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RESEARCH ARTICLE

Xducation of Things (XoT): Harnessing AI and Edge Computing to Educate All *Things*

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ABSTRACT Most English foreign language (EFL) studies focus solely on human beings. This research explores how edge computing can facilitate learning for all *things*. The XoT (Xducation of Things) framework was proposed to educate both human and all *things*. All *things* encompass two terms: AI-Agent and *smartthings* (covering physical and digital smart objects). At the core of this framework is Smart Question Answer Forwarding Mechanism (SQA-Forwarding), specifically designed to assist all *things* in building knowledge. To demonstrate this, the smartXoT environment was developed based on XoT framework, and its impacts on EFL learners was assessed. A quasi-experimental study involving 26 EFL learners, divided into an experimental group (EG) and a control group (CG), examined the differences in learning achievement of *smartthings*and EFL learners when using the smartXoT environment with/without SQA-Forwarding. Findings, on one hand, indicated that *smartthings*in the EG developed knowledge bases greater than those in the CG. On the other hand, the interaction between EFL learners and *smartthings*with SQA-Forwarding significantly improved learners' writing skills, with revisions playing a crucial role in enhancing writing quality. Thus, the XoT framework offers a novel and promising approach to educating both humans and all *things*.

INDEX TERMS On-device AI, AI, edge computing, EFL learning, Q&A interactions.

I. INTRODUCTION

Several studies have addressed Internet of Things (IoT) devices as *things* to support the learning process in education. For example, Tagliabue et al. [1] built a smart learning environment with several IoT devices interconnected over the internet to analyze air quality in the classroom. On the other hand, Nehru and Chakraborty [2] defined IoT devices for education purposes as education of things that enable human beings like EFL learners to learn from IoT. However, the aforementioned studies only addressed the one-way direction of interaction between *things* to *things* or *things* to humans.

Moreover, EFL learners could learn to gain knowledge from different interactions with all *things* besides IoT devices in the real and digital world. For example, Nguyen et al. [3] demonstrated that EFL learners had high motivation to learn English writing by describing physical objects surrounding them. Similarly, Chen et al. [4] demonstrated that EFL learners enhanced their English vocabulary acquisition by learning through digital objects like three-dimensional

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content. In addition, several studies in language learning topics have implemented artificial intelligence as AI-agents for writing feedback and writing companion to support EFL learning [5], [6]. However, only human beings act as learners to learn from all *things* like EFL learners learn from IoT devices or physical objects in the real world, and EFL learners learn from digital objects or AI-agents in the digital world.

Therefore, a preliminary study tried to orchestrate all *things* including AI-agent, physical, and digital objects [7]. All *things* act as learners to connect, interact, manage, and educate each other. As a result, the AI-agent, physical, and digital objects have an opportunity, like human beings, to learn and teach each other to build their knowledge. The motivation to turn *things* into learners and build their knowledge is to facilitate communication with human beings during experimental activities. In this research, human beings can ask directly to *things* and gain more knowledge from the *things* about their properties, instead of searching via internet. Hence, these interactions could be advantageous for EFL learning for humans, particularly for EFL learners. In addition, *things*could facilitate them to learn independently and act in real situations. The preliminary study has addressed these interactions among all *things* as X-Education [7].

On the other hand, multiple sensors in mobile devices that empower recognition technologies were rapidly used to support EFL learning [6], [8], [9]. For example, a previous study demonstrated that speech-to-text recognition could recognize and transcribe the EFL learners' English speech into texts for speaking practices [10]. Similarly, location-to-text recognition could recognize EFL learners' location and then provide several lexical resources related to their location [9]. Hence, recognition technologies have been demonstrated to extract authentic contexts in EFL learning, thereby enhancing language acquisition. This process is commonly referred to as contextualization [9], [11].

Similar to mobile devices, IoT devices equipped with sensors and actuators have the ability to recognize their surrounding contexts [11]. Therefore, the information from the surroundings through recognition technologies in mobile devices and sensors in IoT could be utilized to support contextualization in EFL learning. In this study, we integrate the capital letter X with the word ''education'' to create the new term ''Xducation'' highlighting our aim to educate all *things* and explore their potentials to influence our world [12]. Therefore, this research addressed the exploration of educating all *things* and their potential for education as Xducation of Things (XoT).

Most IoT devices relied on cloud services for deploying an AI model [13]. Additionally, mobile devices are rapidly becoming more capable of performing natural language processing tasks, referred to as on-device AI [13], [14]. Sun et al. [15] have demonstrated on-device AI like using TensorFlow-Lite technology and the mobileBERT model for questioning and answering (Q&A) in a mobile device. Hence, EFL learners could pose a question to on-device AI, which identifies potential answers from the knowledge bases stored in the mobile device. Several researchers have addressed the combination of IoT and mobile computing as edge computing [11]. Through edge computing, all *things*can understand human language. For example, an EFL learner as a human being could engage in Q&A interactions with a Smart Trash Bin, which combines a physical object and edge computing, by asking about its properties. Consequently, a trash bin could answer the EFL learners' questions about its properties. In the XoT, the combination of physical/digital objects and edge computing is referred to as *smartthings*.

In the contexts of EFL learning, learners acquire English vocabulary by repetitively retrieving new lexical resources from the *smartthings'* answers during Q&A interactions [15], [16]. Furthermore, *smartthings* also could learn to answer questions posed by human beings. However, the learners in this study were not only limited to human beings but also all *things*. Furthermore, contextualization could be utilized to support EFL learning, particularly during Q&A interactions, which is referred to as Smart Q&A interaction (SQA).

Following the above-mentioned the SQA interaction, Smart Question Answer Forwarding Mechanism (SQA-Forwarding) was proposed in this research to modify a question based on the contextual information of the targeted *smartthings* before being forwarded during SQA interactions. By doing so, the knowledge base building of each *smartthing* could be rapidly improved and it could enrich SQA interactions [17], [18]. The knowledge bases in *smartthings* consist of a collection of sentences that represent unique concepts related to the *smartthings* themselves. In short, a question from EFL learners during the SQA interaction will be forwarded to all *smartthings*. Subsequently, the *smartthings* tried to answer similar questions, thereby building their new knowledge bases. This implies that *smartthings* could learn when a learner asks a question during the SQA interaction. Hence, the whole learning environment in this research is referred to as a smartXoT environment. Therefore, besides *smartthings* that could be taught and learned from each other, EFL learners also benefited from interacting with *smartthings*through SQA interaction. This study not only aim to study whether the knowledge building of all *things* can be enhanced through interactions between learners and *smartthings* with SQA-Forwarding, but also focus on EFL writing and investigate whether there are any significant differences in learning behaviors and achievements. Our contributions are summarized as follows.

- We proposed XoT framework and its potential for education. In XoT framework, the learners were not only human beings but also all *things*.
- We developed smartXoT environment including several *smartthings,*which combined physical/digital objects with edge computing and AI based on the XoT framework for EFL learning.
- We proposed the SQA-Forwarding mechanism to rapidly improved the *smartthings* knowledge bases during SQA interactions.

- We conducted experimental design to analyze the interaction between EFL learners and *smartthings* with/without SQA-Forwarding mechanism and its influence in the knowledge building of all *things*.
- We highlighted significant difference in the learning achievement and learning behaviors of EFL learners with/without the SQA-Forwarding and their influence on EFL writing.

This article is organized into seven sections as follows. Beginning with introduction in Section I, it is followed by section II providing the literature review. Section III provides an explanation of XoT framework and its implementation. Section IV discusses methodology. Section V presents the results and discussion. Section V presents the suggestion, implication and ethical consideration. Finally, section VII concludes the findings of this article.

II. LITERATURE REVIEW

A. THE NEW PERSPECTIVES OF THE EDUCATION SYSTEM FOR ALL THINGS

Most of the technology in education harnessing AI as its intelligence [19]. In this situation, the researchers as human beings also tried to improve AI knowledge. For example, Lu et al. [20] trained the GPT-2 based on the specific topic to generate questions for learners and to evaluate their answers quickly. Therefore, AI has disrupted education perspectives to not only accommodate EFL learning with feedback for human beings but also human beings teaching AI to perform specific tasks [5].

In order to teach AI, several studies have applied transfer learning with fine-tuning methods to perform a similar task with different datasets for edge computing [21]. In addition, the intelligence and knowledge of AI that have been trained before could be transferred to new AI models [22]. In other words, a researcher as a human expert or an AI-agent as a virtual expert could train on-device AI inside edge computing to enhance its intelligence. Hence, there is also the opportunity that education not only occurs between human beings and AI but also the *things* empowering by edge computing to do specific tasks.

B. EDUCATION FOR ALL THINGS WITH AI AND EDGE COMPUTING

Most studies in education only addressed learning activity from human-to-human, such as a teacher teach students in EFL learning [7]. In addition, several previous studies only focused on how EFL learners as human beings learn from things like the AI-agent to receive writing feedback and generate more texts [5]. Only human beings act as learners to learn from all *things*, such as IoT devices or physical objects in the real world, and multimedia objects and AI-agents in the digital world [13]. Therefore, both of these interactions have similar objectives to improve the intelligence and knowledge of human beings only in the real world. In other words, a teacher (as a human expert) and an AI-agent (as a virtual expert) teach learners to enhance their knowledge.

