

## Article

# Adoption of Environmental Information Chatbot Services Based on the Internet of Educational Things in Smart Schools: Structural Equation Modeling Approach

Meennapa Rukhiran <sup>1</sup>, Napasorn Phaokla <sup>2</sup> and Paniti Netinant <sup>2,\*</sup><sup>1</sup> Faculty of Social Technology, Rajamangala University of Technology Tawan-OK, Chanthaburi 22210, Thailand<sup>2</sup> College of Digital Innovation Technology (DIT), Rangsit University, Pathum Thani 12000, Thailand

\* Correspondence: paniti.n@rsu.ac.th

**Abstract:** The Internet of Educational Things (IoET) equips chatbots with real-time environmental information monitoring to prevent student and instructor absences and safeguard their health. Individual behavioral intention toward a chatbot service is essential for better understanding the user's experience and acceptance of monitoring environmental elements such as PM2.5, temperature, humidity, and carbon monoxide. This study aims to apply an integration of an extended framework for smart schools developing an environmental information chatbot service (ENICS) and various users' continued behavioral intentions toward the chatbot system based on the unified theory of acceptance and use of technology model to support health and safety in universities. The proposed framework design can incorporate Internet of Things architecture to develop and utilize the chatbot services. The key results of the partial least square test largely support the validity of the proposed model and the significant effects of IoET, performance expectation, effort expectation, social influence, facilitating conditions, health and safety, behavioral intention, and use behavior on personal environmental information chatbot utilization. This study's findings deal with a better design for environmental system development and understanding the factors influencing an individual's intention to continue using a chatbot service for IoET applications with low-cost information facilities in safe environmental sustainability.

**Keywords:** environment information; chatbot; smart school; evaluation usage; unified theory of acceptance and use of technology; internet of educational things; software development



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## 1. Introduction

The smart city is one of the digital transformations that describes advances in technology, the economy, and society. Possible innovations are based on sensor-based technologies, big data, open data, and new methods of connecting and sharing data, including the internet of things (IoT), radio frequency identification (RFID), and wearable technology. In many modern industrial sectors, including smart schools, numerous technologies are continuously applied to new innovations. Smart schools are an integral component of the concept of a smart city, wherein various school-based elements are connected to the internet via sensing, data monitoring, and data tracking [1]. The internet of educational things (IoET) provides smart mobile devices for school administrators, teachers, students, and parents to monitor and track the information and behaviors of their children [2–4]. The smart digital school framework is designed and presents an integration of systematically connected work processes, one of which incorporates safety as a smart school topic [5–7]. Smart school systems, such as smart digital boards, wireless door locks, temperature sensors, and attendance tracking systems have implemented IoT technology to address multiple aspects of school security, such as property, health, and the environment [8]. The development of an information system for a safe and secure environment could sustainably encourage student learning. The Internet of Things (IoT) equips a smart school with sensors, cameras,

monitoring, and surveillance devices due to the importance of ensuring the safety and security of student health. By equipping a school with real-time safety and security systems, immediate notifications, warnings, and educational actions can demonstrate a substantial improvement [9]. In addition, various environmental information management systems for low-cost sensors and real-time monitoring systems have been investigated in recent research. For environmental information applications, including water pollution source localization [10,11], air quality monitoring systems [12–15], soil moisture measurement [16], and radiation pollution [17], the framework development of sensors and wireless sensor networks is proposed.

The health of students and instructors must take precedence because a conducive learning environment influences the health of students and instructors. The environmental issues in Thailand are well-known and have multiple causes. For example, a forest fire in northern Thailand generated a substantial amount of PM<sub>2.5</sub> dust. In Bangkok, PM<sub>2.5</sub> from automobiles, motorcycles, and industrial exhaust pipes, as well as heat and humidity, have negatively affected the health of students and teachers. The student's health may be negatively impacted when the air quality index (AQI) level [18] is high. It is possible to develop a real-time environmental information center to support environmental information monitoring and notification systems, such as those for PM<sub>2.5</sub> or airborne dust, carbon dioxide (CO<sub>2</sub>), temperature, and humidity. The real-time system can immediately display to a user a variety of environmental sensing data, allowing the user to safeguard their health and avoid potentially hazardous environmental surroundings.

Even though numerous smart school frameworks are widely adopted, IoT technology can more effectively enhance a smart school. User acceptance is essential for effectively implementing any information technology or information system (IS) [19]. The technology acceptance model (TAM) [20] is one of the most commonly cited IT and IS frameworks. Nonetheless, some researchers [21] have argued that the TAM has a number of drawbacks, including (1) insufficient understanding of the individual perspective of the new system; (2) ignoring the indicator and investigating ease-of-use perception (PEOU) and perceived usefulness directly (PU); (3) ignoring the relationship between usage attitude and usage intent. Models of technology acceptance theory from the past and present are diverse. The unified theory of acceptance and use of technology (UTAUT model) is a contemporary model that explains 70 percent of the utilization of technology. The model is also used to assess the likelihood of a new technology's success and the adoption of various technologies [22]. For instance, Hamdani [23] investigated the influential factors of students' video utilization and their learning satisfaction in relation to the use of educational videos available in a business mathematics course. In [24], the identification of rain classrooms based on UTAUT constructs and the efficacy of rain classrooms based on learning outcomes in linguistics courses were investigated. The UTAUT model of teaching mathematics was used to test hypotheses [25] using the factors of performance expectancy (PE), effort expectancy (EE), and social influence (SI). The research results provided an integration strategy for classroom learning.

The majority of studies have focused on air pollution monitoring, which requires extensive development and performance evaluation of smart wireless environmental sensors with cloud servers and internet networks [12–15]. It was hard to find the right research examining and comparing the capability of a smart environmental information system to be used in an educational institution, especially in the context of current health and safety issues arising from the air environment. Prior research was hampered by the inadequacy of their model to address the effectiveness of chatbot adoption based on IoET. PM<sub>2.5</sub> has been reported using various methods through an application indexed air quality. Web platforms, social media platforms, and chatbot services are the methods that air indexed applications adopt the most. However, chatbot services can expeditiously integrate IoT-based technology and continue providing feedback on environmental information in a specific area. In addition, the limitations of chatbot services for reporting environmental information, such as user-friendly interfaces, have been given scant attention.

According to [26,27], educational chatbot services have been implemented and evaluated using an extension of the UTAUT2 model. These studies have not identified all crucial factors that could significantly characterize user behaviors when utilizing the IoET-based chatbot application for environmental information. Another limitation of chatbot services is the need to design and develop a new innovative application, particularly for environmental information reporting. Consequently, this study focuses on essential aspects of an environmental information monitoring and tracking system utilizing chatbot services. The findings could help us comprehend the benefits of enhancing user experience and acceptance. Due to the aforementioned justifications, the authors incorporate a UTAUT-based measure of user acceptance to symmetrize the effective designs of environmental information systems and the user's behavioral intent in using the chatbot system. Migration theories of software development and framework design can express the relationship between individual user tasks, software processes, and users' capacity to possess the entire software for environmental information systems. Thus, smart school services can incorporate health and safety features, such as a real-time environmental information system that monitors air pollution to prevent harmful students and educators from exposing themselves to air pollution.

Therefore, the primary purpose of this study is to develop an expanded framework of smart schools for creating an environmental information chatbot service (ENICS). Proposed is the design of an IoT architecture, the creation of an environmental information system, and the effective use of an ENICS. The second objective is to create a model for chatbot adoption of environmental information services by extending the UTAUT model with new constructs, innovativeness through the internet of education things (IOE), and health and safety (HS) considerations. This study emphasizes contributions not only to the investigation of environmental information system architecture and design but also to the observation of user behavior regarding the relationships between IoET and health-safe factors based on the extension of the UTAUT model. This study's findings are significant enough to represent the development of an IoT-based environmental information chatbot service that any organization can implement. This study also proposes a better understanding of the factors that influence a person's intention to continue using an ENICS in educational institutions and provides crucial implications for the development of health and safety information services in a sustainable manner. The authors intend to address the following research questions:

- (1) What are the architectural design and implementation of IoT-based environmental information services integrated with existing social media platforms?
- (2) What effect and relationship exist between the innovativeness of IoET and health and safety factors that influence individuals' acceptance of the continued use of environmental information chatbots in educational institutions?
- (3) How does an individual's acceptance of environmental information chatbots depend on their perceptions of their behavioral intentions resulting from their usage?

This article's remainder is structured as follows: The literature review for environmental information systems, smart schools, the UTAUT model, the internet of educational things, and chatbot approaches is presented in Section 2. Section 3 describes the research methodology for designing and developing environmental information chatbots and user behavioral intentions. Section 4 provides a summary and discussion of the UTAUT model. Section 5 summarizes the user's behavioral intentions regarding the educational use of an ENICS.

## 2. Literature Review

This study contains the related theories and analyses to support environmental information studies. The weather elements, consisting of dust, PM2.5, heat, humidity, and CO<sub>2</sub>, affect the health of university students and instructors. The recent smart school frameworks related to people and software processes can be implemented in this study. To study a smart school in the areas of IoT devices, software design and development, and software

evaluation on user behavior intentions, the authors looked at previous research on IoET, chatbots, and theories about factors that affect acceptance and use.

### 2.1. Environment Information Studies

The pollution control department of Thailand [18] classifies the pollution levels in different means and colors. The following air quality indices as shown in Table 1.

**Table 1.** Air Quality Index (AQI) classifications of pollution advice.

AQI	Meaning	Color	Description
0–25	very good	Blue	The air quality is very good and suitable for outdoor activities and travel.
26–50	good	Green	With healthy air quality, outdoor activities and travel are possible as usual.
51–100	fair	Yellow	Outdoor activities are typically open to the general public. People who require specialized medical care must be aware of their health conditions. If initial symptoms such as coughing, difficulty breathing, or eye irritation are present, outdoor activity duration should be shortened.
101–200	affect health	Orange	The general public must be vigilant regarding their health. If you experience coughing, difficulty breathing, eye inflammation, chest tightness, headache, irregular heartbeat, nausea, or fatigue, consult a physician.
>201	affect health	Red	Everyone should avoid outdoor activities, high-pollution areas, and those that require personal protective equipment. If you experience any symptoms, you should consult a physician.

In this research, the environmental information components of the air quality index (AQI) are:

- (1) Particulate matter with a diameter of fewer than 2.5 microns (PM<sub>2.5</sub>) is vehicle generated dust with a diameter of fewer than 2.5 microns. Burning agricultural materials, forest fires, and industrial processes can enter the lungs' air sacs. Consequently, it can consequence in diseases of the respiratory system and various lung diseases.
- (2) Carbon monoxide (CO<sub>2</sub>) is an odorless, tasteless, and colorless gas produced by the incomplete combustion of carbon-containing fuels. This gas will compete with blood hemoglobin. As a result, carboxylhemoglobin (CoHb), which aids in delivering oxygen to cells, is diminished. As a result, the body weakens, and the heart has to work harder (expected value of 30 ppm).

The daily air quality index for each air pollutant is derived from the concentration of air pollutants as measured by air quality monitoring stations. Various levels of air pollutant concentration correspond with the air quality index. The equation of a straight line, Equation (1), is used to calculate the air quality index within the level range, as illustrated in Table 2.

$$I = \frac{I_j - I_i}{X_j - X_i} (x - x_i) + I_i \quad (1)$$

When:

I = An air quality sub-index.

X = A concentration value of air pollutants from the measurement.

X<sub>i</sub>, X<sub>j</sub> = The minimum and maximum value of the pollutant concentration range with the value X is defined.

I<sub>i</sub>, I<sub>j</sub> = The minimum and maximum values of the air quality index range correspond to the calculated sub-index concentration range X.

