Technology adoption model for smart urban farming-a proposed conceptual model

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ABSTRACT

Technological advancements have made their way into the heart of human civilization across numerous fields, namely healthcare, logistics, and agriculture. Amidst the sprouting issues and challenges in the agriculture sector, particularly, the growing trend of integrating agriculture and technologies is roaring. The public and private sectors work hand in hand with regard to addressing these complex issues and challenges that arise, aiming for efficient and sustainable possible solutions. This study is a continuation of a previous systematic literature review; hence, the main objective is to deliver a proposed conceptual model for technology adoption specifically for smart urban farming. Innovation diffusion theory (IDT) is used as the main foundation of the proposed conceptual model, supplemented with additional factors drawn from other exisiting technology adoption models both the originals and extended versions. The outcome of the study is expected to reveal valuable insights into the components affecting the technology adoption model in smart urban farming, which will be further laid out upon in the upcoming study, offering a robust framework for future studies and applications in smart urban farming.

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1. INTRODUCTION

In the occurrence of the Industrial Revolution 4.0, almost every field embraced the integration of a conventional sphere with various technologies [1]–[4]. The integration of such technologies definitely brings abundant and valuable benefits to the world. In the realm of agriculture, the integration of technology is termed "smart farming" or "smart agriculture" or "digital agriculture" and others. Cutting-edge technologies, namely the internet of things (IoT), cloud infrastructure, automation, and sensor technologies, to name a few. Smart farming is recognized as a catalyst to increase the quality and quantity of production, maximizing resources while minimizing detrimental effects. The integration of technology into the agriculture sector is a growing trend, gradually accepted by the masses, particularly in developed countries. The global smart farming industry is expected to grow exponentially to $33 billion by the year 2027 [5].

The blooming trends have directly shaped the field of technology adoption. Technology adoption is not distinct from the smart farming field. It has been applied in numerous fields. Various studies, particularly in smart farming, have been done and are expected to increase in the future [6]–[9]. Studies on technology adoption in smart farming are vital for multiple stakeholders, including potential users and policymakers. These studies lay out the challenges and barriers to adoption clearly and offer latent solutions. Some of the challenges and barriers includes the economic and financial conditions, technological infrastructure, relevance tehnological knowledge and behaviors [10]. There is no doubt that understanding these challenges and barriers are extremely vital in technology adoption.

In technology adoption studies, a variety of models have been adopted; some were integrated or extended to fit the nature of the studies. Among the established and well-known models are innovation diffusion theory (IDT), theory of planned behavior (TPB), theory of reasoned action (TRA), technology acceptance model (TAM), and others [11]–[16]. This study is a continuation of a previous systematic literature review, defining the main goal of the study [17]. This study is to deliver a proposed technology adoption model within the context of smart urban farming technology adoption. The additional term "urban" in smart urban farming, as the name suggests, will focus on the urban area. This study is expected to reveal valuable insights into the components affecting the technology adoption model in smart urban farming, which will be laid out in the upcoming study. In accordance with Sustainable Development Goal 2 (SDG2): Zero Hunger, this study will be one of the potential panaceas for addressing challenges that arose [18].

The study is organized as follows. Section 2 presents the technology adoption models. Section 3 discusses the proposed conceptual model for smart urban farming. Finally, section 4 concludes the study.

2. TECHNOLOGY ADOPTION MODELS

Established technology adoption models, derived from previously linked studies are presented. These technology adoption models, and their factors are among the potential candidates under consideration for the proposed conceptual framework. Diffusion of innovation (DoI) or IDT, developed by Rogers [19], is grounded on five key factors: relative advantage, compatibility, complexity, trialability, and observability as shown in Figure 1. For instance, one may be more likely to adopt a new agricultural technology if it is able to show a clear relative advantage, such as reduced resources wastage. Compatibility with existing farming practices could be an important element to the adoption, if the technology could be integrated well with one's routines. Complexity of the agricultural technology should be minimal, ensuring it to be easy to understand and operate. Technology that can be trialed with a limited basis, may have an impact to one's determination to adopt. Observable results of the technology can influence others to follow.