The majority of educational technologies in this digital age use AI [19], [23], which can be made smarter by giving training datasets with a lot of data [24]. In this situation, the researchers as human being also tried to improve the AI knowledge and then later perform such a specific task. For example, in language learning, an AI-agent by OpenAI with LLM, such as Generative Pre-trained Transformer 3 (GPT-3) that is trained with 175 billion parameters can perform NLG to generate new sentences by giving the input prompt [24]. Furthermore, Ouyang et al. [25] enhanced the GPT-3 to GPT-4 by evaluating the mechanisms through human interactions data. As a result, the generated texts from GPT-4 were more human-like than GPT-3. Furthermore, GPT-4 can be used to empower EFL learning, and it is easy to use because it was deployed in the cloud servers as cloud-based AI by OpenAI [25]. In the other study, Lu et al. [20] trained the GPT-2 (that is the open-source version of GPT-3) based on the specific topic to generate questions for learners and to evaluate their answers quickly. Therefore, AI has changed the way that people view education in the digital age. Not only does AI now support humans in the real world, but humans also enable AI to function more effectively in the digital one. For example, by giving AI a specific prompt, researchers are teaching it to generate new sentences.

On the other hand, several studies addressed human-to-machine interaction, such as training AI to improve its intelligence and knowledge, and subsequently perform a specific task [14]. In addition, IoT devices with on-device AI, edge computing could perform transfer learning between two edges devices [7]. Conversely, AI can also perform few-shoot transfer learning or the fine-tuning method to improve the capability of the AI model [22]. Therefore, these interactions bear similarities to advances in machine intelligence and knowledge, like AI and edge computing in the digital world. Stated differently, a researcher serves as a human expert, training an AI model or edge computing system to become more intelligent, while an AI-agent performs the role of a virtual expert.

Furthermore, previous studies have demonstrated that on-device AI could learn from another AI with a large language model like GPT-3, which has more knowledge and ability [7]. Because of on-device AI, edge computing had the capability to understand human language. For example, the Smart Trash Bin as one example of a smart physical object that combination of a trash bin and edge computing. Hence, a trash bin was able to understand human language and its properties or conditions. Moreover, smart physical objects in the real world need to be taught or trained to enhance their knowledge.

Similarly, the multimedia object in the digital world also has its own identity with the blockchain mechanism. Dowling [26] mentioned that a digital thing could have its unique blockchain address as an identity to distinguish it from others, namely a non-fungible token (NFT). Therefore, multimedia with NFT in the digital world could be integrated with edge computing in this research, namely a smart digital object.

Therefore, there is also the opportunity that education not only occurs between human beings and AI, but also with edge computing devices as objects. Hence, we proposed that interactions in education occur not only for humans, but also for all *things* in the digital and real world with AI and edge computing.

C. KNOWLEDGE BASES BUILDING WITH SQA-FORWARDING

All *things* had similar aims to increase their knowledge and intelligence. Therefore, mechanisms were needed that could benefit all *things* to improve their knowledge. One possible mechanism is the SQA interaction. It is because several studies have demonstrated that Q&A with the AI-agent was useful for learning [27]. However, most of the edge computing that could perform on-device AI relied on the knowledge bases [14]. On the other hand, AI-agents like GPT-4 could help to perform natural language generation to generate texts as new answers if on-device AI inside edge computing is unable to answer [25]. Therefore, SQA-Forwarding was proposed in this research to speed up the knowledge base for all *things*. Through the SQA-Forwarding, a question during SQA will be modified and forwarded to all *things*, so the other *things* could learn how to answer it with the help of NLG.

D. SQA INTERACTION FOR EFL LEARNING IN CONTEXTUALIZATION

Hwang et al. [9], [28] in the previous studies mentioned that EFL learning in contextualization could benefits to EFL learners. Through the contextualization, EFL learners could connect and extract meaningful situations from their surrounding contexts for learning. For example, EFL learner could enhance their writing by retrieving new vocabularies from their surrounding through recognition technology. In addition, they also could have Question and Answer (QA) with AI to check their essay or ask about the surrounding contexts [10], [28]. In terms of theoretical support, enactivism is a suitable educational theory to address the above-mentioned regarding contextualization for human beings in EFL learning. It is because the learners need to have interaction to gain experiences in the real environment to construct knowledge and develop cognition [25], [27]. However, learners in this study not only human beings but also all *things* could learn in in the smartXoT environment with camera as eyes or microphone as ears and other sensors.

Concerning on the interaction process, the communication theory also applied in this study since all *things* also require communicating with human beings through interactions in the real world or interacting with other *smartthings* in the digital world to build new knowledge base [25]. Similar to other previous studies in communication theory through SQA, mostly the questions posed by human beings and then the AI-agent answers the questions [27], [29]. In this situation, the questions were raised by human beings and then answered by the *smartthings*, which is referred to as human-to-*smartthings* in SQA interactions. The interaction could help both *smartthings* and human beings improve their knowledge since the EFL learners need to construct specific questions and *smartthings* need to answer the questions.

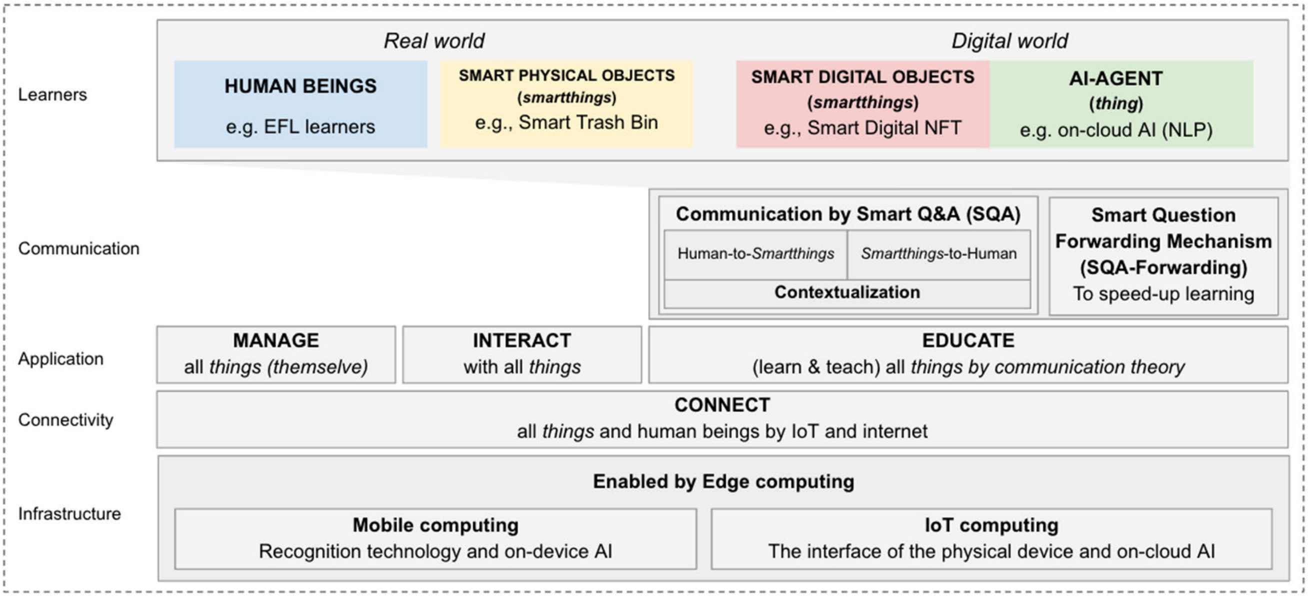
Furthermore, Q&A interactions in the smartXoT environment need to be designed more interactive. In this research, the other interaction of SQA was proposed to reverse the interaction, in contrast to previous studies that only accommodated one-way interaction in the design of human giving question to *smartthings* (Human-to-*Smartthings*) [29]. In this reverse interaction, EFL students respond to questions posed by *smartthings* regarding their essay writing (*Smartthings*-to-Human). This interaction is called reflective-questioning strategy. Reflective means that the EFL learner need to answer the questions from *smartthings* to paid attention to revise the missing part in their writing draft [30]. Thus, since EFL learners are the ones responding to the questions in which this interaction similar to receiving feedback and corrections from others, the *smartthings* questions can help them improve their writing. With these two distinct interactions in the smartXoT environment, hopefully, SQA interactions helped EFL learners create more meaningful sentences based on their personal experiences and the contexts of their surroundings.

E. EFL WRITING WITH AUTHENTIC CONTEXTUAL SUPPORT FOR EFL LEARNERS

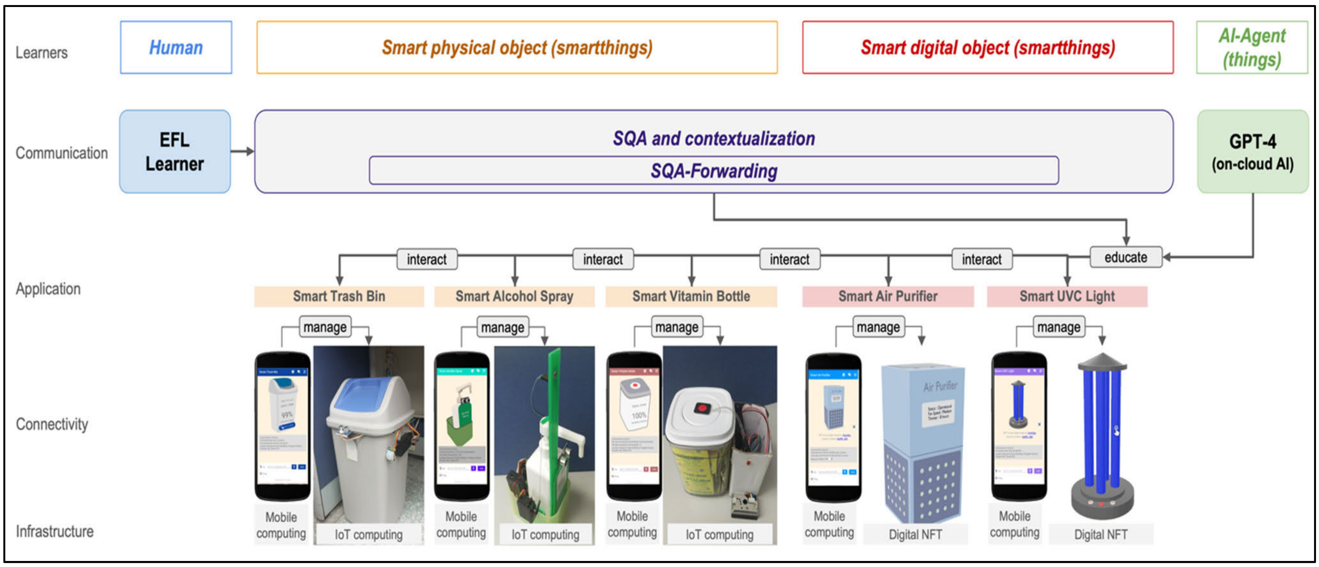
Besides all *things* learned and taught each other through SQA in the smartXoT environment, it is worth investigating its benefit to EFL learners. Several studies have suggested integrating Q&A with essay writing activities [31]. Hence, the SQA with all *things* will be beneficial to EFL learners and it could be tracked and measured through writing activities.