**Table 2.** AQI based on air pollutant concentrations.

AQI	PM2.5 (mg/m <sup>3</sup> )	PM10 (mg/m <sup>3</sup> )	O <sub>3</sub> (ppb)	CO (ppm)	NO <sub>2</sub> (ppb)	SO <sub>2</sub> (ppb)
	Average 24 h Continuously	Average 8 h Continuously	Average 1 h			
0–25	0–25	0–50	0–35	0–4.4	0–60	0–100
26–50	26–37	51–80	36–50	4.5–6.4	61–106	101–200
51–100	38–50	81–120	51–70	6.5–9.0	107–170	201–300
101–200	51–90	121–180	71–120	9.1–30.0	171–340	301–400
>200	>91	>181	>121	>30.1	>341	>401

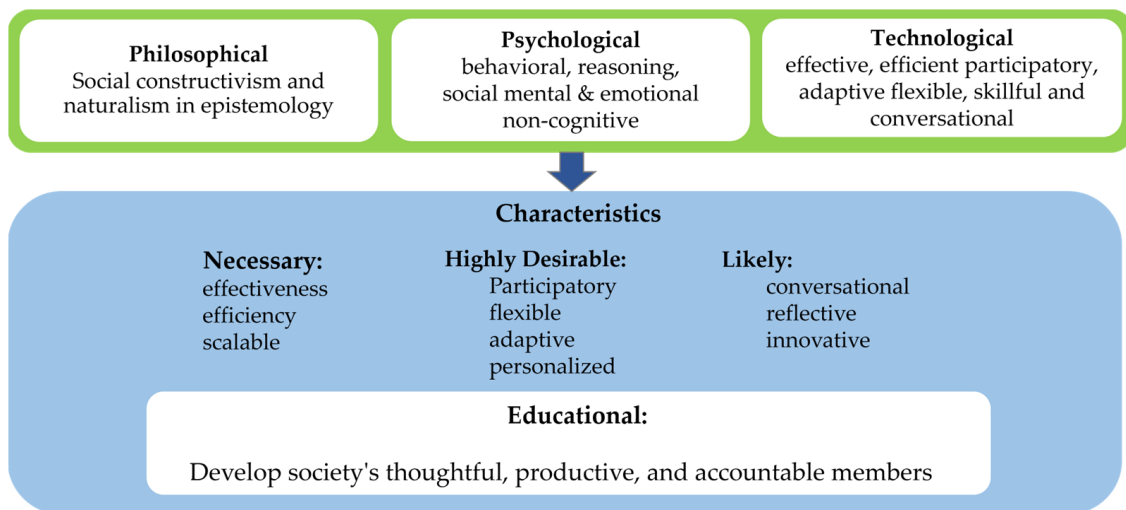
- (3) In some regions, the Thai department of pollution control has devised a heat-related health alert system based on temperature, as illustrated in Table 3. The values use the greatest temperature (maximum temperature) as the condition for alarm communication. Recently published [25] are the consequences of future climate change on Thailand’s heat accumulation and precipitation. The Thailand Meteorological Department has also said that if the air temperature is too high, both hot and cold temperatures could change the way the body works and kill certain organs, which could lead to illness and death.

**Table 3.** Heat classifications alert threshold.

Level	Risk Level	Temperature (Degree Celsius)
1	Surveillance	<38 degrees Celsius
2	Alert	38.1–40.0 degrees Celsius
3	Warning	40.1–43.0 degrees Celsius
4	Danger	>43 degrees Celsius and 3 consecutive days or >45 degrees Celsius

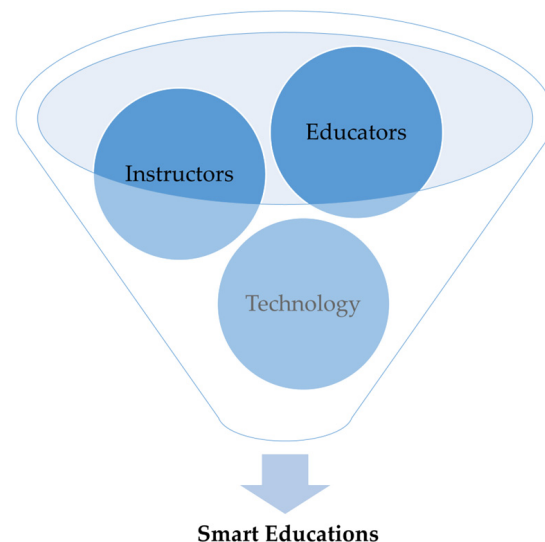
## 2.2. Smart School Approaches

Smart schools are educational institutions that manage, prepare, and educate pupils using technology from the information age. Assigning curriculum, assessment, and course materials as standard teaching and learning components is possible. Information and communication technology (ICT) is the second pillar that supports and develops a smart school. There are many problems with the establishment of smart schools. These facilities include classrooms with multimedia teaching materials and presentation facilities, computer laboratories for teaching multimedia centers, server rooms equipped to support application management, a database, and a web server. They facilitate teaching and learning activities and aid school administration. A smart school development was cited by Hussein et al. [28] and Salimi et al. [29] as one of the most technologically difficult alternatives that created a less stressful atmosphere for management, teaching, and learning and allowed students to express their thoughts independently. Using management and administration software, the smart school management system was introduced [30]. Effective software for management and administration was built exclusively for directors and administrators. The system’s operations, including assignment and scheduling, can be grouped into nine categories: school governance, student affairs, educational resources, external resources, finance, facilities, human resources, security, and technology. Figure 1 shows that a framework for smart learning environments was divided into three domains (philosophical, psychological, and technological) to enable stakeholders to understand each other’s roles and features in the educational process.



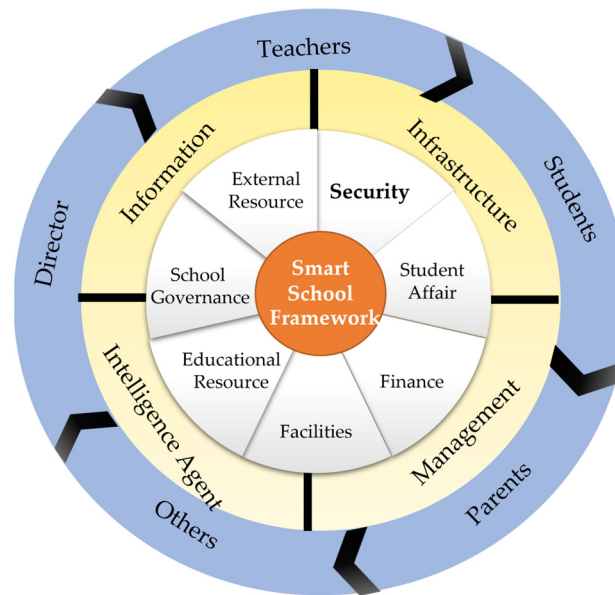
**Figure 1.** Smart learning environment framework adapted from [31].

As indicated in Figure 2, a smart educational system identifies important learning components based on digital learning stakeholders [32]. The framework consists of instructors communicating instructional design through the use of technology. Through the application of technology, learners and students had independent access to and studied a large diversity of instructional content.



**Figure 2.** Stakeholders-based smart education system adapted from [32].

As depicted in Figure 3, a framework for smart schools was separated into three layers of significant components [5]. Users comprised the initial layer, including instructors, students, parents, directors, and others. The second layer provided support for system architectures, which include an intelligence agent, data, management, and infrastructure. The third layer consisted of school components and services, including external resources, student affairs, finances, facilities, instructional resources, school administration, and safety. By analyzing recent research on a framework for smart school information, the critical concern for enhancing the stability of smart school information systems was a security component. The framework introduced a security system to the primary framework for smart schools. Physical and logical settings that can be applied to IoT devices and sensors, such as camera surveillance and environmental air quality, pollution, and ultraviolet concentration, constitute the security components.



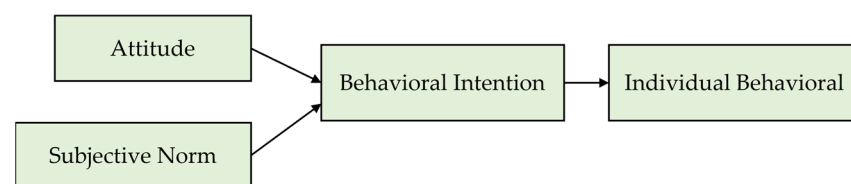
**Figure 3.** Conceptual framework of smart school information system adapted from [5].

### 2.3. Theories Related of Factors Influencing Acceptance and Use

Theories related to user/individual behavioral intention, which are grounded in the principles of human psychology, have been widely utilized as a guideline or framework for examining the aspects that influence an individual's adoption of innovations and information systems.

#### 2.3.1. Theory of Reasoned Action

The theory of reasoned action (TRA) is a theory [33] that refers to the general behavior of humans in which all human acts result from rationality and information to decide whether or not to act. Therefore, the prediction of human behavior must consider the components of or influences on human decision-making. As depicted in Figure 4, individual behavioral intentions are influenced or motivated by attitude and subjective norms.



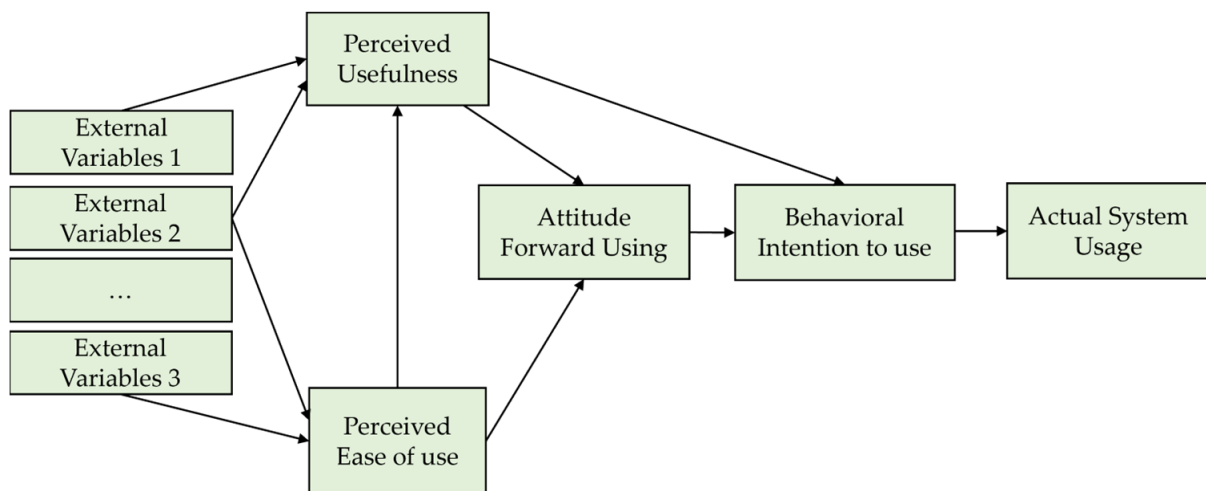
**Figure 4.** Model of relationship between factors according to TRA theory adapted from [33].

Figure 4 depicts the theory of reasoned action (TRA or ToRA), which describes the relationship between human activities' attitudes and behaviors. It is mostly employed to forecast the behavior of people based on their prior beliefs and behavioral intentions.

#### 2.3.2. Technology Acceptance Model

In [19], the authors, who developed the concept of TRA by TAM, will focus on the study of factors affecting acceptance or decision to use. User acceptance of technology or innovation is the main factor that directly affects user acceptance of technology or innovation.

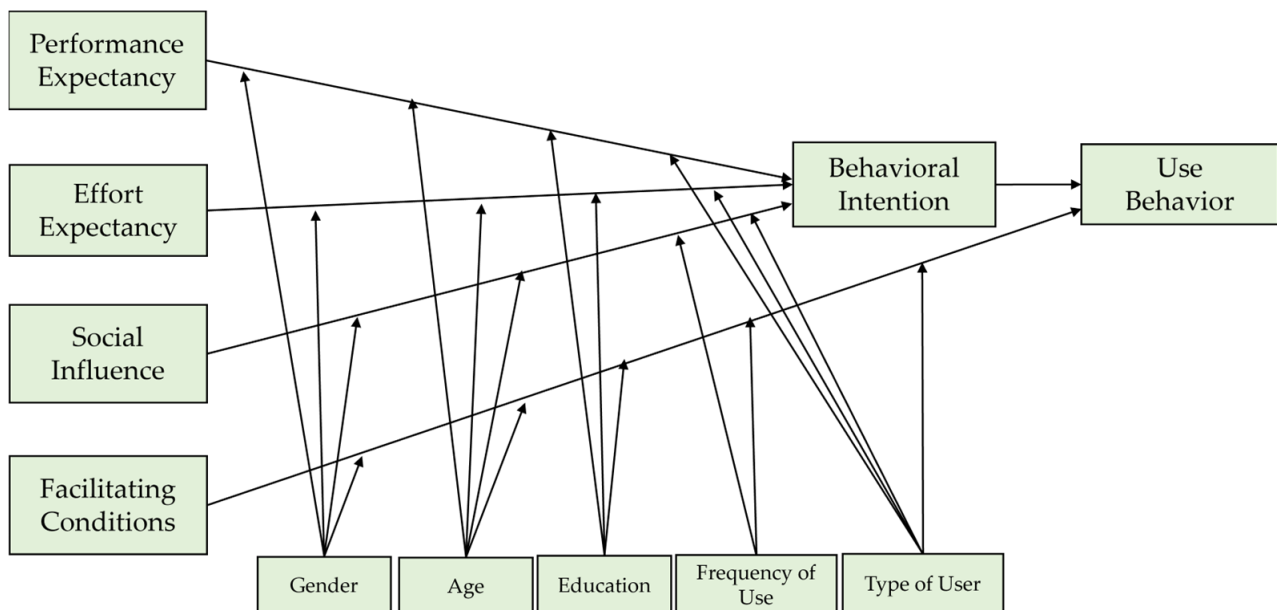
The TAM model consists of perceived ease of use (PEOU) and perceived usefulness (PU). The four characteristics that influenced behavioral intention to use were: (1) extraneous variables, (2) perceived ease of use (PEOU), (3) perceived usefulness (PU), and (4) attitude, which, in the end, determine behavioral intents to utilize the technology.



