IoT in the Agricultural Industry

Subjects: Behavioral Sciences

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Agriculture resulted in the birth of sedentary human civilization and remains one of the world's most significant sectors. However, despite its importance, a vast majority of agricultural techniques remain conventional. With a predicted worldwide population of 9.6 billion by 2050, a 70% increase in global food production is required to fulfill the ever-rising demand. Internet of Things (IoT) is a term that has become increasingly popular in recent years in this context. The capacity to deal with dynamic workflow environments enables the IoT to address many current agricultural concerns. The IoT and its accompanying technologies have huge potential to boost agricultural productivity and can play a critical role in reshaping the agriculture industry.

Keywords: agriculture ; internet of things ; Willingness to Pay ; Emerging Economy ; Bangladesh

1. IoT and Its Application in Agriculture

The IoT is a relatively new paradigm that "connects real-world objects to the Internet, allowing objects to collect, process, and communicate data without human intervention" [1]. Users can get smarter services from IoT technology applications due to their utilization of ubiquitous computing and real-time processing. The IoT is a massive network that links people, data, and applications, and enables digital services management and control [2] (**Table 1**). The IoT's underlying network architecture can connect a wide range of smart devices—ranging from microsensors to huge agricultural tractors—over the Internet. Smart farms, intelligent greenhouses, scientific diseases, pest monitoring, livestock movement monitoring, controlled fertilizer usage, irrigation management, and asset tracking may all benefit from the IoT [3]. The IoT equips farmers with automated technologies and decision-making tools that seamlessly integrate information, services, and goods for higher quality, productivity, and profitability in farming [4]. A multitude of papers illustrating the uses of the IoT in agriculture now exists [3][4][5][6][7][8][9].

Table 1. Usage of IoT for various agricultural purposes.

Application	Functions
Analysis of yield data	**Composite layers are created by condensing numerous years' worth of yield data [10]**
Variable-rate technologies	**Allow the application of site-specific agricultural inputs [11]**
Field mapping using GPS	**Achieve accurate acreage measurement for fields and roads using maps created by farmers [11]**
Weather forecasts at the field-level	**Measurements made by sensors aid in the forecasting of local weather and precipitation [12].**
Autosteer technology	**Allows precision farming machinery to operate on autopilot, improving accuracy and production for farmers [11].**
Optimization tools for machines	**Agriculture inputs are reduced via the use of precise Global Positioning Systems (GPS) and sensors to record agricultural activities [13].**
Services measuring productivity	**Yield monitoring systems collect data from harvesting trucks and sensors on soil conditions, moisture, and crop yields [11].**

It is primarily through the IoT that conventional agriculture can benefit from the increased sensing and monitoring of production processes, improved understanding of specific farming conditions (e.g., weather, environmental conditions, and pest and disease management), concise and remote control of farm operations such as application of fertilizers and pesticides, and autonomous weeding [14][15] (**Table 2**).

Table 2. Research on the adoption of IoT in the agricultural industry.

Sources	Research Method/Sample Size/Country	Analysis Tools	Theoretical Framework/ Models	Factors	Limitations
[16]	Empirical /Farmers' interview/220/ India	PLS-SEM	Behavioral reasoning theory	Attitude, reason for, reason against, and value of openness to change	Personal innovations and risk-taking ability could be used as the moderator
[17]	Literature Review	MICMAC methods	Modified total interpretive structural modeling	Crop management, government initiative, soil quality management, and irrigation management	Results are based on a literature review and are not an empirical research
[18]	Empirical/ Farm owners and managers' interview/395/ Thailand	SPSS/ Multiple regression	Technology acceptance model	IoT readiness, e-learning, and institutional support perceived usefulness.	Results are based on only small farms and did not consider government support as a construct
[11]	Empirical/ Questionnaire survey/492/USA	SEM-STATA	None	Perceived risk, perceived value, trust, age, farm size	Did not consider contextual factors such as price value and other constructs like trust.
[19]	Empirical/ Face-to-face farmers' interview/400/Tanzania	Structural Equation Modeling (SEM) (AMOS)	Innovation diffusion theory	Awareness, relative advantages, ease of use, compatibility, visibility	Trust and perceived risk factors could be included to enhance the explanatory power
[20]	Empirical/company experts/35/China	Cross-Impact Matrix Multiplication Applied to Classification (MICMAC) analysis	Interpretive structural modeling	Cost savings, perceived benefit, external pressure, technical knowledge, executive support, trust, technological compatibility, complexity, scale of the enterprise, and government support.	The study is limited to its analysis method as no robustness was tested using other latest statistical methods
Current study	Empirical/ Farmer's interview/345/ Bangladesh	SEM-AMOS	UTAUT 2	Personal innovativeness, social influence, effort expectancy, willingness to adopt, facilitating condition, performance expectancy, hedonic motivation, price value, government support, and trust.	