Furthermore, essays as a learning outcome from writing activities can be evaluated by experts with a scoring rubric and automatic mechanisms. For example, Nguyen et al. [3] evaluated the EFL writing assignments based on the TOEFL independent writing scoring rubric with the help of two experts. The writing rubric consists of four dimensions such as content, organization, grammar & vocabulary, and cohesion & consistency.

On the other hand, several studies have used automatic mechanisms, such as software like L2SCA software to measure syntactic complexity and lexical diversity [5], [7]. Yang et al. [32] demonstrated that EFL learners with high scores of writing quality that were evaluated by teachers significantly correlated with dimension syntactic complexity, particularly clauses per T-unit. Hence, essays with a higher score in the clauses per T-unit indicate the ability of EFL learners to communicate complex ideas in their writing [5], [32]. On the other hand, lexical diversity refers to the variation of words that are used in the essay [33]. Hence, essays with a lower score in lexical diversity indicate that EFL learners tend to use similar words repeatedly in their writing. Furthermore, several studies suggested using Vocd-D or the measure of textual lexical diversity (MTLD) to measure lexical diversity [5], [33].



(a)



(b)

FIGURE 1. The XoT framework (a) and its illustration (b).

Therefore, high scores on four dimensions (content, organization, grammar & vocabulary, and cohesion & consistency), syntactic complexity, and lexical diversity, indicate that EFL learners write well. Consequently, it presents a chance to apply the dimensions for the questions in reflective questioning. By retrieving the questions from the *smartthings*, EFL learners were triggered to reflect on the missing information in their essay writing.

III. XoT FRAMEWORK AND ITS IMPLEMENTATION

A. XoT FRAMEWORK

With the integration of generative AI, IoT, and mobile computing, edge computing can provide a means of enabling the new paradigm in education. Therefore, the XoT framework was proposed in this research to educate humans and all *things* including AI, physical objects, and digital objects, as shown in Figure 1.

There are five layers in XoT framework. The novel in this framework is the learners not only human but also all *things*. All *things* refer to the *things* that have ability to perform natural language understanding, like AI-agent and *smartthings*.

1) Human beings: Humans have their intelligence, particularly intelligence of English skills. For example, EFL learners write meaningful essays after engaging in Q&A interactions with all *things*.

2) AI-agent (*thing*): LLM hosted on a cloud server that is called on-cloud AI, such as GPT-4 by OpenAI, which is more knowledgeable and capable in performing natural language generation tasks for generating texts for knowledge bases and answering questions. It is acted like virtual teacher to teach the *smartthings* become more knowledgeable.
3) Smart physical objects (*smartthings*): The integration of physical objects and edge computing. For example, a Smart Trash Bin that integrated a trash bin with edge computing to perform natural language understanding. Through the on-device AI inside the edge computing, it can answer questions from EFL learners related to trash bins' properties. We have demonstrated the smart physical objects like Smart Trash Bin in Appendix A.
4) Smart digital objects (*smartthings*): The integration of digital objects and edge computing. For example, a Smart Air Purifier that integrated a 3D NFT with edge computing to perform natural language understanding. Through the on-device AI inside the edge computing, can answer questions from EFL learners related to air purifiers' properties. We have demonstrated the smart digital objects like Smart Air Purifier in Appendix B.

In the infrastructure layer, edge computing enables *smartthings* in the real and digital worlds (smart physical objects and smart digital objects, respectively) to use recognition technology to identify their surroundings, on-device AI to manage their knowledge bases, and AI-agent learning to acquire new knowledge bases. In terms of connectivity in the second layer, all *things* are connected via the internet to communicate with each other's to gain their knowledge bases. In the application layer after they connect each other through internet; *smartthings* can manage their knowledge bases; interact with other *smartthings,* human, and the AI-agent. Hence, they can communicate to learn and teach each other. Furthermore, they communicate though our proposed method like SQA interaction with contextualization to learn from each other based on the surrounding contexts and SQA-Forwarding mechanism to speed up their learning. As such, all *things* as learners in the XoT framework are able to learn and teach each other rapidly.

B. SMARTXoT ENVIRONMENT

We have designed and implemented a learning environment based on the XoT framework to facilitate EFL learners and all *things* to learn from each other, namely smartXoT environment. It was built in this research, including several prototypes of all *things*, as shown in Figure 2 (or see Appendix A and B). It shows all *things,*particularly the *smartthings* in the smartXoT environment for EFL learning includes smart physical objects, such as (a) Smart Trash Bin, (b) Smart Vitamin Bottle, and (c) Smart Alcohol Spray; and smart digital objects, such as (d) Smart Air Purifier, and (e) Smart UVC Light; and (f) the EFL writing editor with technology-supported like grammar feedback, revision tracking, and SQA history. Furthermore, EFL learners could

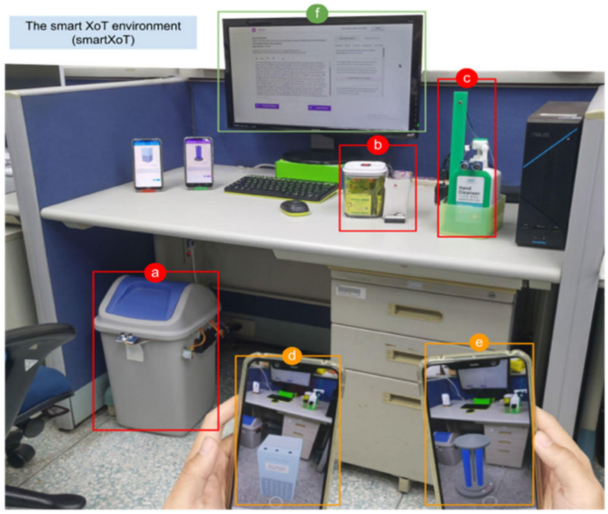


FIGURE 2. The prototype of the smartXoT environment for EFL learning.

learn from all *things* and all *things* also learn to build their knowledge bases through our SQA-Forwarding. Afterward, EFL learners participated in EFL writing activities using the EFL writing editor in smartXoT environment.

C. SMART Q&A INTERACTIONS (SQA)

The primary interaction in the smartXoT environment is Smart Q&A (SQA) interactions to enhance knowledge bases of *all things* and human beings as well, meaning the EFL learners as human beings asking a question and then *all things* trying to answer. As demonstrated in Figure 3, we also include one more interaction to assist EFL learners in reflecting on and checking the missing parts of their writing draft based on the questions generated by *smartthings* after completed SQA interactions.

In the SQA interactions, EFL learners can ask questions to the *smartthings*, and then the *smartthings* will provide meaningful answers to EFL learners, including the contextual information, as shown in Figure 4. For example, an EFL learner asks a Smart Trash Bin, "where your current location and can I move you to my room?" and then it answers, "My current location is Research Center Building. You can move me to your room, but you need to ask permission from your office management". This answer includes contexts from the surroundings, like location (i.e., the location through a GPS sensor). Hence, the EFL learner can learn new lexical resources related to the *smartthings* and the contextual information surrounding the *smartthing*. Therefore, the *smartthings* provide meaningful answers that includes contextual information for EFL learners (see Appendix A and B). Furthermore, in this research also focuses on building specific knowledge bases to accommodate specific questions asked by EFL learners with the SQA-Forwarding. Afterward, EFL learners write the first draft essay as a learning outcome with the EFL writing editor, as shown in Figure 5.