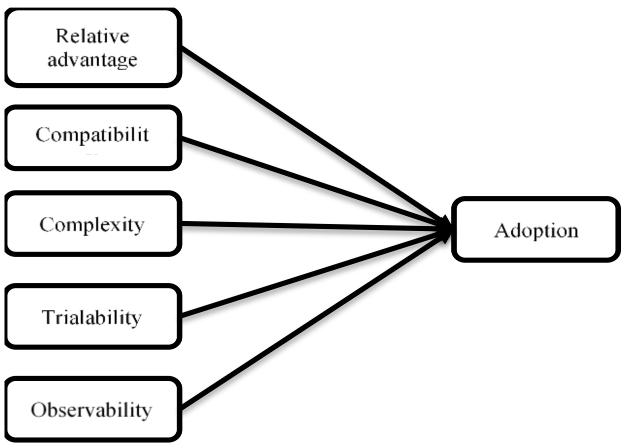

Figure 1. IDT model [19]

The TPB, developed by Ajzen [20], is driven by intention, which are grounded on attitude, subjective norms and perceived behavioral control shows in Figure 2. The model highlights the importance of social influence which can be vital in technology adoption. For instance, if positive attitude of one towards a sustainable technology-driven farming practices is supported and see fit by the community with an adequate resources and skills, the adoption rate is likely higher.

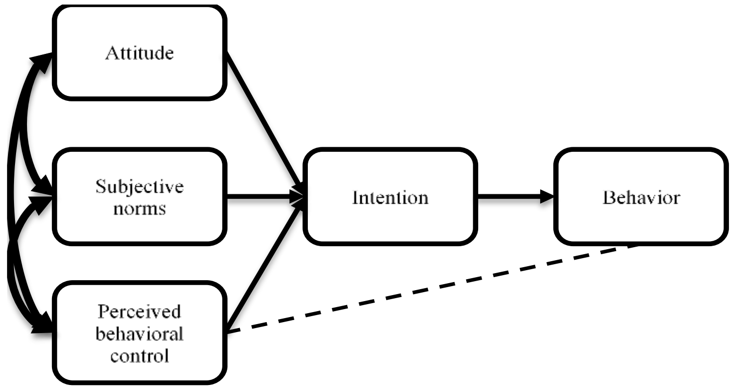

Figure 2. TPB model [20]

The TAM, proposed by Davis [21], is grounded on two primary elements; perceived usefulness and perceived ease of use, which in turn influence attitude and behavioral intention shows in Figure 3. This model has been widely applied in numerous fields, including agriculture, where one's perceptions may lead to an effective technology adoption. For instance, if a new farm monitoring system software is perceived by one as useful by providing valuable insights and improve efficiency, more people are likely to adopt it. Similarly, more people are likely to adopt it if the new farm monitoring system software is user-friendly and easy to use.

The attention-interest-desire-action (AIDA) model is a framework model for marketing and advertising but has its relevance in technology adoption, it has gained popularity with the advancement of technology over the years. This model is grounded on; as the name suggests attention, interest, desire, and action as shown in Figure 4. For instance, one's attention is captured towards a new agricultural technology through a demonstration. Once one shows interest, supplementary materials on the technology can advance the desire by highlighting the advantages and potentials of the technology to increase yields. Then, easy access provided towards the technology to purchase or trials program enable the action element, which encouraging the technology adoption.

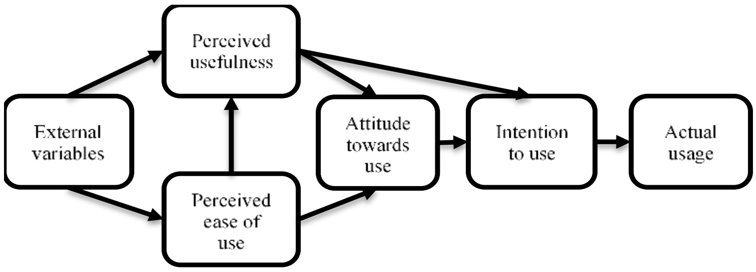

Figure 3. TAM model [22]