2. UTAUT 2 and Hypothesis Formulation

According to the first UTAUT, only extrinsically motivating elements are considered, and a heavy focus is placed on the utilitarian value of the technology. This is represented by the construct of performance expectancy in the sense of utility, which also represents the strongest influencing factor for the intention to use in the UTAUT [21]. This extrinsic motivation component, according to Venkatesh et al. [22], is augmented by the inner motivation component and hedonic motivation, in the UTAUT2. Along with the existing construct (Personal innovativeness, social influence, effort expectancy, willingness to adopt, facilitating condition, performance expectancy, hedonic motivation, price value, except habit) of the UTAUT2, this study experiments with three additional constructs, including trust, government support, and willingness to pay (**Figure 1**). The constructs are subsequently explained.

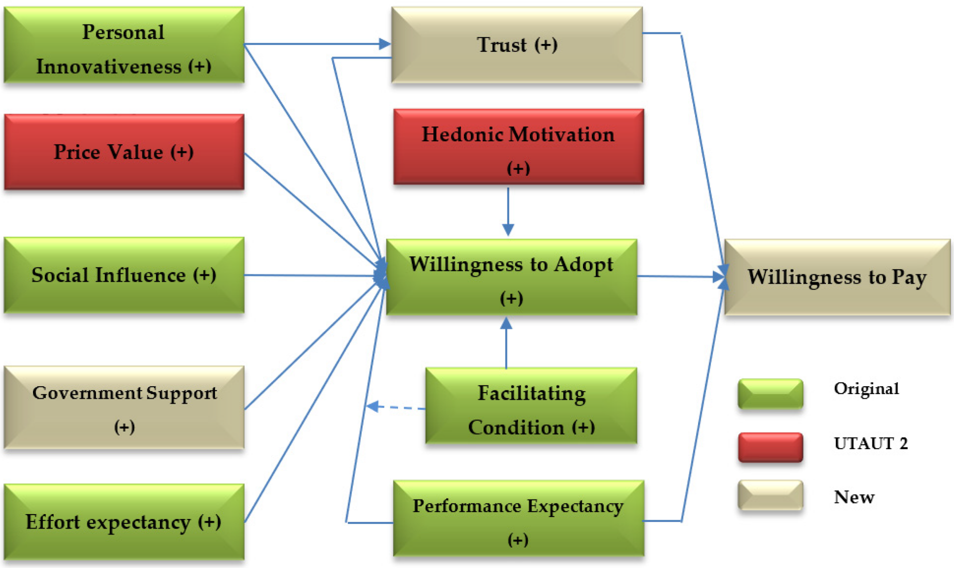

Figure 1. Conceptual framework.