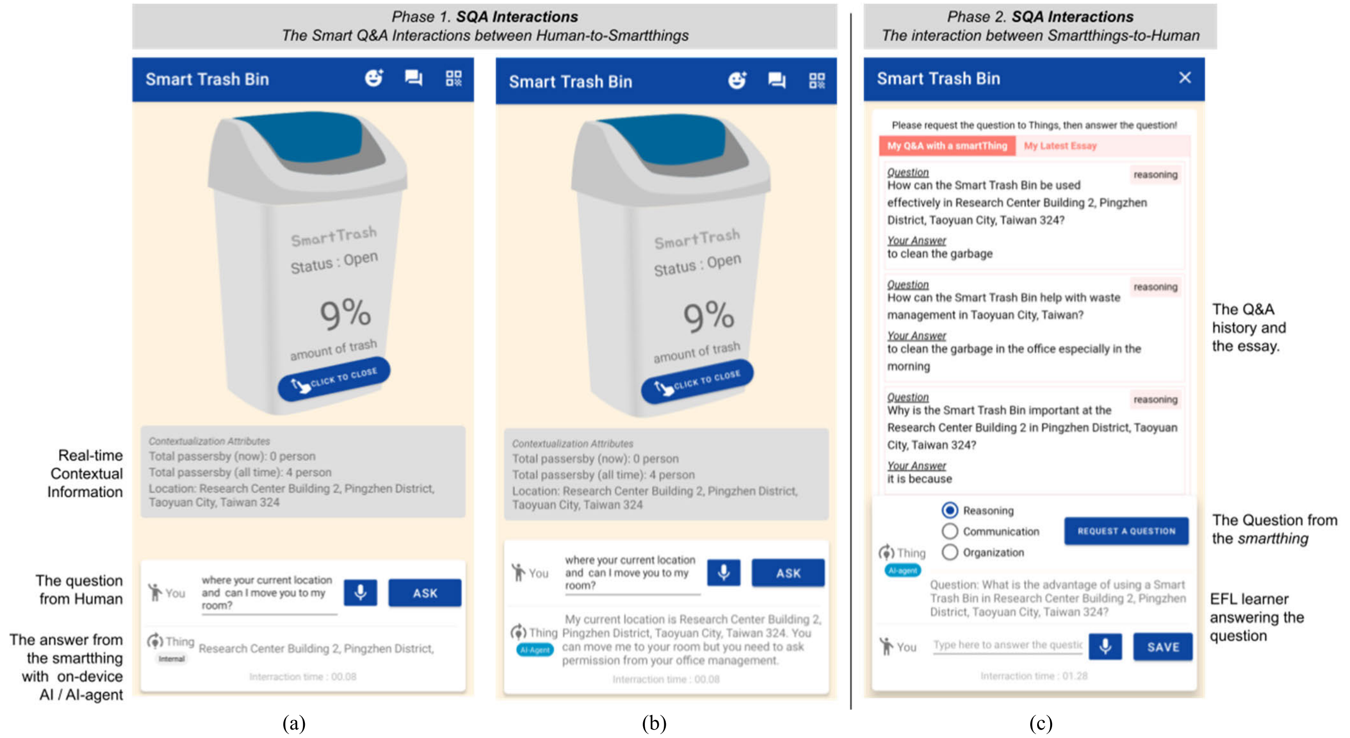


FIGURE 3. The SQA interactions in smartXoT environment such as (a) The SQA interaction with the answer from on-device AI; (b) The SQA interaction with the answer from the help of AI-agent; and (c) The SQA interaction to help EFL Learner reflect their writing.

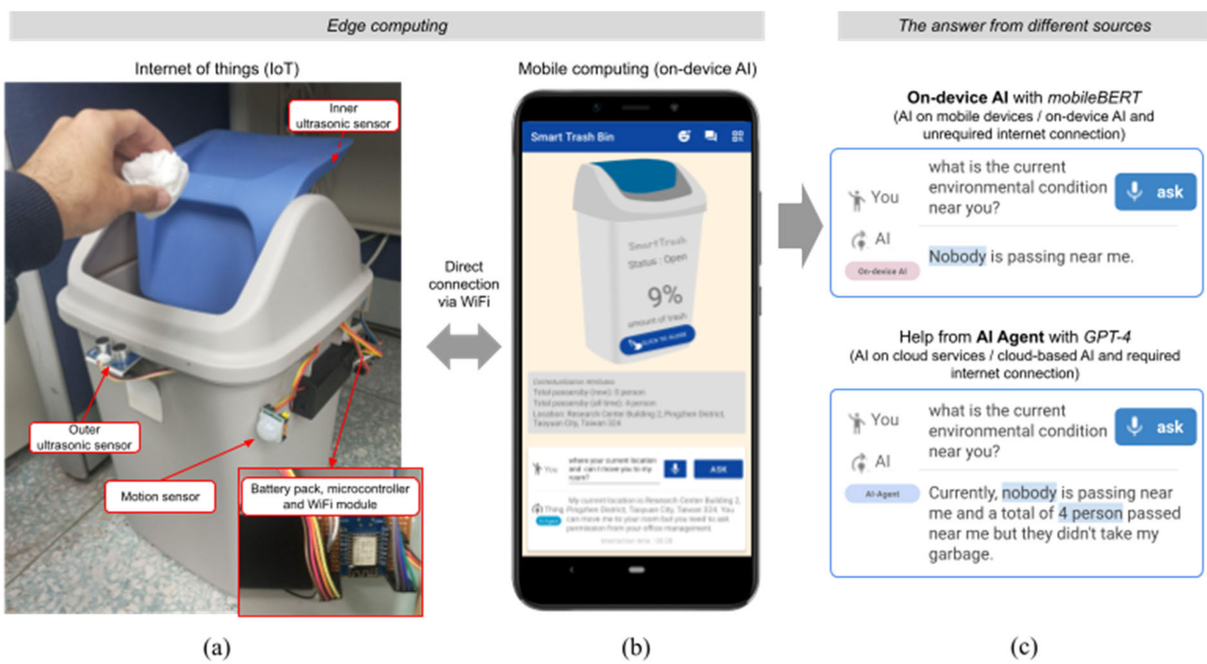


FIGURE 4. One example of *smartthings* such as a Smart Trash Bin, including: a) the physical device with IoT; b) mobile computing, and c) the answer including the real-time contextual information from different sources.

In the second phase of SQA interactions, the *smartthings* generate a question by combining information from the question bank, contextual data, and the first draft of the EFL learners' essay. The detailed process of the interactions, first, an EFL learner requests a question based on the dimension. Second, based on the first draft essay and contextual details like the location, the *smartthings* create a question. Third, after attempting to type or speak their response, the student

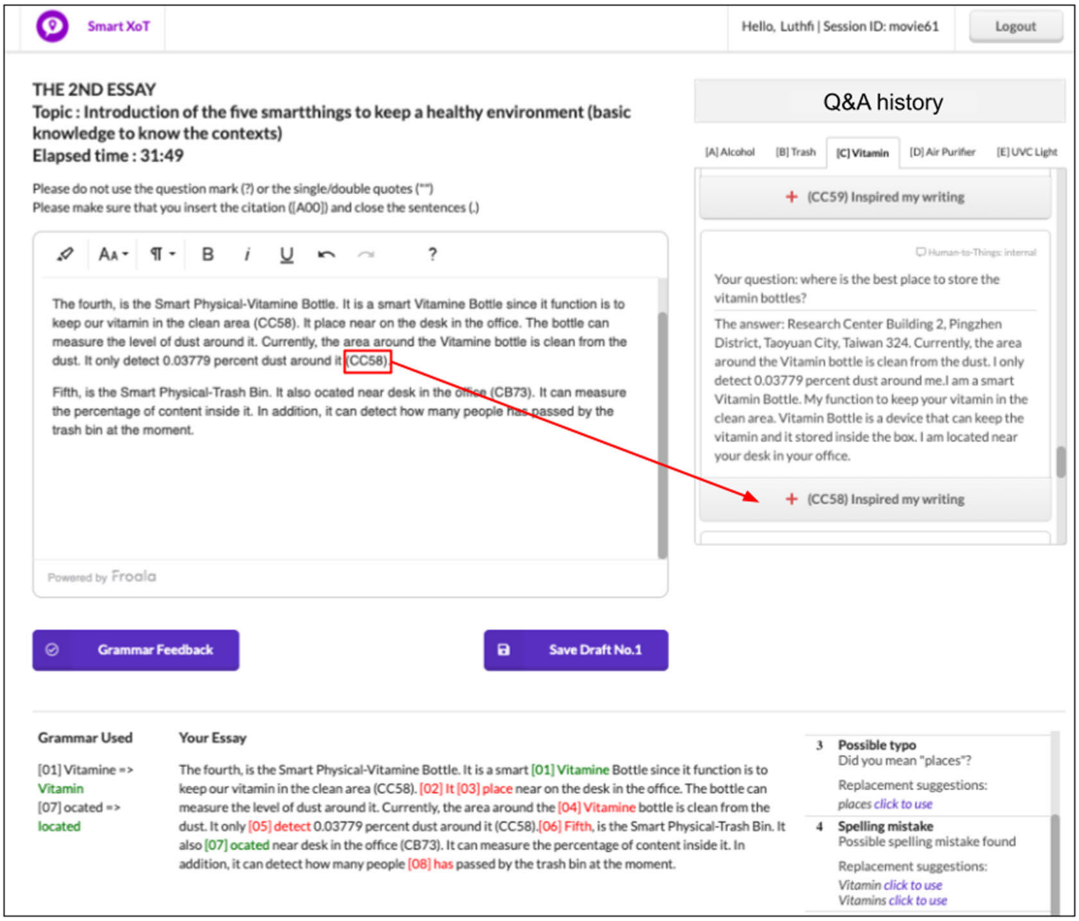


FIGURE 5. **The interface of EFL Writing editor in smartXoT environment has several features, such as Q&A history, grammar feedback, and revision tracking.**

saves the Q&A. Finally, as a learning objective for this exercise, EFL students utilize the EFL writing editor to refine their first draft based on the information received in the SQA interaction and create a second draft essay.

D. SMART QUESTION ANSWER FORWARDING (SQA-FORWARDING)

In the SQA interactions, there are two interactions at the same time when a learner asks a question, such as the regular flow and the forwarding flow with SQA-Forwarding, as shown in Figure 6. In the smartXoT environment, after the EFL learners ask a question by speaking in the mobile phone, an original question will be sent to two processes, such as sent to a targeted *smartthings* directly (see R1 in Figure 6), and the other will processed in the SQA-Forwarding mechanism (see F1 in Figure 6).