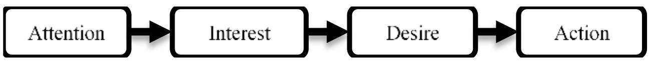

Figure 4. AIDA model [23]

The technological-organizational-environmental (TOE) model, proposed by Tornatzky *et al*. [24], is grounded on three contexts; technology, organization, and environment as shown in Figure 5. This model emphasizes the need to consider both internal and external factors influence in technology adoption. For instance, a farm's decision to adopt a particular agricultural technology might depends on the technological readiness of exisiting available manpowers, tools and equipments, the culture of the organization whether it supports innovation in farming practices, and regulations by local authority. Each and every factor embedded in these models are unique. Integrating these factors in the proposed conceptual model can lead the way to an effective and efficient development of technology adoption in smart urban farming.

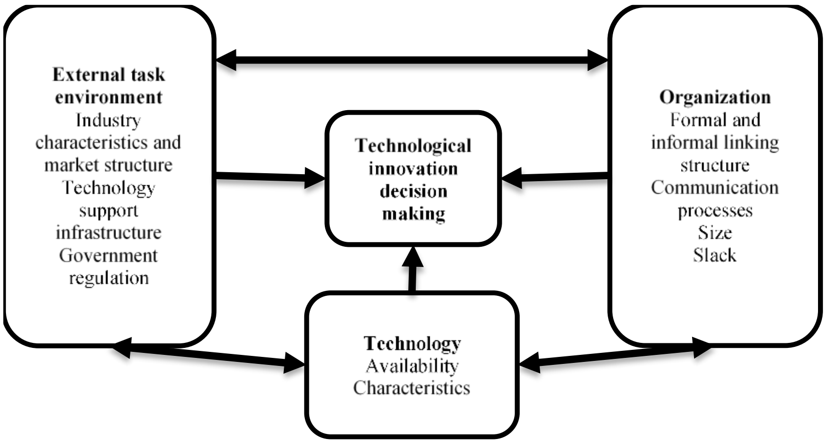

Figure 5. TOE model [25]

3. PROPOSED CONCEPTUAL MODEL FOR SMART URBAN FARMING TECHNOLOGY ADOPTION

The proposed conceptual model is rooted mainly in the IDT, with additional factors embraced from the other technology adoption models. Three factors from IDT were selected: relative advantage, compatibility, and complexity. Additional factors selected were subjective norms from the TPB model, behavioral intention from the TAM model, interest from the AIDA model, IT knowledge, financial cost, innovativeness, government support, digital environment change from the TOE model, and finally, urban farming characteristics as an additional external factor shows in Figure 6. The following hypotheses are proposed:

Relative advantage can be defined as "*The degree to which the new proposed smart urban farming technology is perceived as better than the existing alternatives*". Relative advantage is a crucial factor, as it reflects the perceived benefits of adopting new technology compared to existing practices [26], [27]. The adoption of technology was significantly influenced by the advantages highlighted in previous studies with the technology's integration, where efficiency, productivity, and cost savings were weighed in. In the context of smart urban farming, the technologies mentioned are those that, namely, enhance crop yields, reduce resource wastage, or improve efficiency.

H1: *Perceived relative advantage positively influences the behavioral intention to adopt smart farming urban technologies*.

Compatibility factor can be defined as "*The degree to which the new smart urban farming technology fits with the potential users' existing values, experiences, and needs*". Compatibility refers to how well the new technology aligns with the existing values, past experiences, and needs of potential adopters. Technologies are more likely to be adopted if they are fully compatible with conventional current practices and social norms [28], [29]. In the context of smart urban farming, the compatibility of existing farming practices and urban infrastructure is important to ease the integration and acceptance by individuals. Emphasizing the compatibility of a new technology with the potential users' values and needs may assist in smoother integration and wider acceptance, contributing to a more effective and sustainable urban farming practice.

H2: *Higher compatibility of smart urban farming technologies within existing practices reduced perceived complexity*.

Complexity refers to "*The degree of perceived difficulty in understanding and using the new smart urban farming technology*". Potential adopters may be resistant to adopting particular technologies that are deemed complex or difficult [30], [31]. Simplifying the technology specifically for potential users can definitely reduce the concerns that arose, making it attainable to individuals in smart urban farming. By focusing on user-friendly interfaces, training programs, simplified infrastructure, and system design, smart urban farming technologies can become more accessible and appealing to potential adopters.