2.1. Performance Expectancy (PE)

Following the basic concept of PE and its adaptation to the current situation, researchers defined this factor as the degree to which individuals feel that accessing the IoT will assist them in undertaking a certain activity [23][24][25]. In the agricultural industry, PE is defined as the degree to which a device can assist users in monitoring their daily yield data analysis, GPS field mapping, productivity measurement, and field-level weather forecasts [11]. If farmers' perceptions of improved harvest management, easier access to agricultural services, more efficient use of resources, and higher overall productivity enhance their PE for connected crop care equipment, then their willingness to use and pay for these devices will rise accordingly. The BI to utilize healthcare technology has been strongly associated with PE in previous studies [23][26][27], and according to Gu and Liu [28], PE is positively associated with the willingness to pay for Q&A platforms.

2.2. Government Support

The IoT business, particularly in the agriculture sector, relies heavily on government backing. The government's willingness to engage in the business may help the agricultural business flourish via the enactment of policies that benefit both investors and service providers. According to research by Goo and Heo [29], government involvement has a favorable influence on the growth of Fintech owing to the lowering of uncertainties. According to research conducted by Chong and Ooi [30] on the acceptance of RosettaNet in Malaysia, the Malaysian government actively encourages the use of the standard by offering grants and tax exemptions. Following Marakarkandy et al.'s [31] findings, government support for new technologies has a favorable correlation with their adoption.

2.3. Facilitating Conditions

FC is the user's belief that support and infrastructure are available to assist them in the usage of their desired technology [22]. Technical and infrastructure support for system utilization is usually classified under FC, as it has an impact on both user intent and actual use [21][22]. Technology or organizational assistance is required by farmers to employ crop care equipment. The government should encourage the development of the physical, network, and electrical infrastructure, as FC makes it possible for users to have a better understanding of the resources and facilities available to them, such as their talents, technical expertise, and the help and direction of IT experts [25][32]. Boontarig et al. [33] discovered that FCs have a favorable effect on behavioral intention in their investigation. FC is perceived as the most important factor in determining a consumer's intention to utilize mHealth [34][35].

2.4. Social Influence

As highlighted in several studies, SI has a multifaceted role in the acceptance of new technology [36][37]. To put it another way, SI is the degree to which people believe that important individuals agree with their actions or technological choices [21][25][34]. Specifically, SI has demonstrated an excellent predictive power in the context of health-related technology use [37][38][39], wireless devices, smartphones [40], and mobile diet applications [38].

2.5. Hedonic Motivation

Hedonic Motivation (HM) has been defined as the degree to which the usage of new technology results in satisfaction or pleasure, and it has been identified as playing a critical role in the adoption of new technology and its use [22]. Joy, fun, entertainment, playfulness, and other intangible benefits are all included in HM (usefulness, efficiency, performance, etc.). To encourage clients to accept new technology, it is important to show them how the use of the new technology will provide them joy and happiness [41][42]. If a person thinks that the usage of mobile applications for healthcare services is amusing, interesting, and pleasant, he or she is more likely to use the application [34][43]. Consequently, a customer's desire for new technologies such as the IoT employing GPS-based mapping or yield control systems could infuse fun or enjoyment in its usage, which in turn increases the user's behavioral intention towards the IoT.

2.6. Effort Expectancy

People's willingness to utilize a new technology is influenced by its ease of usage [23]. EE refers to "the ease with which a system may be used" [21]. Farmers who utilize IoT devices are more likely to perceive technology as good and useful when EE is present. As a result, the amount of energy required to run the system increases [44]. Innovation in technologies that are quick and easy to implement with minimal effort is often viewed as a sign of progress by users [45][46]. Researchers [26][32][47] discovered that EE was an excellent indicator of behavioral intention. Thus, because farmers, in many cases, are less educated and less technology conscious, they are likely to adopt the IoT if they perceive or discover that it is not a complex system to operate, or requires less effort to learn.