**Figure 5.** Technology acceptance model adapted from [19].

### 2.3.3. Unified Theory of Acceptance and Use of Technology (UTAUT)

The UTAUT theory combines eight technology acceptance theories and uses TRA, TPB, TAM, MPCU, DOI, MM, SCT, and C-TAM-TPB. Under the collective theories, these theories can identify the factor relationships that lead to the formation of individual technology adoption and usage models. As depicted in Figure 6, the UTAUT model can clearly demonstrate the links between existing factors in eight models and theories [22].



**Figure 6.** Unified technology acceptance and use of technology theory adapted from [22].

### 2.4. Internet of Educational Things

The internet of educational things (IoET) is a technology that uses internet-connected digital gadgets and sensors for an educational system. IoET is a subclass of IoT that focuses on smart infrastructures and departments, educational and research facilities, and daily activities and tasks. In educational institutions, IoT devices may effortlessly link and transmit data between sensors and device controllers. Microcontrollers such as Raspberry Pi, Arduino, and NodeMCU may manage and command internet-connected sensor devices to collect data in a systematic manner. Cloud computing enables internet data storage and management. All users, including teachers, staff, and students, can utilize programs to control devices and check their privacy data. The benefit of utilizing IoET is the capacity to



integrate technologies effectively, such as transmitting digital data at all times and lowering academic personnel's efforts. In addition, the premise of data operations in IoET is to manage and analyze data in real-time, regardless of the size of the data being managed or analyzed. The objective is to develop a wireless sensor network (WSN) gateway model before the back-end server for various environmental monitoring applications. The data logs can be created in multiple sensors with a transmission load balance to account for the heterogeneity of sensor signals, the stability of data transfer, and the cost of mobile communication [34]. The proposed WSN gateway consists of three bridged functions, including a serial listener, a transaction logger, and an internet listener, to enable analog and digital signal conversions, physical data classifications, threshold determinations, database redundancy, and mobile communications [35,36]. Using WSN technology, Shkurti et al. [37] created a web-based environmental monitoring system. Utilizing a node MCU controller, a sensor node is created. Through Web Application Programming Interface (API) requests, WSN sensor nodes provide data to the cloud-based database. They are programming the node MCU using the Arduino IDE language.

Shaqrah and Almars [4] investigated IoET adoption utilizing an extended unified theory of technology acceptance and use. Principal factors of IoET application and IoT integration in education and training were identified by the association between perceived ease of use and IoET behavioral intentions. Romero-Rodríguez et al. [38] investigated IoT adoption determinants in universities. Utilizing the UTAUT paradigm, we investigated behavioral intentions to utilize IoT apps. Results indicated a positive correlation between performance expectations, enabling conditions, and attitudes toward IoT technology.

### 2.5. Chatbot Approaches

Chatbots are a type of computer software that interacts with users utilizing natural language via text, graphics, and sounds. In the 1960s, the technique was developed to test whether chatbots could convince consumers that they were actual humans. A chatbot system is not only designed to simulate human dialogue. Other applications of chatbots in education systems include interactions with instructional material [39], entertainment [40], learning [41], and coaching [42]. The artificial linguistic internet computer entity/artificial intelligence mark-up language (ALICE/AIML) is the foundation for several chatbot development systems in electronic commerce. Wallace first introduced ALICE in 1995. In AIML, Alice's knowledge remained conversational [43]. The following interactions are applied to chatbots:

- **Menu/button-based chatbot:** A chatbot system enables users to select a question based on intent patterns via menus or buttons. A series of responses can respond to a question with an error. The menu/button-based chatbot is primarily appropriate for handling frequently asked questions (FAQ). However, complex inquiries or complaints can be addressed via a selection of chat options with employees. The settings menu lets the user send a direct message to the staff.
- **Keyword recognition chatbot:** A chat system must not allow users to select buttons from a menu. The user can directly type an inquiry into a chatbot. This chatbot interaction requires the user to type a response into the chatbot. Thus, the user can examine the intent of the questions and respond via feedback responses.
- **Contextual chatbot:** This chat system is the most sophisticated sort of chatbot that uses machine learning (ML) and artificial intelligence (AI). The keyword-based questions must be answered using only the specified terms. The contextual chatbot can remember questions and learn from them. A question has been posed and refined to meet future users' requirements better.

Using a chatbot service in schools provides students and teachers with various benefits, including continuous learning, a preference for conversation, student entertainment, and information interactions. Anything can be studied through a chatbot system. Students usually prefer conversing with chatbots rather than with their peers. A chatbot system is an innovative educational tool that entertains students [40]. Consequently, it may be

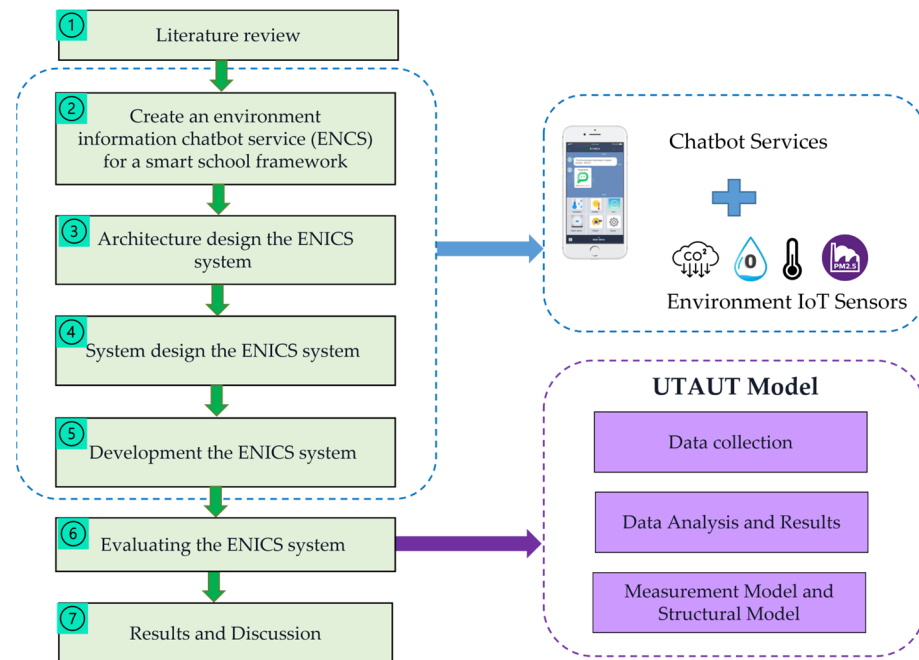
necessary to integrate a chatbot service into a learning environment to examine student acceptance and utilization of the technology.

Using structural equation modeling, Almahri et al. [41] advocated the student acceptability and utilization of a chatbot learning system. The study modified UTAUT2 to examine performance expectations, effort expectations, social influence, facilitating conditions, hedonic motivation, habit, and behavioral intentions. The conclusion of the analysis significantly impacts behavioral intentions to utilize chatbot technology.

Terblanche and Kidd [42] examined the adoption determinants and moderating variables influencing the intention to utilize a coaching chatbot. The chatbot system was designed utilizing the AI coach framework, which recommends merging characteristics of a human coaching relationship with chatbot design best practices and empirical coaching theories. Performance expectation, social influence, and favorable conditions played significant roles in deciding the desire to use the coaching chatbot.

### 3. Materials and Methods

This section describes the research methodology used to symmetrize IoT architecture design and develop an environmental information system using a chatbot service, as illustrated in Figure 7. The practical usage of an environmental monitor and notification chatbot by extending the UTAUT model to support IoET solutions for health and safety. There are seven steps through the following methodology consisting of reviewing recent literature research about research gaps, current problems, and IoT solutions, proposing an extended framework of an environmental information chatbot system for a safe, smart school system, designing the IoT architecture of the real-time environmental information system, developing the ENICS, evaluating the ENICS by using the extended UTAUT model based on the structural equation modeling (SEM model), and summarizing the results.

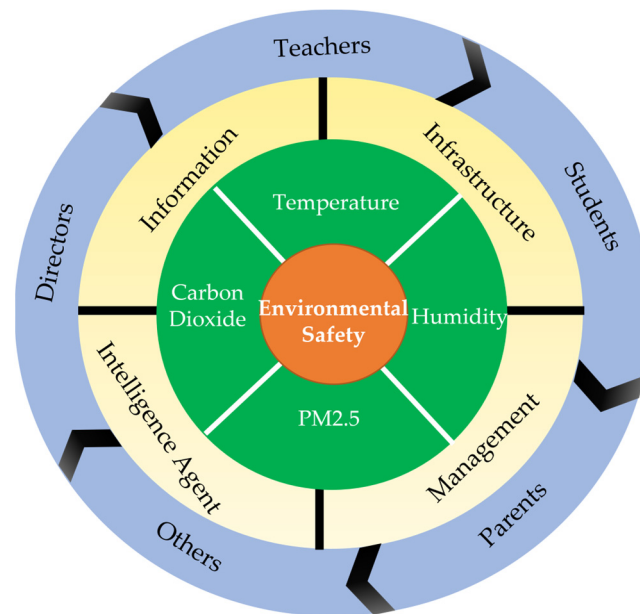


**Figure 7.** Research methodology.

#### 3.1. Adapted Framework of Health and Safety for Smart School Services

A framework for an expanded smart school safety system is proposed as one of the primary concerns for enhancing the stability of environmental information management [5]. The framework appended a security system to the main framework for smart schools. Physical and logical environments, such as IoT camera surveillance, environmental air quality, pollution, and ultraviolet concentration, consist of security components. Signifi-

cantly, ecological quality influences the instructors' and students' health and education. The environmental information system for smart school design focused on temperature, humidity, carbon dioxide (CO<sub>2</sub>), and PM2.5 dust. The framework of the environmental information system consists of IoT environmental sensors that transmit data to a database, including CO<sub>2</sub>, humidity, temperature, and PM2.5 sensors. As depicted in Figure 8, the data is then analyzed to provide diverse information and notifications to users via the ENICS's mobile application (ENICS).



**Figure 8.** Extended framework of safety smart school service for environmental information.

### 3.2. Information IoT Architecture of Environment Information Chatbot System

One of the primary concerns of an educational institution is safety management, such as the prevention of student injuries and illnesses caused by substandard environmental conditions that can interrupt teaching and learning systems [35–37]. By considering a safety system, the architectural design as a whole is deliberate. As shown in Figure 9, the architecture layers are separated into three subsystems: the front-end layer, the chatbot service layer, and the IoT service layer (Line message push/reply multicast).

The layered architecture of environment information chatbot services for smart schools is depicted in Figure 9 as follows:

- (1) The front-end layer: the Line account is accessed as an official account by two types of users: a sender and an action receiver, such as a recipient who adds the Line official account as a member via Line ID or Line QR code. Consequently, the environment information chatbot can send environmental information to members in response to information requests.
- (2) The chatbot service layer: A messaging API enables the exchange of data between an intelligent agent server and the Line social media platform. The requests are transmitted in JSON format over HTTPS.
- (3) The IoT service layer: The IoT service layer consists of four primary sensors: PM2.5 sensor trapping devices that capture PM2.5 dust indoors and outdoors, temperature and humidity sensors that detect heat and humidity, and CO<sub>2</sub> sensors that detect carbon monoxide from smoke or industrial combustion. The IoT controller utilizes sensors to record environmental data. The controller can operate through connected devices and sensors, transmitting data to an IoT cloud server using WSN. In addition, the dashboard station is installed for reporting environmental information using an LCD TV in front of the building areas.