H3: *Lower perceived complexity positively influences the behavioral intention to adopt smart urban farming technologies*.

Subjective norms refer to "*The degree of influence of social pressure for smart urban farming technology adoption from the surrounding communities on an individual's decision*". This factor involves the influence of the communities' pressure towards the adoption of a particular technology and can be in the form of motivation or judgement [32], [33]. According to Ajzen [20], it could be peers, family, or society designating the communities. In the context of smart urban farming, positive public endorsements from the communities would definitely aid in the acceptance and adoption of smart urban farming technology.

H4: *Subjective norms positively influence the behavioral intention to adopt smart urban farming technologies*.

Behavioral intention can be defined as "*The degree to which an individual is inclined to use the new smart urban farming technology*". According to Davis *et al*. [22], behavioral intention is a key to actual technology adoption for potential users. It indicates the intention of users' to actually use the technology based on its usefulness and ease of use [34]–[36]. Understanding, enhancing, and easing the adoption of technology in smart urban farming will lead to increased utilization and the benefits offered by smart urban farming technology.

Interest can be defined as "*The degree of curiosity and engagement that potential users exhibit towards the new smart urban farming technology*". The AIDA model fundamentally emphasizes the process of attraction for potential individuals. Interest is a crucial factor in catching and sustaining the attention of potential adopters [23], [37]–[39]. In the context of smart urban farming, integrating this factor, which includes educational programs, showcasing real-world applications, and providing interactive experiences, can encourage the adoption of smart urban farming technology among potential adopters.

H5: *Interest in smart urban farming technologies positively influences the behavioral intention to adopt them*.

IT knowledge refers to "*The degree of understanding and skills of individuals related to information technology in smart urban farming*". In utilizing new technologies effectively, IT knowledge is essential [30]. Individuals with higher levels of IT knowledge are better prepared for the implementation of technological innovations [40]. In smart urban farming, an adequate level of IT knowledge among potential individuals is vital for the successful implementation of the technology. By enhancing IT knowledge through education and training programs, a smooth transition to technology integration can be achieved.

H6(a): A *higher level of IT knowledge positively influences interest in smart urban farming technologies*.

H6(b): A *higher level of IT knowledge positively influences innovativeness towards smart urban farming technologies*.

H6(c): A *higher level of IT knowledge positively influences adaptation to digital environment change*.

Financial cost refers to "*The degree of expenses associated with the adoption of the new smart urban farming technology*". Financial cost is a significant factor to consider in the adoption of a new technology [41]–[43]. It is more likely to be a barrier when the initial costs are fairly high [24], [44]. Reducing the cost or making the technology affordable, particularly in smart urban farming, would definitely enhance the adoption rate [45]. Some other alternatives, such as financial incentives and affordable options, may also achieve the same outcome. By focusing on this strategy, smart urban farming technology can be more accessible and attractive to potential adopters.

H7: *Lower financial costs positively influence the behavioral intention to adopt smart urban farming technologies*.

Innovativeness refers to "*The degree of which an individual's openness and willingness to adopt new ideas or technologies for smart urban farming*". Highly innovative individuals are more likely to adopt new technologies [9], [19], [30], [33], [46]. Cultivating innovative rationale and culture within the community, providing education and training programs, and creating support networks would significantly drive the adoption of smart urban farming technology.

H8a: *Innovativeness positively influences the behavioral intention to adopt smart urban farming technologies*.

H8b: *Innovativeness positively influences interest in smart urban farming technologies*.

Government support refers to "*The degree of policies, incentives, and resources provided by the local government to assist in the technology adoption of smart urban farming*". Pillar programs by the government have a role in facilitating technology adoption [24], [37], [47]. In the context of smart urban farming, government support can be a game changer by creating an enabling environment for the masses. Fair and effective policies, financial incentives, and resource allocation with additional support networks from public-private partnerships can significantly break the barriers and boost smart urban farming technology adoption rates.