In detail, through SQA-Forwarding mechanism, the original question is modified based on the contextual information and knowledge bases of other targeted *smartthings* with the help of AI-agent with GPT-4 by openAI. We sent the information of the origin *smartthing's* information, origin *smartthing's* knowledge bases, an original question, targeted *smartthing's*information, and targeted *smartthing's* contextual information to AI-agent and then instruct AI-agent to change the original question to the new questions by prompting the GPT-4 through API. Furthermore, the contextual information gathered from multiple sensors will help targeted *smartthings* to generate a modified question based on the contextual information. The process of the SQA-Forwarding mechanism from the original question to a suitable question for other target *smartthings* is demonstrated in Table 1.

One of example interaction in the first process is when an EFL learner asks a question to a Smart Trash Bin, "How many people have opened the trash bin today". The question will be sent to Smart Trash Bin themselves (see R1 in Figure 6). In the meantime, SQA-Forwarding receives the original question and modifies it in light of the other targeted *smartthings* (see F1 in Figure 6). For example, the original question will changed to "How many people have turned on the air purifier today?" before the question is sent to the other targeted *smartthings* like Smart Air Purifier.

In the second process, the targeted *smartthing* attempts to answer the original question with their on-device AI (see R2 in Figure 6) and the other targeted *smartthings*

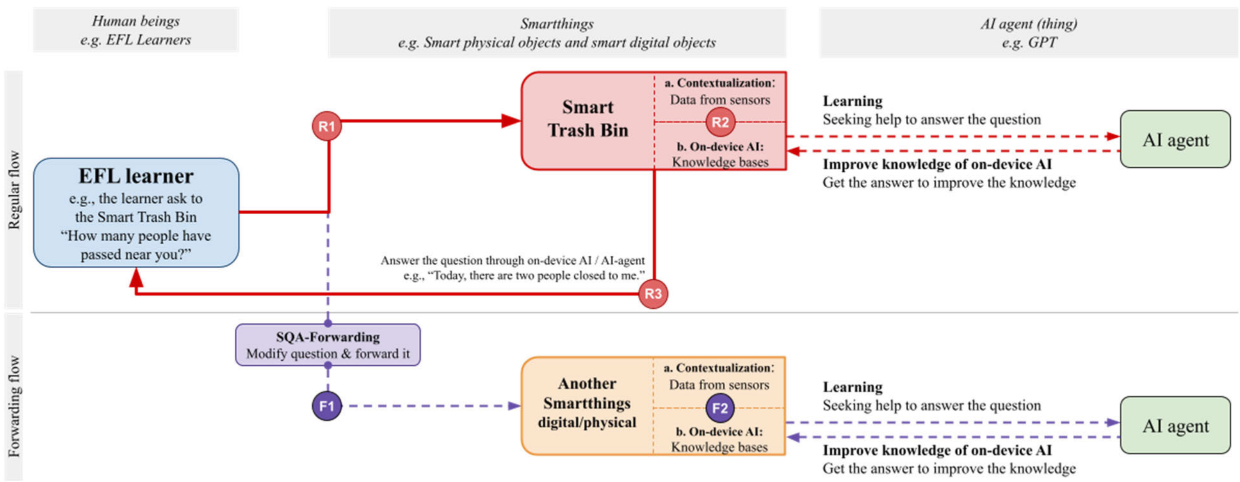


FIGURE 6. The workflow of SQA-Forwarding mechanism.

TABLE 1. The example of SQA-Forwarding.

An original question	Targeted *smartthings*	Modified question
A question from Smart Trash Bin (smart physical object) "How many people have open the trash bin today?"	*Smart digital object*	
	1. Smart Air Purifier	How many people have turned on the air purifier today?
	2. Smart UVC Light	How many people have turned on the UVC light to improve air quality?
	Smart physical object	
	1. Smart Vitamin Bottle	How many people have opened to you to take vitamins today?
	2. Smart Alcohol Spray	How many people have used the smart alcohol spray today?

also undertake to answer modified question from SQA-Forwarding (see F2 in Figure 6). Furthermore, on-device AI inside each of *smartthings* interacts with sensors to retrieve situations about the surroundings, such as the temperature, location, or conditions. The on-device AI inside *smartthings* will perform NLU for semantic searching in order to answer the question based on their knowledge bases. But occasionally, the *smartthings* are unable to provide a correct response since they do not have the knowledge about the question. In order to get a correct answer, the *smartthings* turn to an AI-agent for assistance. As shown in Figure 4, this allows the *smartthings* to learn and add new information to their knowledge bases.

Hence, the interaction not only occurs on human to a *smartthing*, but also other *smartthings* can listen and learn to have ability in answering the question based on their contexts. Therefore, SQA-Forwarding mechanism can speed-up the knowledge bases building in the *smartthings*.

IV. METHODOLOGY

A. RESEARCH QUESTIONS AND HYPOTHESIS

The study addressed two research questions with respective null (H0) and alternative hypotheses (H1).

- RQ1: Is there any significant difference in the interactions between EFL learners and *smartthings* with/without the SQA-Forwarding and its influence in the knowledge building of all *things*?
  The hypothesis of RQ1 is stated as follows.
  H0-RQ1: There is no significant difference in the interactions between EFL learners and *smartthings* with/without the SQA-Forwarding and its influence in the knowledge building of all *things*.
  H1-RQ1: There is significant difference in the interactions between EFL learners and *smartthings* with/without the SQA-Forwarding and its influence in the knowledge building of all *things*.
- RQ2: Is there any significant difference in the learning achievement and learning behaviors of EFL learners with/without the SQA-Forwarding and their influence on EFL writing?
  The hypothesis of RQ1 is stated as follows.
  H0-RQ2: There is no significant difference in the learning achievement and learning behaviors of EFL learners with/without the SQA-Forwarding and their influence on EFL writing.
  H1-RQ2: There is significant difference in the learning achievement and learning behaviors of EFL learners with/without the SQA-Forwarding and their influence on EFL writing.

B. THE PARTICIPANTS

The twenty-six graduate learners were selected using a convenience sampling technique, assigning learners into two different groups—one group as the experimental group (EG) and the other as the control group (CG)—while ensuring both groups had the same prior knowledge. EG consisted of 13 EFL learners (6 female and 7 male) who learned with the SQA-Forwarding in the smartXoT environment, while CG consisted of 13 EFL learners (4 female and 9 male) without the SQA-Forwarding. The EG and CG learners used

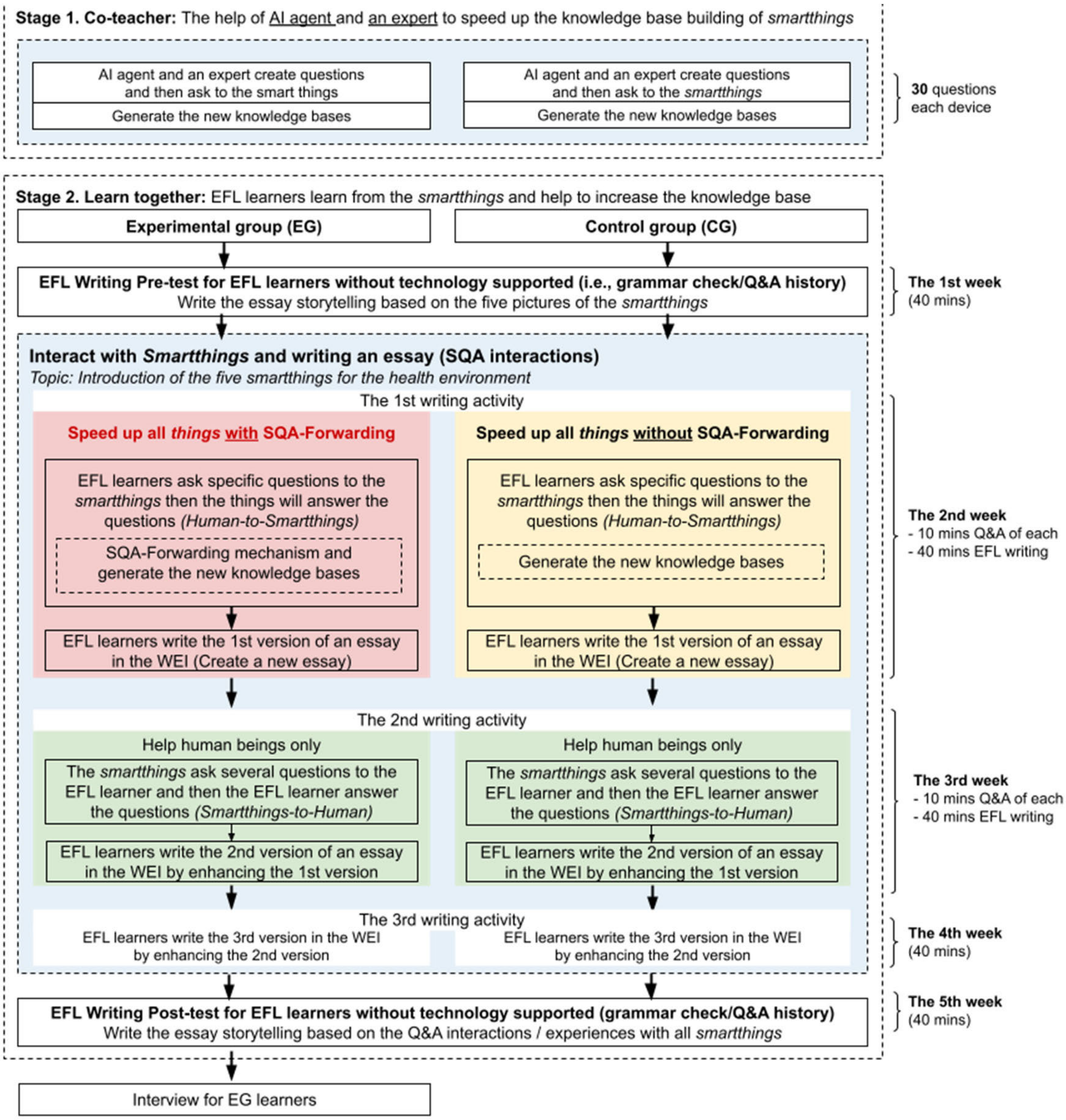


FIGURE 7. **The experimental procedure.**

smartXoT environment including five smart devices including smart physical objects and smart digital object (see Figure 2 or Appendix A and B), later these devices were called *smartthings*.