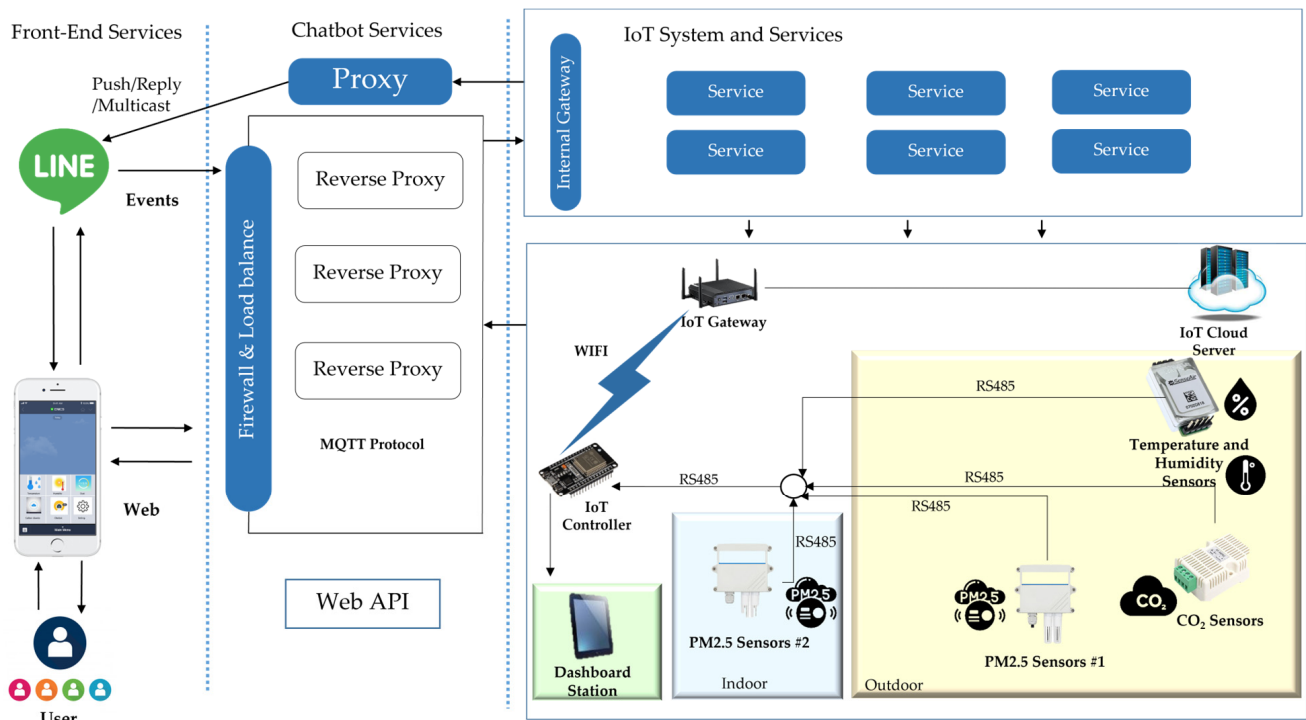


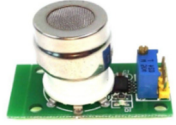



Figure 9. System architecture layering design of an environment information chatbot service.

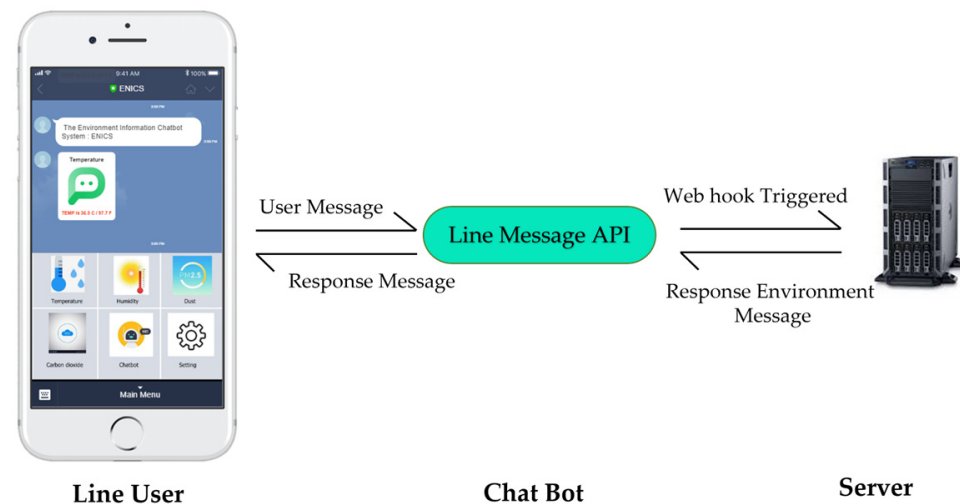
### 3.3. Hardware and Software Configuration

In this research, the authors provided IoT services using a PM2.5 air quality sensor with a breadboard adapter kit-PMS5003. The temperature and humidity sensor was a DHT22 module. A carbon dioxide sensor used MG811 carbon dioxide (CO<sub>2</sub>) sensor module. The IoT devices and sensors were connected via a microcontroller using ESP32-S3 Module as shown in Table 4.

Table 4. IoT environmental information system using sensors and a microcontroller.

Model	Details	IoT Sensor
PM2.5 sensors	The air quality sensor using detects dust PM2.5 both indoors and outdoor.	
Temperature and humidity sensor	The temperature and humidity sensor using detect temperature and humidity.	
Carbon dioxide (CO <sub>2</sub> ) sensor	The carbon dioxide (CO <sub>2</sub> ) sensor using detects carbon dioxide gas.	
Microcontroller	The multimedia development board supports a connection of all devices and sensors.	

By configuring Line chatbot software development with the messaging API, environmental data can be transferred between the chatbot server and the Line social media platform. The Line chatbot was written using Python programming language. Figure 10 demonstrates that the messaging API connects users through the official Line account. In addition, the messaging API can send a request to accept a user as a friend member of the account for the ENICS system and send an interactive format of responding messages to users via the LINE@ manager page setting or server exporting.



**Figure 10.** System interfaces of the Line chatbot official account and the environmental server.

The server of the chatbot must be connected to the Line social media platform. A user can request to add the Line official account as a friend or send a message requesting interactive information to the ENICS system based on Line social media platform. A webhook enables the chatbot server to immediately respond to a request by registering the user as a member through the official Line account. In addition, the messaging API can transmit environmental data from the chatbot server to the Line user via the Line chatbot platform. The user requests are in a natural language format. The user then requests that the format be converted to JSON. The chatbot server retrieves information based on user requests. The server then retrieves sensor data and responds to the user. The mobile application can immediately display environmental data and alert the user of poor air quality if the PM2.5 value exceeds the standard threshold.

### 3.4. Chatbot User Interface

Figure 11 depicts a comprehensive menu of chatbot capabilities. The user interface design provides an extensive menu from which to select various operations. A user subscribes to the Line ID @ENICS to access ENICS. When a user becomes a member of a chatbot's environmental information, the system module's extensive menu is displayed. The rich menu allows users to navigate to commands and display environmental information, such as temperatures, humanities, PM2.5, and CO<sub>2</sub>, chat with a chatbot via text, and select a location to request environmental information in the vicinity. When something terrible occurs in the environment, the chatbot service can immediately notify users. A real-time environmental information system will automatically notify users about excessively high or low temperatures, humidity, dust, PM2.5, and CO<sub>2</sub> levels.

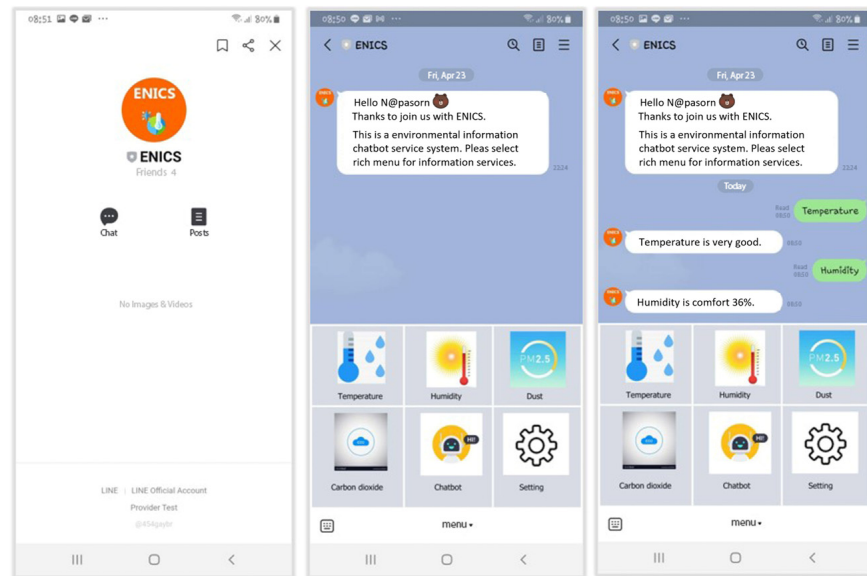


Figure 11. User interface of an environment information chatbot service.

### 3.5. Hypotheses Formulation and Model Evaluation

#### 3.5.1. Hypothesis Development

The system development of ENICS is an extended safety smart school service framework. The environmental information chatbot system is implemented by the conceptual framework of the smart school information system for the security component. The extended UTAUT model [43] was used to investigate chatbot usage in smart schools to study a user’s behavioral intention to use the chatbot service. This study utilized four primary UTAUT model factors: (1) the expectation of performance, (2) the expectation of effort, (3) social influence, and (4) facilitating conditions. In addition, new factors were explored: (1) innovativeness through the internet of education things (IOE) and (2) health and safety (HS). The conceptual framework proposed for this study is depicted in Figure 12.

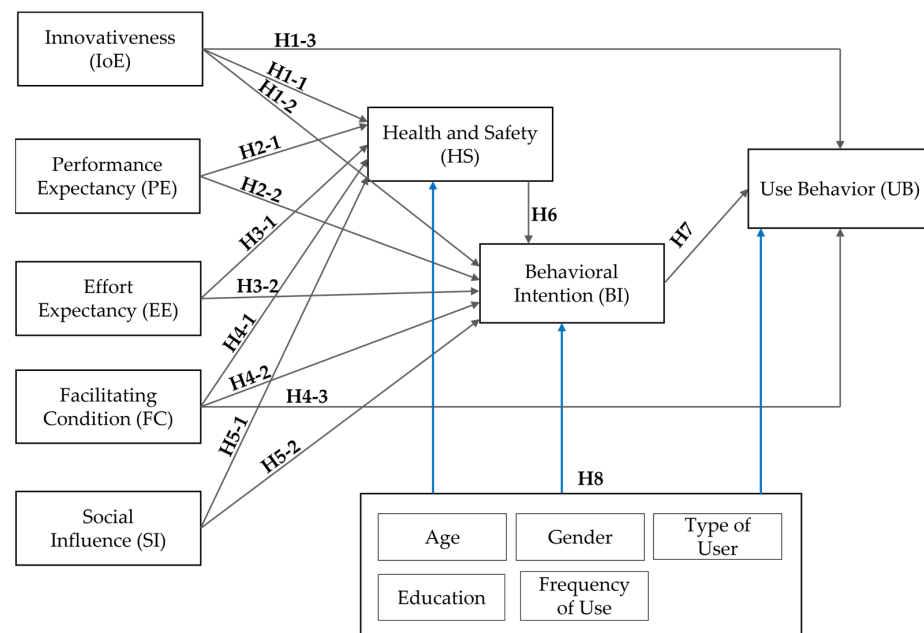


Figure 12. Proposed conceptual framework of hypothesis development.

A chatbot is a real-time response technology that facilitates connectivity between the university and students. Previous research [21,22,24,26,27] indicates that the UTAUT

model can predict user intentions to continue using a chatbot in an educational system. According to a previous finding, students and teachers are receptive to new communication technologies. In order to comprehend the continued adoption of an IoT-based chatbot for environmental information services of health and safety concerns, this study also considers the new factor of innovativeness through the internet of education things (IOE) [4,44,45]. IOE describes how the application of smart devices and sensors influenced the growth of environmental information monitoring. The authors propose the following hypotheses.

