable Cities and Communities) [79]. Additionally, the MLAFv3 may act as a roadmap for policymakers in devising policies to improve ML adoption amongst rural businesses, which may include farms.

6.3. Practical implications

The findings from this research, in the form of the proposed interface for crop management in Fig. 4, may encourage and support rural-based businesses like farms to effectively and efficiently integrate ML into their operations cost-effectively and conveniently, where this interface would ensure a seamless transition for business owners to ML-driven operations within their businesses.

6.4. Problems/limitations

One of the main limitations was the sample not being fully representative of rural regions within the countries of Algeria, Egypt, Morocco, Tunisia and the UAE. Another limitation of the study was the inability of the study to include more countries from the MENA region, which may have affected the representativeness of the results from the study. The single method of semi-structured interviews was another limitation, which may have led to constrained insight regarding attitudes to ML adoption before and after the pandemic era.

6.5. Recommendations

The authors recommend that future studies investigating ML adoption amongst rural farms in the whole MENA region ensure the inclusion of participants from all MENA countries to ensure a sample and results representative of the MENA region.

The authors would also advise future researchers to conduct a mixed-methods research study to capture a large representative sample via survey and to gain additional insight via follow-up interviews, which would ensure rich and reliable data in relation to drivers and barriers for ML adoption.

The authors would also encourage future studies to conduct a comparative analysis of ML adoption habits between rural farms in Western and Eastern regions, eg a comparison between Europe and Asia will provide significant insight related to ML adoption habits driven by geographic culture.

Finally, the authors advise that the MLAFv3 be adopted and further developed by authors undertaking future ML adoption-related studies.

Ethical approval

The ethical approval was authorised by the ethics committee at Westford University College (Sharjah, UAE) in January 2023.

Informed consent

Consent was gained from participants before their inclusion in the research study where they also gained for findings related to them to be published. However, they instructed for their identity to be anonymised.

CRediT authorship contribution statement

Sayed Abdul Majid Gilani: Writing – review & editing, Writing – original draft. **Mohamed Ashmel Mohamed Hashim:** Writing – review & editing, Writing – original draft. **Abigail Copacio:** Supervision, Software, Methodology. **Rommel Sergio:** Writing – review & editing, Writing – original draft. **Issam Tlemsani:** Writing – review & editing. **Ansarullah Tantry:** Writing – review & editing.

Declaration of competing interest

No competing interests can be confirmed for the authors of this manuscript.

Data availability

The authors do not have permission from the participants to share the raw data.

Appendix

Table A
Findings from the Interviews conducted before the COVID-19 pandemic era.
Yes = 1, No = 2, Unsure = 3, Reduced Cost = RC, Improved Product = IP, Cost = *C*, Knowledge/Training = *K*/T, Culture = CU and Infrastructure = *I*.

Nation	Rural region	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8
Algeria	Ah1	2	Not Applicable	1	2	3	3	C	2
	Ah2	2	Not Applicable	1	2	2	3	C and K/T	2
	F 1	1	2	1	2	2	3	K/T and CU	2
	F 2	1	2	2	2	2	3	C and CU	2
	G 1	1	2	2	2	2	3	C and CU	2

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Table A (*continued*)

Nation	Rural region	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8
	G 2	1	3	2	2	2	3	K/T and CU	3
	Hi 1	2	Not Applicable	2	2	2	3	K/T and CU	2
	Hi 2	1	2	2	2	3	3	K/T and CU	2
	Z 1	2	Not Applicable	1	2	3	3	K/T and CU	3
	Z 2	2	Not Applicable	2	2	3	RCs	C	3
Egypt	Am 1	1	3	1	2	3	3	C	2
	Am 2	2	Not Applicable	1	2	3	3	C	2
	Asy 1	1	2	2	2	3	3	C	2
	Asy 2	2	Not Applicable	2	2	3	3	C	2
	Ba 1	2	Not Applicable	1	1	3	3	K/T and CU	3
	Ba 2	2	Not Applicable	1	2	2	RCs	C and CU	3
	Bal 1	1	2	2	2	2	RCs	C and CU	3
	Bal 2	2	Not Applicable	1	2	2	IPs and RCs	C and CU	2
	Da 1	1	2	1	2	2	3	K/T	2
	Da 2	2	Not Applicable	1	2	2	RCs	K/T and CU	2
Morocco	Asi 1	2	Not Applicable	1	2	3	3	C and K/T	2
	Asi 2	2	Not Applicable	1	2	3	3	K/T and CU	2
	Bha 1	1	2	2	2	3	3	C and K/T	2
	Bha 2	2	Not Applicable	2	2	2	3	CU	3
	El J 1	1	2	1	2	2	3	C, CU and K/T	2
	El J 2	2	Not Applicable	1	2	2	IPs and RCs	C, CU and K/T	2
	Mir 1	2	Not Applicable	1	1	3	IPs and RCs	K/T and CU	2
	Mir 2	1	2	2	1	2	3	K/T and CU	3
	Ris 1	1	2	2	2	2	3	C, CU and K/T	2
	Ris 2	2	Not Applicable	2	2	2	3	C, CU and K/T	2
Tunisia	Car 1	1	2	2	2	1	3	C and K/T	3
	Car 2	2	Not Applicable	1	2	2	3	C and K/T	3
	Ham 1	2	Not Applicable	1	2	3	3	C and K/T	2
	Ham 2	2	Not Applicable	1	2	3	3	C and CU	2
	Kai 1	2	Not Applicable	1	2	3	IPs and RCs	C and CU	2
	Kai 2	2	Not Applicable	1	2	2	IPs and RCs	K/T and CU	2
	Sf 1	2	Not Applicable	1	2	2	IPs and RCs	CU	2
	Sf 2	2	Not Applicable	2	2	3	RCs	K/T and CU	2
	Sou 1	2	Not Applicable	2	2	3	RCs	CU	3
	Sou 2	2	Not Applicable	1	2	3	IPs	C and CU	3
UAE	Al A 1	1	3	2	2	3	3	K/T	3
	AA 2	1	2	2	2	1	3	C and K/T	2
	Al B 1	2	Not Applicable	1	2	2	3	K/T and CU	2
	AB 2	1	3	1	1	3	IPs and RCs	C and CU	2
	Al D 1	2	Not Applicable	2	2	3	RCs	CU	3
	AD 2	1	2	2	2	2	3	C and K/T	2
	Al F 1	2	Not Applicable	1	1	1	3	C and K/T	2
	AF 2	2	Not Applicable	1	2	2	RCs	C and K/T	3
	Al K 1	2	Not Applicable	2	2	2	IPs	K/T	3
	AK 2	1	2	1	2	2	3	C and CU	3