C. THE EXPERIMENTAL PROCEDURE

The experimental procedure as shown in Figure 7, in the first stage or the technical experiment, we built the foundational knowledge base for *smartthings* in the smartXoT environment, as shown as stage 1 in Figure 7. In the beginning, we curated 6 basic information related to *smartthings* from Wikipedia as the initial knowledge bases. Furthermore, the AI-agent acted like a human being and an independent expert helped to speed up the process of knowledge base building for each *smartthing*. Subsequently, an independent expert also managed the gained knowledge bases to remove incorrect answers that led to unnecessary knowledge bases.

The quasi-experiment (the second stage) was conducted without randomly assigning participants to the comparison groups (EG and CG). We investigated the influence of SQA-Forwarding on the knowledge bases of *smartthings* and the learning achievement of EFL learners, as shown in stage 2 in Figure 7. A pre-test was given during the first week of the program to ascertain whether or not the EFL learners in the two groups had comparable prior knowledge. Learners needed to write an essay within 40 mins based on the five pictures of the *smartthings* they had seen. They were required to finish three writing assignments using the EFL writing editor from the second to the fourth week. In the second week, EFL learners had the SQA interaction with *smartthings* (see phase 1 in Figure 3). They had 10 mins to ask the contextualized questions. After taking a break for 10 mins, learners had to write the first draft of the essay based on their interactions with the *smartthings* within 40 mins. The essay topic was the introduction of the five *smartthings* (i.e., smart alcohol spray, smart trash bin, smart vitamin bottle, smart air purifier, and smart UVC light) for a healthy environment.

In the third week, EFL learners completed the second phase of SQA interactions. They had 10 mins to answer the contextualized question from the *smartthings* based on their first draft. After a 10 mins break, EFL learners were required to write the second draft of the essay based on their interactions with the *smartthings* to enhance the first draft within 40 mins. In addition, in the fourth week, EFL learners had to revise the second essay to become the third draft based on their two SQA interactions within 40 mins. In the fifth week, a post-test was conducted to evaluate their learning performances by writing an essay within 40 mins based on the *smartthings* they had seen. The topic for the post-test was utilization of the five *smartthings* to keep a healthy environment and make your life better in the future. Finally, an interview was conducted to investigate the perceptions of the EG learners deeply. Prior to the experiment, researchers confirmed that every participant had read the consent form and had given permission to have their interview recorded. We expected that besides EFL learners gained their learning achievement, they also helped to improve the knowledge base of *smartthings* with/without the SQA-Forwarding.

D. THE RESEARCH VARIABLES, MEASUREMENT, AND DATA ANALYSIS

In the first stage, the total number of knowledge bases gained on each *smartthing*were collected. In the second stage, the variables were divided into three categories, such as the EFL learning behaviors from interactions with the *smartthings*, writing activities, and EFL learning achievement.

In terms of the interactions, the quantity variables were collected, such as the total number of gained knowledge bases on each *smartthings* and the total number of SQA interactions. In addition, the quality of SQA interaction was also checked, such as the AI answer quality.

In terms of EFL learning achievement for writing activities, the quantity and the quality variables were collected. The two English experts evaluated the total writing score based on the TOEFL independent writing rubric [3]. The total score of the scoring rubric was 20 points, including 5 points for each dimension. Furthermore, the score from two English experts in the pretest and posttest were check with inter-rater reliability analysis. Finally, the learners in EG were interviewed with semi-structured questions to understand the perceptions of the EG learners. The interview questions were adapted from the previous study and evaluated with data coding to understand deeply the reason behind the usefulness, easy, and understandable to use smartXoT environment [7].

In this research, the non-parametric statical were used since the data were not normally distributed and to address the validity issues. Furthermore, the evidence for quantity and quality of variables were provided, such as the total number knowledge base, learning behaviors include essay writing (i.e., MTLD, Clause per T-unit) with deep explanation. Furthermore, the perceptions were obtained from interview to support statistical results.

All variables in this research were evaluated using several data analysis methods, as described in Table 2. In this research, the average number of knowledge base building gained from each participant using were analyzed with data visualization in the Python v3 and Mann-Whitney comparison test in SPSS v23 to answer the RQ1 related to the technical experiment.

To answer RQ1 related to the quasi-experimental, the quality of AI-generated questions or answers in SQA interactions were evaluated by experts in the first phase of the SQA interactions and Python program in the second phase of SQA interactions. The experts determined whether the answers were relevant and well-addressed with the score, while Python program classified question labels using fine-tuned GPT-3 based on the other study [34]. Results showed strong correlation between human and automatic evaluations, with an accuracy of 0.843 and an F1 score of 0.864, indicating effective question quality classification analysis for SQA interactions. In addition, Mann-Whitney test in SPSS v23 program was used to compare the SQA interactions between two groups and Spearman's Rho correlation in SPSS v23 program to check the correlation for SQA-Forwarding mechanism.

To answer the RQ2 related to the EFL learning, pre-test, writing activities, and post-test were evaluated using Python program and human experts. The Python and L2SCA programs were used to obtain the MTLD score and clauses per T-unit score, respectively. In terms of the expert's evaluation, two English experts evaluated the writing score of the pre-test and post-test based on the TOEFL independent writing rubric. The Mann-Whitney statistical analysis was used with the SPSS software to determine the difference in the gained knowledge bases, EFL learners' prior knowledge, and EFL learning achievement between the two groups. Further, the Python program was used to create data visualization for the gained knowledge bases on each *smartthing*.

V. RESULTS AND DISCUSSIONS

A. THE ANALYSIS OFTHE COMPARISION OF SQA INTERACTIONS AND KNOWLEDGE BASES BETWEEN THE TWO GROUPS

We analyzed the comparison between two groups such as experimental group (EG) and the control group (CG) about their SQA interactions and the gained knowledge bases of the *smartthings*in smartXoT environment.

1) THE COMPARISON OF SQA INTERACTION BETWEEN TWO GROUPS

Regarding the first research question about the interactions between EFL learners and *smartthings*, the source of the

TABLE 2. The summary of the data analysis in this study.

RQ	Data analysis	Tools	Description
RQ1 (technical experiment)	Data Visualization	Python v3	To show the gained knowledge bases during SQA interactions on each *smartthing*.
	Mann-Whitney test	SPSS v23	To determine the differences in the gained knowledge bases during SQA interactions between the two groups.
RQ1 (quasi-experiment)	Mann-Whitney test	SPSS v23	To determine the differences in the SQA interactions between the two groups [7].
	Spearman's Rho correlation	SPSS v23	To check correlation of the SQA interactions with gained knowledge base to determine usefulness of the SQA-Forwarding.
	Content analysis of AI answers in the 1st SQA	Expert and SPSS v23	The good quality counted as one score, which is the question that is relevant to the *smartthings,* and the answer has addressed the question well, otherwise, zero scores.
	Content analysis of AI question in the 2nd SQA	Python v3	The GPT-3 model based on the LearningQ dataset was fine-tuned to evaluate the questions [34].
RQ2	MTLD Score	Python v3	To measure the writing quality with textual lexical diversity [5, 34].
	Clauses per T-unit	L2SCA	To measure the writing quality with syntactic complexity [5, 34].
	Writing Score a) Inter-rater reliability b) Scoring rubric	 SPSS v23 Expert and SPSS v23	 a) To check the agreement of the pre/post-test scores between two English expert. b) To measure the quality of writing content that will be evaluated from two experts based the scoring rubric [3].
	Mann-Whitney test	SPSS v23	To determine the writing content in the pre-test and post-test between the two groups.

answers during SQA interactions was compared, whether the answer came from the on-device AI in *smartthings* or whether it needed help from an AI-agent when answering the questions, as shown in Table 3. There were significant differences in the mean of the answer from on-device AI in both the smart digital objects ($U = 39.000$, $Z = -2.346$, $p < .05$) and the smart physical objects ($U = 16.000$, $Z = -3.521$, $p < .001$) between two groups.

It indicated that the smart digital objects ($M = 17.61$) and smart physical objects ($M = 29.61$) could directly fulfill the specific questions with on-device AI inside *smartthings* from the EG learners. One possible reason could be that by utilizing SQA-Forwarding in EG, it allowed to contribute to the creation of unique knowledge bases four times more than the CG did. As a result, the on-device AI had richer, unique, and specific knowledge bases that could be used to answer specific questions directly to EG learners. In contrast, the *smartthings* in the CG still relied on help from the AI-agent. Furthermore, a correlation analysis was conducted to understand the SQA-Forwarding for knowledge bases building in the EG only ($n = 13$). The results of Spearman's rho correlation analysis revealed that the total number of generated answers obtained through SQA-Forwarding had significant correlations with the total number of gained knowledge bases in all *smartthings*, including the smart digital objects ($r_s = .653$, p = .015) and smart physical objects ($r_s = .698$, p = .008). It indicated that the proposed SQA-Forwarding could help the *smartthings* to learn from each other with the help of the AI-agent, answer the questions, and then build new specific knowledge bases rapidly. This results in line with the previous study that the knowledge could be transferred between the AI-agent and other AI [35], [36], [37].