**Hypothesis 1-2 (H1-2).** *Innovativeness (IOE) has significantly positive influences behavioral intention (BI) of ENICS.*

**Hypothesis 1-3 (H1-3).** *Innovativeness (IOE) has significantly positive influences use behavior (UB) of ENICS.*

This research investigates based on user behavior intention of the UTAUT model. The authors hypothesize the UTAUT model to predict the factors affecting users' behavioral intentions toward using the chatbot service in this study. The six factors are performance expectation (PE), effort expected (EE), facilitating conditions (FC), social influence (SI), Behavioral Intention (BI), and Use Behavior (UB). The proposed factors are utilized to determine the occurrence of an unfavorable environment concerning usage and behavioral intentions. PE denotes what a user requires from the chatbot system to complete their tasks. EE measures how simple the chatbot system was to use. FC refers to the technical and organizational infrastructure that supports its use. SI determines how others perceive the utility of the new system. Moreover, most related studies have examined PE [46–50], EE [46,47,49,50], FC [26,46,49,50], SI [46,48–51], BI [22,47–49,52], and UB [22,47,48,52] as majority factors influencing the external variables of the UTAUT model. Based on this discussion, the following hypotheses are proposed.

**Hypothesis 2-2 (H2-2).** *Performance expectancy (PE) has significantly positive influences behavioral intention (BI) of ENICS.*

**Hypothesis 3-2 (H3-2).** *Effort expectancy (EE) has significantly positive influences behavioral intention (BI) of ENICS.*

**Hypothesis 4-2 (H4-2).** *Facilitating conditions (FC) has significantly positive influences behavioral intention (BI) of ENICS.*

**Hypothesis 4-3 (H4-3).** *Facilitating conditions (FC) has significantly positive influences be use behavior (UB) of ENICS.*

**Hypothesis 5-2 (H5-2).** *Social influence (SI) has significantly positive influences behavioral intention (BI) of ENICS.*

**Hypothesis 7 (H7).** *Behavioral intention (BI) has significantly positive influences use behavior (UB) of ENICS.*

To investigate implementing an IoT-based chatbot service to monitor and communicate air quality information to educators for their health and safety. The health and safety (HS) construct can be analyzed to ensure that users utilize the environmental information chatbot services for their concerns. Previous research [35,47] has confirmed the effect of the health-safety construct. This study, therefore, proposed the following hypothesis.

**Hypothesis 1-1 (H1-1).** *Innovativeness (IOE) has significantly positive influences on health and safety (HS) of ENICS.*

**Hypothesis 2-1 (H2-1).** *Performance expectancy (PE) has significantly positive influences on health and safety (HS) of ENICS.*

**Hypothesis 3-1 (H3-1).** *Effort expectancy (EE) has significantly positive influences on health and safety (HS) of ENICS.*

**Hypothesis 4-1 (H4-1).** *Facilitating conditions (FC) has significantly positive influences on health and safety (HS) of ENICS.*

**Hypothesis 5-1 (H5-1).** *Social influence (SI) has significantly positive influences on health and safety (HS) of ENICS.*

**Hypothesis 6 (H6).** *Health and safety (HS) have significantly positive influences on behavioral intention (BI) of ENICS.*

The demographics of the users are a significant factor that can impact the continued use of technologies [53–55]. In conjunction with various moderating variables, the constructs have a direct impact on the evaluation of behavioral intention [22]. Young users, particularly those with a higher level of education, may be familiar with the user-friendly technology [56]. Several studies [57,58] have found that a user's gender can affect his or her intent to use an information system. In this study, not only can students and instructors express their acceptance and adoption of chatbots, but it also focuses on the moderating variables of students, instructors/staff, directors, and parents who used the ENICS. This study considers age, gender, user type, educational level, and frequency of use as moderating variables. The analysis conducted thus far has led us to the following hypothesis.

**Hypothesis 8 (H8).** *The levels of health and safety (HS), behavioral intention (BI), and behavior (UB) are significantly different among demographic and behavioral variables (gender, age, type of user, and frequency of use through ENICS).*

### 3.5.2. Research Evaluation Design and Data Collection

Using the extended UTAUT model, this study investigated the factors influencing the adoption of ENICS. The SEM model validated and verified the proposed hypothesis [43]. According to [59–61], at least 200 participants were required for an acceptable SEM analysis or at least 5 cases per parameter for a simple SEM model. Since this study contained 31 observable variables, the minimum sample size was  $31 \times 5 = 155$ . Students, instructors, employees, parents, and administrators were used to select 600 user samples randomly. Users may first request to join ENICS's official Line account. The ENICS system was utilized for almost twelve months. Each user then completed an online survey via a questionnaire form to provide feedback on how they utilized the website. Data collection and screening, a total of 600 valid surveys were retained for analysis. Forty users were requested to determine the end-user perception of the mobile learning English web application. There were 600 responses, representing a 100% response rate. In addition, all study participants were given informed consent to ensure their participation was voluntary. Any information gathered was anonymized. The information provided was solely for the purpose of research. Justice, respect, autonomy, compassion, and confidentiality were all guaranteed as ethical values.

### 3.5.3. Questionnaire Development

The ENICS usage questionnaire contained two sections. The first section addressed the respondents' demographic and behavioral information. The second section focused on the proposed model's measurement components. The majority of the measurement items utilized in this study were adapted from prior research [43,62]. The measurement instruments consisted of a seven-point Likert scale ranging from strongly disagree (1) to



strongly agree (7). The independent variables in the proposed model were Innovativeness through internet of educational things (IoE, five items), Health and Safety (HS, five items), performance expectancy (PE, four items), effort expectancy (EE, four items), social influence (SI, three items), and facilitating conditions (FC, three items). Two constructs comprised the dependent variables: behavioral intention (BI, three items) and use behavior (UB, four items). There are 31 items of measurement, and Table 5 provides information on the constructs.

**Table 5.** Questionnaire variables based on the extended UTUAT model.

Construct	Item	Observed Variable	References
Innovativeness (IOE)	IOE1	Using IoET helps me achieve things connecting internet speedily.	Adapted from [4,44,45]
	IOE2	Using IoET tools increases my productivity.	
	IOE3	Using IoET tools increases my opportunity of realizing things that are vital to me.	
	IOE4	Using IOET, I seek out a lot of EIS about learning environmental system services.	
	IOE5	Smart education should adopt IoET to provide educational services	
Health and Safety (HS)	HS1	The environmental information devices using IoET technology would assist to health safe from risks.	Adapted from [35,47]
	HS2	The environmental information devices using chatbot technology would assist to health safe from risks.	
	HS3	The environmental information devices using chatbot technology would support against possible notification of personal healthy in a sustainable way.	
	HS4	Health and safety are one of personal concerns while studying in universities.	
	HS5	Health and safety, especially for environmental information devices, should be a service of educational information services.	
Performance Expectancy (PE)	PE1	The chatbot service can report information more quickly and efficiently than conventional methods, such as listening to the radio or using an application.	Adapted from [46–50]
	PE2	The chatbot service is available for physical environment safety systems with high quality of life.	
	PE3	The chatbot service can reduce the amount of time spent monitoring environmental data.	
	PE4	As expected, the chatbot service can display and alert all environmental information.	
Effort Expectancy (EE)	EE1	The environmental information is accessible via a chatbot from any location at any time.	Adapted from [46,47,49,50]
	EE2	The use of a smartphone to report environmental information can save money, time, and resources.	
	EE3	The chatbot service has effortlessly environmental reports, such as PM2.5, and CO <sub>2</sub> .	
	EE4	The chatbot service requires no technical expertise to operate.	
Social Influence (SI)	SI1	The chatbot service can alert users of potentially hazardous environments.	Adapted from [46,48–51]
	SI2	The supervisor/instructor encourages the use of the chatbot service for environmental monitoring.	
	SI3	The development of the chatbot service affects social aspects of air pollution.	
Facilitating Conditions (FC)	FC1	Using a chatbot service on a mobile device does not interfere with the use of other mobile services.	Adapted from [26,46,49,50]
	FC2	I possess the technological expertise to utilize a chatbot appropriately.	
	FC3	I think the chatbot service facilitates a safety condition for my organization.	
Behavior Intention (BI)	BI1	I use the chatbot service to continuously report environmental information.	Adapted from [22,47–49,52]
	BI2	In the future, I will utilize the chatbot service to monitor environmental information.	
	BI3	I intend to recommend the chatbot service to others to monitor the environmental information.	
Use Behavior (UB)	UB1	I use the chatbot service to facilitate the awareness of environmental information surrounding before attending to the university.	Adapted from [22,47,48,52]
	UB2	I use the chatbot service to facilitate the environmental information before I am going to the university.	
	UB3	I utilize the chatbot service to monitor real-time environmental data.	
	UB4	I prefer to use a comprehensive menu in application to receive environment information.	

#### 3.5.4. Data Analysis

SmartPLS 4.0.8.3 was utilized for partial least squares-structural equation modeling (PLS-SEM) and can be applied to software engineering [61,63]. In addition, PLS-SEM works well with advanced structures and imposes no limitations on sample size or data distribution. When there is little prior knowledge of the proposed hypotheses in developing the conceptual model or when the attention is more on exploration than confirmation, PLS-SEM is considered an excellent aesthetic [62]. Acceptance of PLS-SEM and its successful application in the information system, software design, and domain render PLS-SEM effective, primarily when used for theory development and exploratory research [64]. Due to this study's exploratory nature and the hypotheses mentioned earlier, PLS-SEM is considered the appropriate method for this study's context. Therefore, the developed research model is validated in a two-step process. The first involves the evaluation of the outer measurement model, while the second involves evaluating the inner structural model development [65]. Perception and hypotheses were developed using the steps suggested in [66]. The proposed method establishes a list of components to evaluate, establishes items in each element, specifies the measuring scale, and tests the model's reliability and validity. Content validity, Cronbach's alpha ( $\alpha$ ) [67], compound reliability (CR), convergent validity (AVE), and item analysis were employed as indications in the final step.

### 4. Results and Discussion

#### 4.1. Introduction

The first study explored an expanded smart school framework [4,5] for supporting health and safety-based security aspects in the corner of an environmental information chatbot service. The proposed design of an IoT architecture and the development of an environmental information system was successfully demonstrated by the system architecture's successful integration of health and safety services into the Line social media platform. The subsequent study examined the relationship and effect of individuals' acceptance of using environmental information chatbots in educational institutions. The extended UTAUT model was initially developed and analyzed using the two new variables. The innovativeness of IoET and health-safety factors were elucidated to validate the relationship between the utilization and efficacy of IoET for the smart school framework. In addition, this study revealed highly significant user perceptions of the user acceptance of an environmental information chatbot service based on Internet of Things (IoT) technology, which has significant implications for the sustainable development of health and safety information services. The causal relationships between the relevant factors were evaluated using a partial least squares structural equation model (PLS-SEM) [68]. PLS-SEM has been shown to predict factors related to individuals' attitudes toward technology accurately and can simultaneously analyze measurement and structural models. The content and classification accuracy results were obtained using composite reliability statistics (CR) [69], average variance extracted (AVE) [70], convergent validity [70–72], and discriminant validity [73–77]. Based on these features, PLS-SEM was the most applicable methodology for this study.

#### 4.2. Descriptive Statistic Results

In this research, the principles of descriptive statistics were applied to describe the collected data, and the principles of inferential statistics were used to describe the analysis data. The research questionnaire was surveyed via the questionnaire form from June 2021 to May 2022. The total responses to the chatbot services amounted to 600 participants. The surveyed samples were at the Chiangrai Rajabhat University, Thailand. The researcher conducted data analysis with demographic details as exposed in Table 6.