Table B
Findings from the Interviews conducted after the COVID-19 pandemic era.
Yes = 1, No = 2, Unsure = 3, Reduced Cost = RC, Improved Product = IP, Cost = *C*, Knowledge/Training = *K*/T, Culture = CU and Infrastructure = *I*.

Nation	Rural region	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8
Algeria	Ah1	1	2	1	1	3	IPs and RCs	C	2
	Ah 2	2	Not Applicable	1	1	2	IPs and RCs	C	2
	F 1	1	2	1	1	2	IPs and RCs	CU	2
	F 2	1	2	1	1	1	IPs and RCs	C and CU	2
	G 1	1	2	1	1	1	IPs and RCs	C and CU	2
	G 2	1	3	1	1	1	IPs and RCs	K/T and CU	2
	Hi 1	1	1	1	2	2	IPs and RCs	I	2
	Hi 2	1	2	1	1	3	IPs and RCs	I	2
	Z 1	2	Not Applicable	1	1	2	IPs and RCs	I	2
	Z 2	1	3	2	1	1	IPs and RCs	C	2
Egypt	Am 1	1	3	1	1	1	Improved overall efficiency	C	2
	Am 2	2	Not Applicable	1	1	1	IPs and RCs	C	2
	Asy 1	1	2	1	1	1	IPs and RCs	C	2
	Asy 2	1	1	1	1	1	IPs and RCs	C	2
	Ba 1	1	2	1	1	3	IPs and RCs	CU	2
	Ba 2	1	2	1	2	2	IPs and RCs	C	2
	Bal 1	1	2	2	1	2	IPs and RCs	C and I	2
	Bal 2	2	Not Applicable	1	1	1	IPs and RCs	C and I	2
	Da 1	1	2	1	1	1	IPs and RCs	K/T	2
	Da 2	1	2	1	1	1	IPs and RCs	K/T	2
Morocco	Asi 1	1	2	1	1	1	IPs and RCs	C	2

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Table B (*continued*)

Nation	Rural region	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8
	Asi 2	1	1	1	1	3	IPs and RCs	CU	2
	Bha 1	1	2	2	1	1	IPs and RCs	C and K/T	2
	Bha 2	2	Not Applicable	1	1	1	IPs and RCs	CU	1
	El J 1	1	2	1	1	1	IPs and RCs	C, CU and K/T	2
	EJ 2	1	2	1	1	1	IPs and RCs	C, CU and K/T	2
	Mir 1	1	2	1	1	1	IPs and RCs	I	2
	Mir 2	1	2	2	1	1	IPs and RCs	I	3
	Ris 1	1	2	1	2	2	IPs and RCs	C, CU and K/T	2
	Ris 2	2	Not Applicable	2	2	2	IPs and RCs	C, and K/T	2
Tunisia	Car 1	1	2	1	1	1	IPs and RCs	I	2
	Car 2	1	1	1	1	1	IPs and RCs	I	2
	Ham 1	1	1	1	1	1	IPs and RCs	C	2
	Ham 2	1	2	1	1	1	IPs and RCs	CU	2
	Kai 1	2	Not Applicable	1	1	1	IPs and RCs	C and CU	2
	Kai 2	2	Not Applicable	1	1	2	IPs and RCs	K/T	2
	Sf 1	1	2	1	1	1	IPs and RCs	Nothing	2
	Sf 2	1	2	2	1	1	IPs and RCs	K/T	2
	Sou 1	1	1	1	1	1	IPs and RCs	CU	3
	Sou 2	2	Not Applicable	1	1	2	IPs and RCs	C	3
UAE	Al A 1	1	3	2	1	1	IPs and RCs	I	1
	AA 2	1	2	1	1	1	IPs and RCs	C and K/T	1
	Al B 1	1	2	1	1	1	IPs and RCs	I	1
	Al B 2	1	3	1	1	1	IPs and RCs	C	1
	Al D 1	1	1	2	1	1	IPs and RCs	C	2
	Al D 2	1	2	1	1	1	3	K/T	1
	Al F1	1	1	1	1	1	IPs and RCs	C and K/T	1
	Al F2	1	1	1	2	1	IPs and RCs	C	1
	Al K 1	1	2	1	1	1	IPs and RCs	I	1
	Al K 2	1	2	1	2	1	IPs and RCs	C	2

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