In the first activity related to *smartthings* answering questions from humans in order to help EFL learners, the results of the Mann-Whitney test showed the sound good quality of answers in the smart digital objects ($U = 13.000$, $Z = -3.691$, $p < .001$) and smart physical objects ($U = 18.000$, $Z = -3.424$, $p < .01$) were significant differences between the two groups. The possible reason is that the knowledge bases in the EG were richer and unique compared to CG because of the SQA-Forwarding. Hence, the on-device AI could provide more good answers for the EG.

In the second activity related to *smartthings* proposing questions, the EFL learners received questions from each *smartthings*. The results of the Mann-Whitney test showed that there was a significant difference in the sound good questions of the organization dimension (U = 31.500, Z = -2.962, p <.01). In the EG, the good questions in the organization dimension (83.33%) were better than CG (75.00%). EG had more well-formed questions from *smartthings* than CG, which helped EG fill in the missing information in their essay. Moreover, the prompt input for the AI-agent in the smartXoT environment was important in generating good questions [5].

2) The COMPARISION OF KNOWLEDGE BASE BUILDING OF SMARTTHINGS BETWEEN TWO GROUPS

The AI-agent acted as co-teacher with a human expert to seed the knowledge bases for the first time in the first stage. Then,

TABLE 3. The comparison of the SQA Interactions between two groups.

Smartthings	EG		CG		Mann-Whitney test		
	M	*SD*	*M*	*SD*	*U*	*Z*	*p*
Answers from on-device AI.							
1. Smart digital objects	17.61	2.66	14.38	3.33	39.000	-2.346	.019*
2. Smart physical objects	29.61	8.45	19.23	3.21	16.000	-3.521	.000***
Answers from AI-agent.							
1. Smart digital objects	8.85	4.48	11.38	5.29	56.500	-1.441	.149
2. Smart physical objects	11.38	6.19	11.69	7.45	69.000	-.797	.426

Notes. *$p < .05$; ***$p < .001$

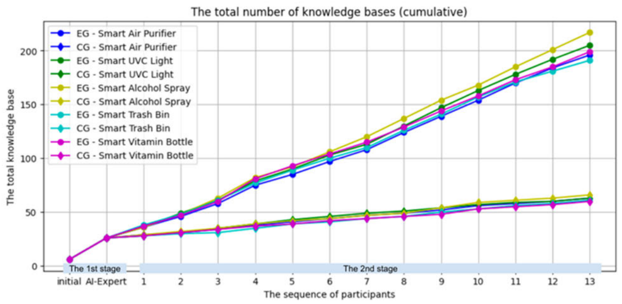


FIGURE 8. The cumulative knowledge bases building on each smartthings between two groups in the smartXoT environment.

EFL learners as participants completed their SQA interactions with *smartthings* for EFL learning in the second stage. The results show that the cumulative knowledge bases on each *smartthings* between the two groups increased over time, as shown in Figure 8.

In the first stage, the *smartthings* had 6 initial basic knowledge. Furthermore, each *smartthing* gained ±20 new unique knowledge bases. As a result, each *smartthing* had a total of 26 general knowledge bases equally in the on-device AI that could be used for EFL learning in the second stage. Furthermore, it has been demonstrated that the AI-agent could act as a knowledge source to help enrich the new information to on-device AI as knowledge bases in the *smartthings*.

In the second stage, EFL learners and the *smartthings* learned together in SQA interactions to build the *smartthings'* knowledge bases. For further analysis, the gained knowledge bases of the three smart physical objects were combined into the variable smart physical objects, and the two smart digital objects into smart digital objects. However, in this research the *smartthings* learned from others and it increase the knowledge bases only and it cannot increase their intelligence.

Therefore, the comparison of the gained knowledge bases building of *smartthings* between two groups with Mann-Whitney analysis revealed that the smart digital objects (U =.000, $Z = -4.347$, p <.001) and the smart physical objects (U =.000, $Z = -4.344$, p <.001) were significant differences. Furthermore, the EG ($M = 13.42$; $M = 13.56$) had four times more knowledge bases in the *smartthings* compared to the CG ($M = 2.85$; $M = 2.79$). It is because EG used SQA-Forwarding mechanism in the smartXoT environment. It implied that the *smartthing* with more knowledge bases might be useful for the new EFL learners when they engaged in the SQA interactions in the future.

The actual physical/digital object behind the *smartthings* was passive, however, the physical/digital object empowered with edge computing be able to actively answer the questions, particularly with SQA-Forwarding. In this situation, the smartXoT environment is crucial to trigger the interaction among all *things*. It is because the *smartthings* used the enactivism theory by applying the knowledge in the surroundings with on-device AI and *smartthings* also got feedback from AI-agent. By actively interact in smartXoT environment, the knowledge of all *things* could be improved. Hence, smartXoT environment with SQA-Forwarding mechanism could be address as highly interactive environment and it could be used for educational activities, such as EFL learning.

B. LEARNING ACHIEVEMENT AND LEARNING BEHAVIORS OF EFL LEARNERS

We analyzed the comparison between two groups such as experimental group (EG) and the control group (CG) about their learning achievement, in which the SQA-Forwarding mechanism that could help EG learners in smartXoT environment.

1) THE COMPARISON OF EFL LEARNING ACHIEVEMENT BETWEEN TWO GROUPS

Two English experts reached inter-rater reliability about the final scores in the pre-test was.923 and post-test was.835, which indicated that two raters reached good agreement. Regarding the second research question about the EFL learning, the results of the Mann-Whitney analysis in Table 4 shows that the prior knowledge of EFL learners were not significantly different between the two groups in the pre-test. Hence, learners could participate in the experiment with smartXoT environment.

The result of comparison analysis showed that there were significant differences in the number of words in the post-test essay (U = 35.000, Z = -2.538, p <.05) and the post-test score (U = 32.500, Z = -2.675, p <.01) of the post-test between two groups. The number of words in the EG post-test essay (M = 493.77) was significantly higher than the CG (M = 329.61). It was evident that the EG wrote the essay in greater detail after reading it carefully and comprehending the details regarding *smartthings*in the SQA.

TABLE 4. The comparison of learning achievement of EFL writing between two groups.

Variables	EG		CG		Mann-Whitney test		
	M	*SD*	*M*	*SD*	*U*	*Z*	*p*
Writing content of pre-test							
1. The number of words	311.61	134.36	254.69	101.46	62.000	-1.154	.248
2. MTLD	53.29	12.22	49.92	13.77	71.000	-.692	.489
3. Clauses per T-unit	1.64	.34	1.66	.42	80.500	-.205	.837
Pre-test Score	11.23	3.24	10.26	1.80	75.000	-.489	.625
Writing content of post-test							
1. The number of words	493.77	154.97	329.61	92.95	35.000	-2.538	.011*
2. MTLD	50.23	6.84	48.68	10.82	75.000	-.487	.626
3. Clauses per T-unit	1.74	.29	1.77	.52	81.000	-.180	.857
Post-test Score	17.19	2.58	14.31	2.86	32.500	-2.675	.006**

Notes. *$p < .05$; **$p < .01$

Furthermore, the EG (M= 17.19) was superior to CG (M = 14.31) in the post-test scores. The EG might have benefited more from SQA interactions because EG had a lot of information. It is because the *smartthings* in the EG had more knowledge bases because of the SQA-Forwarding mechanism that caused EG to ask anything related to the information of *smartthings*. By doing so, the EG had deeper interactions with *smartthings* during the SQA interactions. The various feedback that the EG received from *smartthings*have potential to broaden learners' knowledge and enrich their writing contents [38]. The feedback received from *smartthings* in the SQA interaction could lead learners to do reflection process and evaluated the essay [38]. As such, the EG triggered to revise their essay by adding all information received from *smartthings* in their essay when completing writing activities [3]. Hence, the EG was able to outperform CG.

2) THE BENEFITS OF THE SQA INTERACTION FOR EFL LEARNING PERFORMANCE OF THE EG LEARNER

The learners wrote a first draft essay until the third draft essay as a learning performance with the EFL writing editor in smartXoT environment after they had the SQA interactions. However, we did not analyze the third writing activity deeply since EFL learners did not have SQA interactions in the third writing activity. Regarding the first draft essay, the results of the Mann-Whitney analysis showed no significant differences in the writing content and behaviors between the two groups, as shown in Table 5. It might be because both groups give similar questions to *smartthings* to explore the common information about *smartthings*. This result in line with the previous study that learners in the stage of knowing *smartthings* at the first time [7].

The contrast results were showed in the second draft essay in which the knowledge base of the *smartthings* became increased caused by SQA-Forwarding in the previous activity that benefited to the EG learners. The results of the Mann-Whitney analysis show there were significant differences in the writing content and behaviors between the two groups after the reflective questioning. Regarding the writing content, there was a significant difference in the total number of words (U = 29.000, $Z = -2.846$, p <.01). It indicated that EG learners (M = 590.69) have increased the number of words of the second draft compared to the CG learners (M = 402.76) after the SQA interactions.

Regarding the writing behavior of the second draft essay, there were significant differences in the total use of the Q&A history (U = 38.000, Z = -2.397, p <.05) and total revisions (U = 35.500, Z = -2.324, p <.05) between the two groups. It indicated that EG learners received more inspiration through their interactions and revised their writing to improve the quality of the second essay by citing the Q&A history compared to the CG learners. It is because revision was an important process to motivate learners to write more meaningfully based on their understanding and ideas [28], [39]. In the interview, most of EG students said that the SQA interactions could improve their essay since they got inspiration from *smartthings*.