**Table 6.** Participants' demographic profile (N = 600).

Demographic	Category	Samples	Percentage
Sex	Male	356	59.30
	Female	244	40.70
Age	18–20	252	42.00
	21–30	178	29.70
	31–40	54	9.00
	41–50	96	16.00
	51–60	14	2.30
	>60	6	1.00
User Type	Student	380	63.30
	Instructor/Staff	132	22.00
	Director	10	1.70
	Parents	78	13.00
Educational Level	Less than Bachelor's degree	376	62.70
	Bachelor's degree	184	30.70
	More than Bachelor's degree	40	6.70
Frequency of use	Every day	154	25.70
	5–6/week	226	37.70
	3–4/week	130	21.70
	2–3/week	76	12.70
	Once a week	14	2.30

Table 6 showed that 59.30% of the demographic participants were male, whereas the rest were females. Most participants were between 21 and 30 (42%), and the following were between 31 and 40 (29.70%). Most of the user types were students (63.30%) currently studying at the university, and the follow groups were instructors and staff (22.00%) as well as parents (13%), whereas the rest were directors of the university. The educational level of participants was less than a bachelor's degree (62.70%) since most participants were current undergraduate students studying at the university. On the other hand, the followed educational level was a bachelor's degree (30.70%) as participants were staff and parents. The majority of participants used the system between 5 and 6 days a week (37.70%), then used the system every day (25.70), whereas only a few of them used the system once a week (2.30%).

#### 4.3. Measurement Model Analysis

Numerous measurements, including reliability and validity, were taken during the research, which must be confirmed during the evaluation of the measurement model [68]. Reliability is the extent to of a scale yields consistent and stable measures over time [69]. Typically, it is measured by calculating the coefficient of variation "Cronbach's alpha" as well as "Composite Reliability" (CR). Cronbach's alpha and compound reliability (CR) values were calculated to measure structure reliability. Cronbach's alpha and composite reliability values must exceed 0.70 for acceptance. To confirm the validity, both "convergent validity" and "discriminant validity" must be established [68]. Convergent validity considers factor loads, average variance, and compound reliability [69]. AVE must be greater than 0.5, and CR must be greater than AVE, according to [60] ( $CR > AVE$ ;  $AVE > 0.5$ ). However, AVE values below 0.5 are acceptable if other reliability criteria for convergent validity are met [70–72]. The convergent validity indicated the degree of overlap between the contested scale and other criteria measuring the same structure. The factor loads indicated the weight and correlation value of each factor. The "Fornell–Larcker criterion", the "Heterotrait–Monotrait ratio", and the "cross-loadings" are all indicators of discriminant validity, which refers to the extent to which a construct is truly distinct from other constructs based on empirical criteria [68]. According to the Fornell–Larcker criterion, the square root of the AVE for each construct must be greater than its highest correlation with other constructs.

The “Heterotrait-Monotrait ratio (HTMT)” of correlations refers to the average correlations of all indicators across variables that measure unique variables. An HTMT value of 0.85 or less must be determined. Regarding cross-loadings, the outer loading of an indicator on the associated variable should be greater than the sum of its correlations with other variables. These measurements contributed to establishing the reliability and validity of convergent validity.

Table 7 displays each structure’s factor loading,  $R^2$ , Cronbach’s alpha, AVE, and CR values. Cronbach’s alpha ranges between 0.773 and 0.934, AVE ranges between 0.567 and 0.883, CR (rho\_a) ranges between 0.794 and 0.970, and CR (rho\_b) ranges between 0.866 and 0.957. Figure 13 indicated that more variability of observed data was explained by the good model. Cronbach’s alpha values were high, exceeding the 0.70 threshold. All indicated acceptance of the achieved and recommended convergent validity measures and values [70] ( $AVE > 0.5$  and  $CR > 0.7$ ). All measured and suggested values and measurements demonstrated convergent validity. Therefore, convergent validity has been established. As shown in Table 7, the  $R^2$  values for health and safety (HS), behavioral intention (BI), and use behavior (UB) are statistically significant at 47.90%, 56.00%, and 47.10%, respectively. The coefficient of determination is reflected in the chart of Figure 14. The  $R^2$  demonstrates unmistakably that the developed structural model is good and valid; as a result, it could provide an excellent explanation of ENICS’s actual application.

**Table 7.** Acceptable convergence validity results.

Factors	Item	Factor Loading	$R^2$	Cronbach’s Alpha $\alpha$	AVE	CR (rho_a)	CR (rho_b)
Innovativeness (IOE)	IOE1	0.941	-	0.904	0.736	0.907	0.932
	IOE2	0.677					
	IOE3	0.757					
	IOE4	0.937					
	IOE5	0.940					
Health and Safety (HS)	HS1	0.747	0.479	0.810	0.567	0.823	0.867
	HS2	0.700					
	HS3	0.794					
	HS4	0.718					
	HS5	0.803					
Performance Expectancy (PE)	PE1	0.758	-	0.809	0.636	0.814	0.874
	PE2	0.786					
	PE3	0.826					
	PE4	0.817					
Effort Expectancy (EE)	EE1	0.821	-	0.803	0.628	0.821	0.871
	EE2	0.757					
	EE3	0.730					
	EE4	0.857					
Social Influence (SI)	SI1	0.953	-	0.934	0.883	0.970	0.957
	SI2	0.961					
	SI3	0.903					
Facilitating Conditions (FC)	FC1	0.837	-	0.773	0.683	0.794	0.866
	FC2	0.814					
	FC3	0.829					

Table 7. Cont.

Factors	Item	Factor Loading	R <sup>2</sup>	Cronbach's Alpha $\alpha$	AVE	CR (rho_a)	CR (rho_b)
Behavioral Intention (BI)	BI1	0.873	0.560	0.822	0.737	0.826	0.894
	BI2	0.860					
	BI3	0.842					
Use Behavior (UB)	UB1	0.825	0.417	0.864	0.710	0.872	0.907
	UB2	0.899					
	UB3	0.813					
	UB4	0.831					

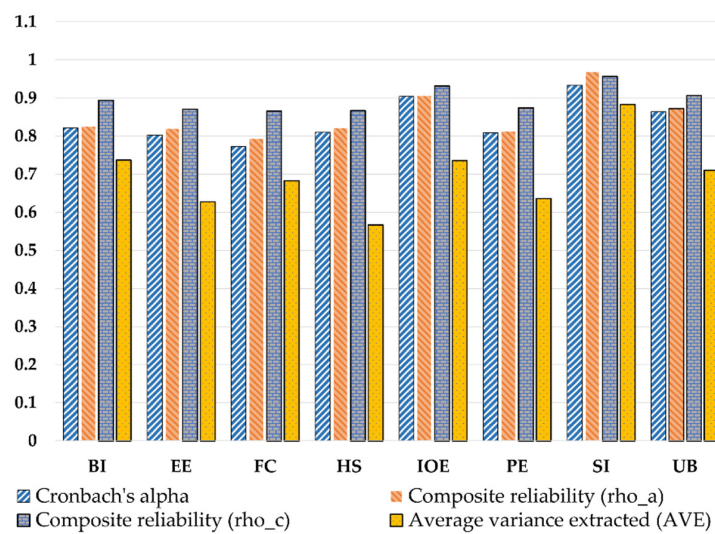


Figure 13. Establishing assessed variables for the coefficient of determination measure.

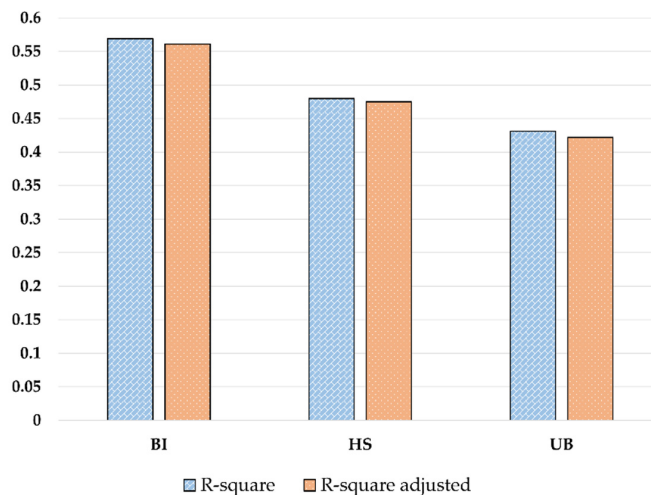


Figure 14. The measure in the assessment of a statistical model.

The validity test for the discriminant of the Fornell–Larcker criterion is displayed in Table 8. AVE’s square root of each construct exceeded their respective estimates of inter-construct correlation, establishing the discriminant’s validity [73–77]. Moreover, the diagonal values must be greater than the off-diagonal values in the columns and rows that correspond to them. Cross-loading of constructs is illustrated in Table 9. Table 10

displays the discriminant of the Heterotrait-Monotrait ratio's validity test (HTMT), which determines an HTMT value of less than 0.85. Tables 8–10 demonstrate that all criteria are met, confirming discriminant validity.

**Table 8.** Discriminant validity: Fornell–Larcker criterion.

Construct	BI	EE	FC	HS	IOE	PE	SI	UB
BI	<b>0.858</b>							
EE	0.602	<b>0.793</b>						
FC	0.633	0.706	<b>0.827</b>					
HS	0.604	0.534	0.558	<b>0.753</b>				
IOE	0.662	0.668	0.702	0.626	<b>0.858</b>			
PE	0.632	0.636	0.628	0.637	0.719	<b>0.797</b>		
SI	0.057	−0.032	−0.026	0.008	−0.069	−0.042	<b>0.939</b>	
UB	0.632	0.473	0.474	0.437	0.513	0.54	−0.031	<b>0.843</b>

Notes: Bold diagonal elements are the square root of Average Variance Extracted (AVE) for each construct. Off-diagonal elements are the correlations between constructs.

**Table 9.** Discriminant validity: Heterotrait-Monotrait ratio (HTMT).

Construct	BI	EE	FC	HS	IOE	PE	SI	UB
BI								
EE	0.726							
FC	0.776	0.849						
HS	0.73	0.629	0.666					
IOE	0.767	0.775	0.824	0.715				
PE	0.768	0.768	0.776	0.767	0.838			
SI	0.083	0.045	0.037	0.076	0.075	0.048		
UB	0.742	0.554	0.554	0.497	0.572	0.634	0.047	

Notes: Bold diagonal elements are the square root of Average Variance Extracted (AVE) for each construct. Off-diagonal elements are the correlations between constructs.

#### 4.4. Structural Extended UTAUT Model Assessment

As outlined in Hair et al. [72], a bootstrapping procedure employing 5000 bootstrap samples via SmartPLS 4.0 was employed to determine the significance of the developed hypotheses. Correspondingly, the proposed essential criteria for evaluating the structural model in PLS-SEM should include testing path coefficients. Figure 15 represents the result of implementing the proposed model with PLS-SEM. Table 11 proves end-user characteristics of usage ENICS as technology adoption and the direct findings of examining the hypotheses. IOE was found to be significantly and positively linked with HS, BI, and UB, as the  $p$ -value is less than 0.05 and the  $t$ -value is greater than 1.96, and  $p$ -values are less than 0.1 and  $t$ -values are greater than 1.31 ( $df = 30$ ,  $\alpha = 0.1$ ), confirming the significance of the effect ( $p < 0.001$ ,  $p < 0.01$ ,  $p < 0.05$ , and  $p < 0.1$ , respectively). Since the path co-efficient value is 0.261, 0.220, and 0.139, indicating a positive sign, IOE has a significant positive effect on HS (H1-1), BI (H1-2), and UB (H1-3). Similarly, for the second hypothesis, PE was found to be significantly related to HS and BI, as the  $p$ -value is less than 0.001 and the  $t$ -value is greater than 1.96, confirming the significance of the relationship ( $p < 0.001$ ). PE was found to affect HS (H2-1) and BI (H2-2) significantly and positively, as evidenced by the  $p$ -value of 0.000 and 0.000, and the  $t$ -value of 2.466 and 6.579. For the third hypothesis, EE was found to be significantly and positively related to HS (H3-1) and BI (H3-2), as evidenced by the  $p$ -value is 0.096 and 0.001, and the  $t$ -value of 1.304 and 3.163, which confirm the

significance of the effect ( $p < 0.1$  and  $p < 0.05$ , respectively). For the fourth hypothesis, FC was found to be significantly and positively related to HS (H4-1) and BI (H4-2), as evidenced by the  $p$ -value is 0.009 and 0.000, the  $t$ -value of 2.372 and 5.373; however, FC was found to be insignificantly related to UB (H4-3). For the fifth hypothesis, SI was found to be significantly and positively related to HS (H5-1) and BI (H5-2), as evidenced by the  $p$ -value is 0.085 and 0.012, and the  $t$ -value of 1.375 and 2.243, which confirm the significance of the effect ( $p < 0.1$  and  $p < 0.05$ , respectively). For the following hypothesis, HS was found to be significantly and positively related to BI (H6), as evidenced by the  $p$ -value of 0.000 and the  $t$ -value of 6.228. In addition, the final hypothesis, BI was found to significantly and positively affect UB (H7), as the  $p$ -value was 0.000 and the  $t$ -value of 10.912, which confirm the significance of the effect ( $p < 0.001$ ).