2.7. Trust

Trust is the reliance or confidence in a particular service. The IoT will be more widely adopted if people are confident in its ability to deliver on its promises, and in the company that provides it. The IoT application's capacity to function during an emergency may be hampered if users harbor mistrust in the service provider. Although most studies have indicated a favorable association between trust and BI, some have revealed otherwise [45][48][49]. According to Alalwan et al. [45] and Chao [50], trust is a key factor in the adoption of mobile technology. Similarly, the researchers [47][48] discovered trust to have a significant impact on students' BIs toward the utilization of mobile learning; however, Kabra et al. [48] revealed the non-existence of an association between trust and BI. According to Jiang et al. [51], a positive association exists between technological trust and the willingness to purchase and adopt autonomous cars.

2.8. Price Value

Price value is another component that has been included in the UTAUT 2 [22]. Price Value (PV) is defined as a consumer's cognitive tradeoff between the perceived system value and the cost of acquiring or utilizing a new technology [22]. With the usage of new technology, end-users are constantly comparing the cost incurred with the resulting savings that they might derive from the new technology [41][52][53]. With the use of information technology such as the IoT, the agricultural production process may benefit from the delivery of crop care information services at a more affordable rate as compared to the traditional method of physical inspection for pest control or irrigation. By assuming that a product's benefits surpass its expenses, its pricing is considered to be positive [22].

2.9. Personal Innovativeness

Personal innovativeness was defined by Lu et al. [54] as the willingness of an individual to try out new technologies. Adoption of new technologies is mostly driven by a person's willingness to tolerate the existence of the technology. According to this study, user innovativeness is characterized as the readiness to experiment with IoT services and eagerness to explore new technologies. Earlier studies have revealed a correlation between user inventiveness and technological acceptance [55][56][57][58][59], and similarly, Leckie et al. [60] demonstrated the impact of service innovation in the generation of total service value appraisal, customer engagement, and loyalty. O'Cass and Carlson [61] discovered that perceived website innovation predicts a customer's trust. The perceived innovativeness of a website is related to the notions of originality and utility—according to the authors—and these underlying characteristics encourage people to have faith in a website.

2.10. Willingness to Adopt

The model's main idea is hinged around people's willingness to try new things, which is referred to as Behavioral Intention. Many researchers focus on the intention to utilize technology rather than its actual utilization. A close examination of people's (and managers') willingness to pay for the IoT reveals their ability to price it when the technology is launched. The willingness of consumers to pay more for a product or service is influenced by their attitudes toward, and intentions to adopt, newer technology such as green information and communication technologies, renewable heating systems, and electric automobiles [62][63][64].

2.11. Willingness to Pay

Willingness to pay (WTP) is defined as ‘the highest price that a consumer is willing to pay for a product or service’ [65]. Managers must realize that because the utmost number of consumers are willing to pay, they must be ready to create an effective pricing strategy that maximizes profits while also satisfying consumers’ needs and expectations [66]. Individuals’ buying intents and WTP are influenced by product, service, and technology values. While the ‘desire to pay more’ measures the influence of monetary units on values, purchase intention measures consumers’ intention to purchase a service or technology [65]. Although consumers could expect an amazing experience from the use of IoT services, it is crucial to grasp the value–price tradeoff in the market. The value–price tradeoff can be better grasped when included in the ‘desire to pay more’ variables.

2.12. The Moderation Effect of Facilitating Condition

As earlier stated, facilitating condition refers to the necessary facility such as knowledge, technological awareness, and technical and infrastructural support. Various scholars have applied a variety of support facilities as a moderation tool. For instance, Li and Zhao [67] studied the connected classroom climate as a moderating effect in UTAUT constructs such as performance expectancy and behavioral intention and discovered a significant relationship. In their research, Abubakar and Ahmad [68] hypothesized that technological awareness moderates the link between performance expectancy and behavioral intention, while others directly applied the FC as a moderator. For example, Humida et al. [69] assessed the moderation effect of facilitating conditions between the perceived usefulness (same as performance expectancy) and behavioral intention towards the e-learning system in Bangladesh, albeit its infrastructural deficiency among the Bangladeshi students. They concluded that no significant moderation of facilitating conditions was observed, owing to the respondents being students who were knowledgeable about technology.

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