H9: *Government support positively influences the perceived financial cost of adopting smart urban farming technologies*.

Digital environment change refers to "*The degree of occurring evolution and advancements made in digital technologies*". Innovations in technology move in unison with the digital environment. Continuous progress in an evolving digital environment influences the innovation, adaptation, and adoption of new technologies [24]. Conventional agricultural practices must be in the same tone as technological progress to be productive and efficient. Embracing and adapting to the ever-evolving digital environment is essential to fully harnessing the potential benefits of smart urban farming technology integration in the agricultural sector.

H10: *Digital environment changes positively influence government support for smart urban farming technologies*.

Urban farming characteristics refer to "*The degree to which specific factors, such as the size and location of farms within urban areas, influence the adoption of smart urban farming technology*". These unique factors influence technology adoption based on the needs and challenges that arise [7]. Tailoring smart urban farming technologies to these unique needs and challenges can enhance the adoption rate and improve agricultural practices.

H11: *Urban farming characteristics positively influence behavioral intentions to adopt smart farming technologies*.

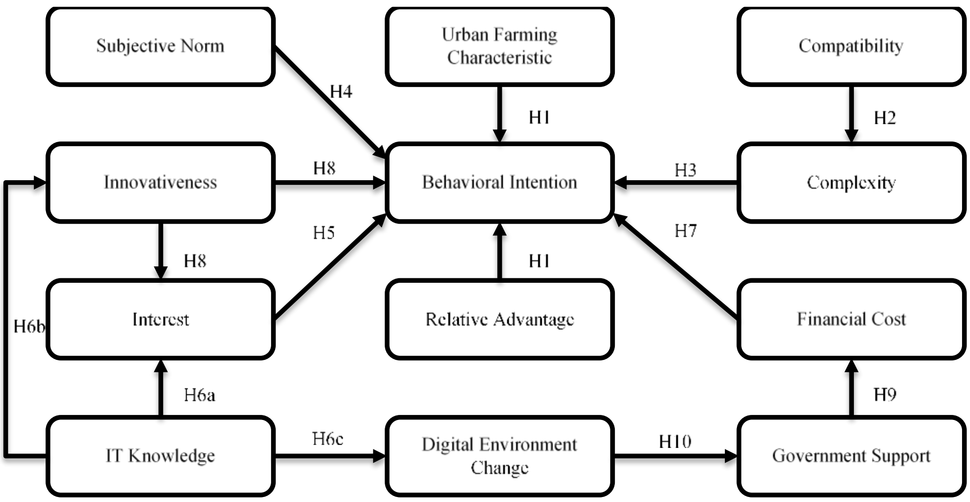

Figure 6. Proposed conceptual model

4. CONCLUSION

In the realm of Industrial Revolution 4.0, smart farming is among the potential remedies for the issues and challenges that arose. The integration of technologies within the agricultural sector marks a significant step towards improving and optimizing both productivity and resources efficiently. The blooming trends in technology adoption in developed nations highlight the necessity of smart farming to secure the future of the industry.

This study aimed to provide a proposed conceptual model for technology adoption in smart urban farming, leveraging IDT as its foundation and supplemented with factors from other existing technology adoption models, including both the originals and extended versions. Through an extensive systematic literature review conducted previously, this study has identified crucial and relevant factors related to the adoption of smart urban farming technologies, including relative advantage, compatibility, complexity, subjective norm, innovativeness, interest, IT knowledge, behavioral intention, financial cost, government support, digital environment change, and urban farming characteristics.

The proposed conceptual model aims to serve as a medium or a bridge, connecting the points of theoretical concepts and practical applications. The proposed conceptual model offers a clear pathway and valuable insights for the successful integration of technology into conventional agriculture. Successful integration of the proposed conceptual model will support Sustainable Development Goal 2: Zero Hunger by eliminating hunger for the world population while promoting sustainable agricultural practices, fostering for a more efficient and technology-driven sector. The proposed conceptual model is expected to reveal valuable insights into the components affecting the technology adoption model in smart urban farming, which will be laid out in the upcoming study. This study not only contributes to the academia but also aims to provide possible strategies for stakeholders in the agricultural sector, driving the change in farming practices.

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