**Table 10.** Cross-loading results.

Construct	BI	EE	FC	HS	IOE	PE	SI	UB
BI1	0.873	0.561	0.588	0.56	0.629	0.637	−0.016	0.581
BI2	0.860	0.483	0.499	0.491	0.535	0.503	0.048	0.534
BI3	0.842	0.502	0.537	0.501	0.534	0.477	0.123	0.509
EE1	0.571	0.821	0.597	0.537	0.606	0.662	0.001	0.43
EE2	0.393	0.757	0.524	0.395	0.499	0.366	0.001	0.347
EE3	0.425	0.730	0.429	0.36	0.427	0.414	−0.042	0.333
EE4	0.487	0.857	0.669	0.365	0.559	0.516	−0.069	0.373
FC1	0.597	0.567	0.837	0.559	0.658	0.632	−0.045	0.498
FC2	0.462	0.613	0.814	0.398	0.519	0.423	−0.022	0.332
FC3	0.485	0.579	0.829	0.393	0.535	0.462	0.01	0.307
HS1	0.45	0.438	0.451	0.747	0.472	0.48	−0.047	0.301
HS2	0.383	0.277	0.294	0.700	0.338	0.359	0.012	0.183
HS3	0.506	0.468	0.484	0.794	0.541	0.488	0.053	0.385
HS4	0.411	0.279	0.299	0.718	0.375	0.414	0.083	0.302
HS5	0.504	0.493	0.519	0.803	0.577	0.613	−0.051	0.426
IOE1	0.564	0.59	0.623	0.555	0.941	0.621	−0.048	0.419
IOE2	0.532	0.479	0.527	0.506	0.677	0.542	−0.092	0.437
IOE3	0.561	0.555	0.57	0.463	0.757	0.633	−0.078	0.485
IOE4	0.576	0.596	0.624	0.574	0.937	0.618	−0.031	0.41
IOE5	0.591	0.624	0.644	0.567	0.940	0.651	−0.047	0.439
PE1	0.482	0.59	0.606	0.432	0.549	0.758	−0.042	0.332
PE2	0.46	0.402	0.399	0.501	0.454	0.786	−0.006	0.4
PE3	0.541	0.562	0.543	0.505	0.654	0.826	−0.055	0.506
PE4	0.53	0.481	0.464	0.582	0.623	0.817	−0.03	0.47
SI1	0.056	−0.033	−0.02	−0.006	−0.073	−0.047	0.953	−0.022
SI2	0.062	−0.024	−0.028	0.004	−0.066	−0.045	0.961	−0.024
SI3	0.037	−0.036	−0.025	0.031	−0.052	−0.023	0.903	−0.047
UB1	0.565	0.455	0.435	0.396	0.513	0.473	−0.052	0.825
UB2	0.571	0.398	0.388	0.386	0.437	0.462	−0.041	0.899
UB3	0.444	0.313	0.324	0.239	0.297	0.357	0.022	0.813
UB4	0.533	0.409	0.436	0.426	0.451	0.51	−0.021	0.831

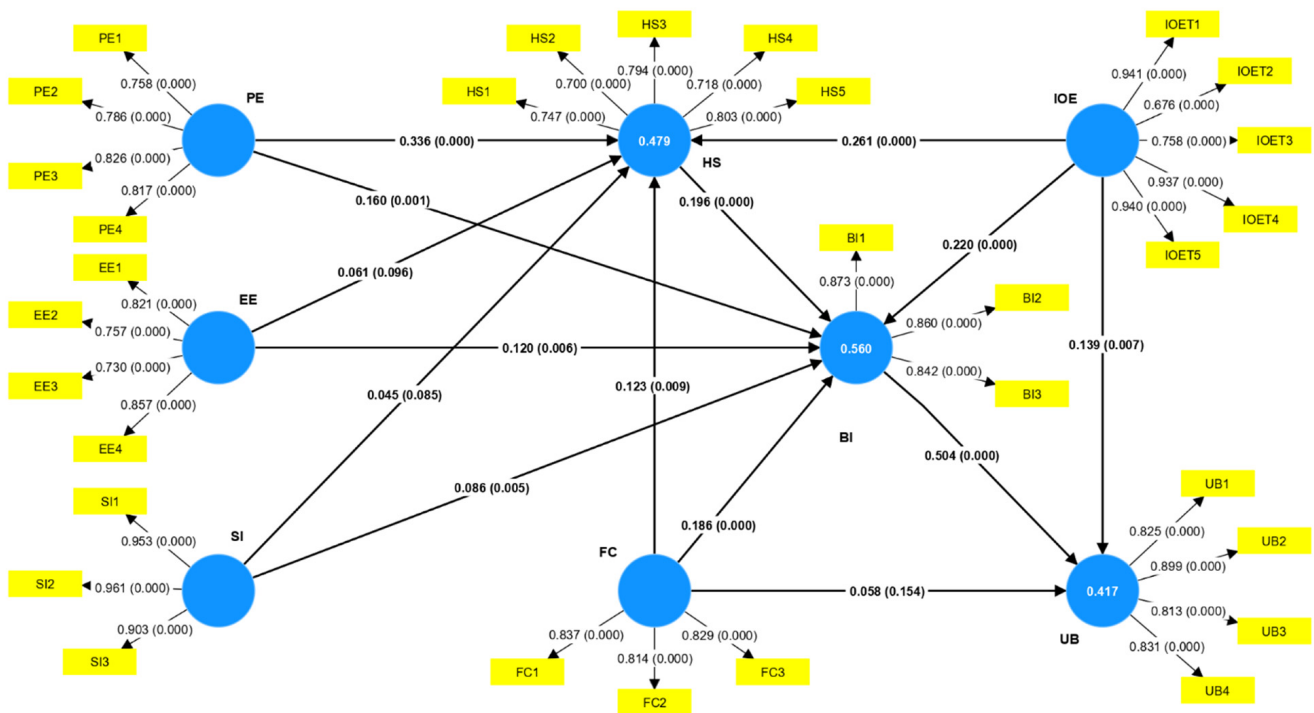


Figure 15. Structure equation modeling (PLS-SEM) results.

Table 11. Structural model results.

Hypotheses	Relationship	Part Coefficient	t-Value	p-Value	Supported?
H1-1	IOE → HS	0.261	5.071	0.000	Yes ****
H1-2	IOE → BI	0.220	3.957	0.000	Yes ****
H1-3	IOE → UB	0.139	2.466	0.007	Yes ***
H2-1	PE → HS	0.336	6.579	0.000	Yes ****
H2-2	PE → BI	0.230	5.240	0.000	Yes ****
H3-1	EE → HS	0.061	1.304	0.096	Yes *
H3-2	EE → BI	0.158	3.163	0.001	Yes ***
H4-1	FC → HS	0.122	2.372	0.009	Yes ***
H4-2	FC → BI	0.248	5.373	0.000	Yes ****
H4-3	FC → UB	0.058	1.021	0.154	No
H5-1	SI → HS	0.045	1.375	0.085	Yes *
H5-2	SI → BI	0.076	2.243	0.012	Yes **
H7	BI → UB	0.504	10.912	0.000	Yes ****
H6	HS → BI	0.234	6.228	0.000	Yes ****

Notes: \*\*\*\*  $p < 0.001$ ; \*\*\*  $p < 0.01$ ; \*\*  $p < 0.05$ ; \*  $p < 0.1$ .

#### 4.5. Moderation Effect Results and Hypotheses Testing

Following the evaluation of the measurement moderation effect model, Table 12 and Figure 16 shows the results of the moderation analysis. According to the analysis results, the H1, H2, H3, H4, H5, H6, and H7 hypotheses indicated all the significances still established identical results with slightly different  $p$ -values and  $t$ -values. The results of the moderation analysis are presented in Table 12 and Figure 16, which reveals that the values fall within the range mentioned in [62] as  $p$ -values are less than 0.05 and  $t$ -values are greater than 1.96, and  $p$ -values are less than 0.1 and  $t$ -values are greater than 1.31



( $df = 30, \alpha = 0.1$ ). Corresponding to the  $p$ -value of 0.041 and the  $t$ -value of 2.56, there is a statistically significant correlation between the moderation of Age and BI (H8-1), whereas  $p < 0.1$ . The  $p$ -value and  $t$ -value for the relationship between the moderation of Age and UB (H8-2) are 0.146 and 1.052, respectively. The interaction between Age and BI, and UB (H8-3) exhibits a significant positive direction, as indicated by the  $p$ -value of 0.091 and the  $t$ -value of 1.332. The interaction between Age and HS, and BI (H8-4) shows a significant direction, as indicated by the  $p$ -value of 0.056 and the  $t$ -value of 1.586. The results have found a significant interaction between Gender and HS, and BI (H8-6). Therefore, H8-1, H8-4, H8-6, H8-8, H8-11, and H8-12 hypotheses have been negatively significant. Only H8-3, H8-7, and H8-9 hypotheses are significantly positive. However, H8-2, H8-5, H8-10, and H8-13 hypotheses have been insignificantly effective.

**Table 12.** Coefficient of determination and predictive relevance results.

Hypotheses	Relationship	Part Coefficient	$t$ -value	$p$ -value	Supported?
H1-1	IOE → HS	0.262	5.113	0.000	Yes ****
H1-2	IOE → BI	0.225	4.108	0.000	Yes ****
H1-3	IOE → UB	0.144	2.585	0.005	Yes ***
H2-1	PE → HS	0.337	6.616	0.000	Yes ****
H2-2	PE → BI	0.164	3.250	0.001	Yes ***
H3-1	EE → HS	0.061	1.298	0.097	Yes *
H3-2	EE → BI	0.115	2.417	0.008	Yes **
H4-1	FC → HS	0.120	2.313	0.01	Yes ***
H4-2	FC → BI	0.188	3.728	0.000	Yes ****
H4-3	FC → UB	0.055	0.983	0.163	No
H5-1	SI → HS	0.046	1.390	0.082	Yes *
H5-2	SI → BI	0.090	2.674	0.004	Yes ***
H6	HS → BI	0.211	4.915	0.000	Yes ****
H7	BI → UB	0.501	10.694	0.000	Yes ****
H8-1	Age → BI	−0.048	1.742	0.041	Yes ***
H8-2	Age → UB	−0.043	1.052	0.146	No
H8-3	Age × BI → UB	0.059	1.332	0.091	Yes *
H8-4	Age × HS → BI	−0.04	1.586	0.056	Yes *
H8-5	Gender → BI	−0.044	0.783	0.217	No
H8-6	Gender × HS → BI	−0.081	1.544	0.061	Yes *
H8-7	Education → BI	0.041	1.472	0.071	Yes *
H8-8	Education × HS → BI	−0.05	1.772	0.038	Yes ***
H8-9	Frequency × FC → UB	0.046	1.456	0.073	Yes *
H8-10	Frequency → UB	0.011	0.362	0.359	No
H8-11	Usertype × BI → UB	−0.119	2.731	0.003	Yes ***
H8-12	Usertype → HS	−0.037	1.372	0.085	Yes *
H8-13	Usertype → UB	0.044	1.075	0.141	No

Note: \*\*\*\*  $p < 0.001$ ; \*\*\*  $p < 0.01$ ; \*\*  $p < 0.05$ ; \*  $p < 0.1$ .

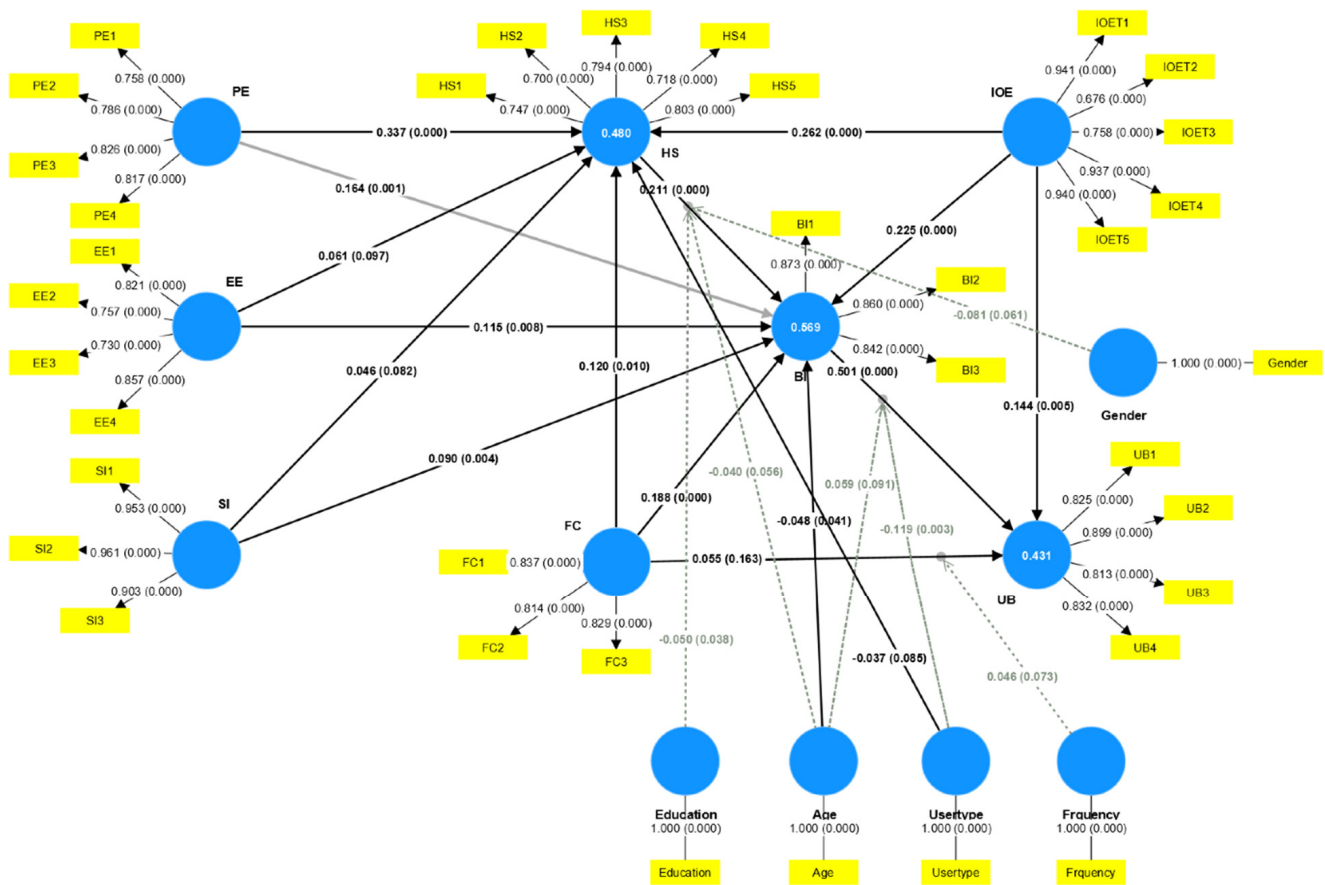


Figure 16. Structure equation modeling (PLS-SEM) moderation results.

Figure 15 depicts the final refined PLS-SEM with path coefficients, factor loadings indicators, and a *p*-value that reflects the significance of the indicator system as a whole. The factor loading values in the PLS-SEM model can reflect this significance. The more consistent the observed endogenous external variables are with the latent variables, the higher the factor loading values [48,52,62–64]. Figure 16 depicts the final refined PLS-SEM with path coefficients, factor loading indicators, and a *p*-value that reflects the significance of moderation in the overall indicator system.

In this study, the authors focus on developing an environmental information system that can respond rapidly to user awareness. Any user can utilize the environmental information chatbot service as an indispensable tool for daily awareness of their surroundings. In addition, IoT-based technology can be used to collect environmental data and generate statistical reports. The chatbot can provide warnings in a variety of formats, including text, images, statistics, graphs, etc., when the surrounding environment in school areas poses a health risk. Environmental factors such as air, heat, humidity, and fine dust impact the health of students, instructors, and support personnel in an educational institution. The real-time environment information chatbot can therefore serve as a practical component of the smart school framework described in [2,5,73,78].

Moreover, it is essential to comprehend chatbot adoption and factors to ensure that the system meets the health and safety needs of users. Thus, this study’s secondary objective is to investigate the impact of health and safety factors. The UTAUT model has been extended to examine the influence of the use of the environment information chatbot service on performance expectation (PE), effort expectation (EE), social influence (SI), facilitating conditions (FC), behavior intention (BI), and use behavior (UB). Furthermore, this study identifies the new factors: innovativeness through the internet of education things (IOE) and health and safety (HS).

The study demonstrates that internet-based educational innovation substantially affects health and safety, behavioral intentions, and use behaviors. The health and safety, behavioral intentions, and use behaviors coefficient of determination ( $R^2$ ) indicated that the developed structural model was valid and satisfactory. In addition, the finding suggests that performance expectations, effort expectations, social influence, and facilitating conditions are significant positive indicators of both health safety and user behavioral intentions with respect to the ENICS. This indicates that the four variables (performance expectation, effort expectation, social influence, and facilitating conditions) are significantly correlated with health safety and user behavioral intentions regarding ENICS use. Moreover, the study reveals that user behavioral intentions and innovativeness through the internet of educational things are significant positive indicators of user behaviors to utilize the ENICS. Undoubtedly, health and safety also had a significant impact on behavioral intention as well as in [35,47]. This verifies that participants intend to use the chatbot service to report real-time environmental information. Consistent with [74,75], the research results showed that the factor influencing the willingness to accept the environment information chatbot service was the behavior intention. These were the significant key factors that influenced the adoption and intention to use the technology, such as an early warning system in higher education [76], the adoption of hospital electronic information management systems [77,79], and the users' perceptions of the role of innovative technology [45–48].

The results of the six tested factors indicate that participants' intention to use the ENICS was influenced by their health and safety perception that the system could support their goal achievement (performance expectancy), use with less exertion (effort expectancy), imagine usage (social influence), and employ current infrastructure requirements (facilitating conditions). The performance expectation was the most significant of the four factors. Similar to previous findings [46–51,80,81], the results indicate that four factors (PE, EE, SI, and FC) significantly positively affect behavioral intentions.

The significance of the innovativeness through the internet of things stems from the fact that the internet of educational things facilitates the participant's accomplishment of tasks through rapid internet connectivity. The significance of health and safety also suggests that educational information services should provide environmental information systems. These findings also suggest that the greater the health and safety experiences through ENICS, the greater the intention to engage in the behavior. In addition, the results indicated that behavioral intentions and the innovativeness of the internet of things positively influence usage patterns. This finding indicates that the greater the innovativeness of ENICS's internet of things of engagement, the greater the use of behaviors and health and safety measures implemented.

The dependent variable constructs were used to examine the moderating effect of all demographic variables (gender, age, user type, frequency of use, and education) and three endogenous variables (HS, BI, and UB). The relationship between each moderate variable was investigated. Age was found to have a moderating effect ( $p = 0.041$ ), indicating that the relationship between behavioral intentions becomes negative as individuals age. Gender acted as a moderator ( $p = 0.061$ ), indicating that female participants were more concerned about health and safety than male participants due to the negative relationship between behavioral intention and intention to use. Education had a moderating effect ( $p = 0.071$ ), indicating that the higher the education level of the participants, the stronger the relationship between behavioral intention and ENICS use. The user types had a moderating effect ( $p = 0.003$ ), indicating that the higher the participants' positions, the less they intend to use ENICS, indicating a negative relationship between behavioral intentions.

## 5. Conclusions

### 5.1. Theoretical Contributions

One of the most important findings of this study is the contribution of software design, development, and evaluation to the actual use of a real-time environmental information system via a chatbot service in an educational institution. The IoET can connect sensors

and intelligent devices to trace and track environmental information and user behaviors to sustainably ensure that educational environments positively affect user health and safety. Considering the ecological dangers posed by air pollution in northern Thailand, a substantial amount of PM<sub>2.5</sub> dust is regularly produced each winter and summer. This study describes the configuration of IoT for environmental information monitoring, the installation of the chatbot service, and the application of the chatbot via a Line official account for real-time environmental information reports. Therefore, user behavior intentions to utilize the chatbot service significantly contribute to ensuring that the chatbot service has an advantage for continued usage intentions over the conventional method of environmental information awareness. As a standard technology acceptance model, the UTUAT model is applied to fill this knowledge gap regarding chatbot usage. By extending the UTAUT model, the authors identify the essential factors of innovativeness through the internet of educational things, as well as health and safety, in relation to using chatbots in IoT-based environmental information systems.

By incorporating the chatbot service into this research finding, the innovativeness of internet-based educational items, performance expectation, effort expectation, facilitating condition, and social influence has a direct impact on health and safety, as well as the behavioral intention of chatbot usage. The health and safety factor is a significant factor in establishing and correlating behavior intent. In addition, innovation through the internet of things and behavioral intent directly influence chatbot usage patterns. The user prefers to interact with the chatbot via a comprehensive menu. According to the findings, user behaviors have influenced the acceptance of the environment information chatbot service. This enables us to comprehend the various outcomes developers may encounter when constructing a chatbot service to support various environmental information services for various users. Health and safety concerns are crucial to users' continued use of the innovative chatbot service.

### 5.2. Practical Implications

This research has contributed to both system design and user evaluations. The study uncovered the extended smart school framework, a design of the information system and architecture, and the creation of a prototype based on an IoT-based environmental information chatbot service with a small number of sensors in a single location. The design and development of the proposed system have been demonstrated to integrate with existing social media platforms and to provide environmental information chatbot system services. With current advances and low-cost IoT devices, the proposed development could be easily implemented and replicated to promote diverse health and safety awareness. This study revealed the factors that influence the relationships between the innovativeness of IoT and the health and safety factors that influence individuals' acceptance of the continued use of environmental information chatbots in an educational institution. The innovativeness of IoT and health-safety factors were found to influence users' actual use intentions for an environmental information chatbot system. Six hundred users of related educational institutions in northern Thailand contributed to the findings. In addition, the results of this study may indicate that each educational institution should equip itself with additional hardware sensors to cover the entire university campus for the health and safety of educators. Additionally, environmental concerns such as fire and dust can be implemented and notified through a chatbot service. As a result, the study's findings have significant implications for educational institutions and other business organizations regarding health and safety.

The extended UTAUT has demonstrated that an environmental information chatbot system is user-satisfying based on the user's behavioral intentions. The system can promptly provide security for health and safety awareness in a smart school framework. This study established explicit new requirements for environmental information chatbot services that could be feasibly adapted to support a variety of health and safety in a comprehensive, dynamically adaptable menu.

### 5.3. Limitations and Future Work

Regarding limitations, the system architecture design is established on client and server architecture. The hardware of this study was based on one environmental information location. The hardware availability was based on the fault tolerance of a single servicing device. The environmental information chatbot security, reliability, and availability services were assumed on the Line social media platforms. The software development was based on the Line social media platforms. The results of this model were proposed and adopted from the UTAUT model.

Future studies could expand in two ways: technology experimentations and user assessments to better understand environmental information chatbot services. For technology experimentations, future studies should include designing the proposed paradigm for different system architectures and platforms, utilizing various IoET devices and sensors, employing multiple devices in broader areas of locations, communicating for an extended range of multiple devices, evaluating architecture servicing performances, and more. Thus, the forthcoming studies should explore methods to perform, identify, evaluate, and notify an environmental information result of broader areas in locations. When reporting general environmental information from multiple IoT stations, a classification or cluster analysis should be employed. User interface design and development should be investigated for better-improving performance and usage. Consequently, user interfaces respond automatically to new services, and the addition of intents can be studied as user responses. For user assessments, other factors of constructors and moderations (education majors and years, accessing times and locations, communication devices and media, occupations, and others) should be examined in the future study to an appropriate user interface design and to increase the use of the environmental information chatbot certainly. To better increase the adoption of IoET regarding environmental information services for health and safety aspects, the environmental information services should deal with broader areas and locations. The following study could investigate the findings using qualitative and qualitative methods. Different concepts may produce different results, which may be valuable in explaining environmental information chatbot acceptance in the health and safety aspect of the smart school framework.

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**Informed Consent Statement:** Informed consent was obtained from all study participants. Participants were at least 18 years old. As part of ethical research, the authors respect the voluntariness, anonymity, freedom, and confidentiality of the participants. The provided data contained no information that could be used to determine the participants' identities.

**Data Availability Statement:** Not applicable.

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