Furthermore, the correlation between the writing content and writing behavior of the second draft was investigated deeply with Spearman's correlation analysis for the EG only (n = 13). It was found that the total number of words in the essay was significantly correlated with the Q&A history (r_s = .559, p = .047). It indicated that the Q&A history could encourage EG learners to write more words. In addition, EG learners also utilized common grammar feedback to enhance their writing content by adding new words that implied the EG learners have more revisions in their essay (r_s = .579, p = .038). Interestingly, the total revisions in the second draft were correlated with the post-test score (r_s = .571, p = .041). It is because they received the question from *smartthings* that mentioned the missing part based on their essay that needs to be improved. In addition, they might be familiar with the *smartthings* and knew the information deeply about each *smartthing* which caused more revisions in the second draft. By doing repetitive revisions to enhance the essay, EFL learners would also learn to acquire vocabulary and improve their writing skills [16].

VI. SUGGESTIONS, IMPLICATIONS AND ETHICAL CONSIDERATION

In terms of the pedagogical aspect, the SQA interactions could benefit EFL learners and *smartthings* to improve their

TABLE 5. The comparison of learning performance of EFL writing draft between two groups.

Stage	Variables	EG		CG		Mann-Whitney test		
		M	*SD*	*M*	*SD*	*U*	*Z*	*p*
The first writing draft	Writing content							
	1. The number of words	347.30	114.91	287.76	90.24	56.500	-1.436	.151
	2. MTLD	51.16	8.91	45.03	8.70	51.000	-1.718	.086
	3. Clauses per T-unit	1.46	.21	1.47	.33	73.500	-.564	.573
	Writing behaviors							
	1. Total used of the Q&A history (cite)	12.23	7.98	11.15	5.98	79.500	-.257	.797
	2. Total used of grammar feedback	4.84	5.17	6.15	5.11	69.500	-.785	.433
	3. Total revisions	8.46	6.39	5.92	3.14	66.000	-.955	.339
The second writing draft	Writing content							
	1. The number of words	590.69	167.93	402.76	134.18	29.000	-2.846	.004**
	2. MTLD	47.93	6.50	45.05	10.003	66.000	-.949	.343
	3. Clauses per T-unit	1.55	.21	1.56	.44	68.500	-.821	.412
	Writing behaviors							
	1. Total used of the Q&A history (cite)	16.30	6.68	9.54	7.83	38.000	-2.397	.017*
	2. Total used of grammar feedback	3.53	4.15	3.69	4.21	70.000	-.276	.782
	3. Total revisions	7.84	5.84	4.46	2.29	35.500	-2.324	.020*

Notes. *$p < .05$; **$p < .01$

knowledge. Therefore, EFL learners were encouraged to ask more questions to inquire about the information in their surroundings before writing the essay. The EFL learners could retrieved several new vocabulary and detailed description about the objects deeply. Hence, it implies that learning English by directly asking the object in authentic contexts could benefit them to enrich their essay and enhance their EFL skills, particularly for EFL writing.

Since the SQA-Forwarding during SQA interactions could speed up the knowledge bases building rapidly, it could also be implemented for the EFL learners in real situations not only for *smartthings* in the digital world. This research recommend that teachers and educators actively trigger EFL learners by posing random questions based on the specific topic. Consequently, EFL learners could learn from each other to solve the problems given by the teachers.

On the other hand, reflective questioning was useful to teach EFL learners to identify missing information in their essays by asking to the *smartthings*. Therefore, the educator or teacher can use this approach by integrating the AI-agent in their learning to generate the questions for EFL learners. It implies that the teacher could receive help from the AI-agent to create questions and address the missing information based on the learners' content essay. Consequently, the questions generated by AI could trigger the EFL learners to deeply understand and revise the missing information in their essay. Hence, it could help EFL learners to enhance their writing individually by the help from AI beside from teacher.

Regarding to the theoretical aspect, in this study we extended the enactivism theory to include all *things* not only human beings to learn from each other, then shapes each other. Therefore, the coverage of enactivism theory include human beings and all *things,*hence, we called this big enactivism. In detail, all *things* not only learn with AI-agent through SQA-Forwarding but also actively learn from their surrounding contexts with their sensors like camera as eyes, microphone as ears and other embedded sensors. Hence, the enactivism become more meaningful since all *things* highly interact with each other and actively learn together. Furthermore, the coverage of enactivism theory include human beings and all *things*, hence, we extend this theory to become big enactivism.

On the other hand, regarding the technological aspect, first, the on-device AI could be replaced with another AI model to improve the ability to answer the question. Second, the cost of the GPT-4 for the AI-agent needs to be considered. It implies that educator needs to be careful when implementing AI in their research or learning process, especially considering the cost and benefit. Third, this research suggests using edge computing with greater computing resources and an embedded chipset for physical objects to infer on-device AI. It implies that the educator needs to improve the current implementation method to enhance English learning in authentic contexts with smartXoT environment efficiently.

In terms of ethical consideration, the *smartthings* could serve as companions for EFL learners or could be independent learners, much like human beings. This is in contrast with the traditional ethical considerations that are limited to humans, such as issues of accountability and reliability. It is possible that in the future, *smartthings* will also need to be considered for their potential to serve as learners' companions or become learners themselves. Meaning the AI was disrupting educational perspectives in which human beings consider themselves to co-exist with *smartthings* in the real world.

VII. CONCLUSION

This study found several contributions for the education perspectives, and it could inspire the next research in education regarding how to design learning actively and improve the interaction between human beings and the environments.

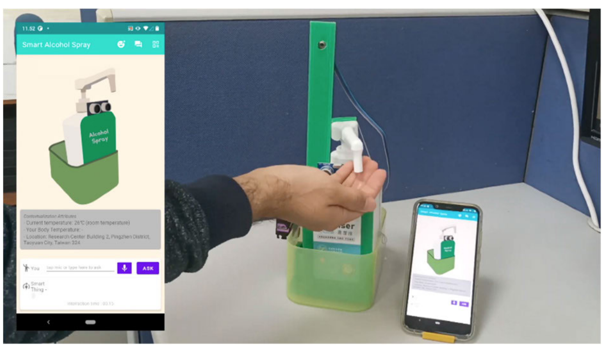
Regarding the first research question, there was a significant difference in the quality of SQA interactions with/without the SQA-Forwarding in the smartXoT environment. In detail, EG learners with the SQA-Forwarding support received better quality of answers during the SQA interaction. In addition, there was significant difference in the knowledge base building of all *things* with/without the SQA-Forwarding in the smartXoT environment. The EG utilizing *smartthings* with the SQA-Forwarding had four times richer specific knowledge bases compared to the CG.

Regarding the second research question, there were significant differences in the learning behaviors of EFL learners with/without the SQA-Forwarding and their influence on EFL writing. In detail, the interaction between EFL learners and all *things* in the smartXoT environment not only increased the knowledge bases of *smartthings* but also helped EG learners enhance EFL writing. In addition, the revision process was crucial to improving the essay quality of EG learners because they benefited more from the smartXoT environment.

There were several limitations of this researcher, such as the first, the on-device AI mostly relied on the knowledge bases for answering the question. Furthermore, the SQA interactions helped on-device AI to increase the knowledge base only, not their intelligence. The second, this quasi-experimental design might raise potential bias caused by few participants. As a result, the data analysis in this study needs to be conducted in non-parametric analysis that is known to have less statistical power than parametric analysis.

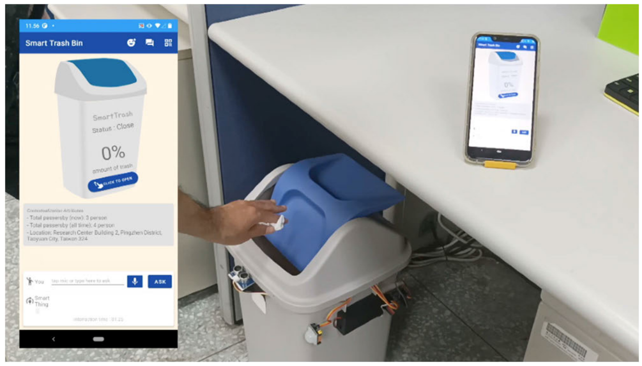
Following the above-mentioned limitation, there were several suggestions to the system and experiments for future studies. The first, the edge computing can be more independently by using the dedicated hardware with chipset and sensors. Second, the number of participants needs to be increased to minimize the validity concern of data analysis and to improve knowledge bases of *smartthings* by interacting with more various human beings in the SQA interaction.

APPENDIX A
SMARTTHINGS: SMART PHYSICAL OBJECTS
A. SMART ALCOHOL SPRAY



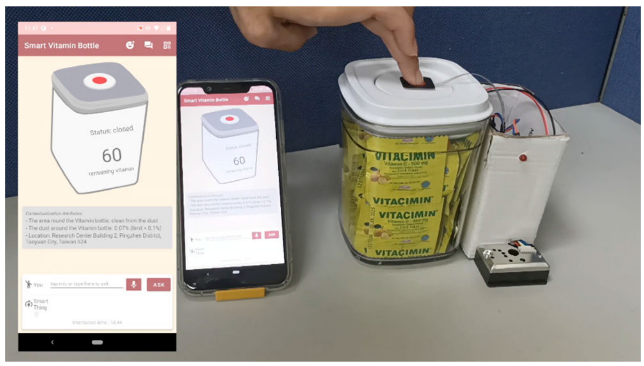
Physical object	It automatically sprayed alcohol onto the hand when the hand was near the sprayer.
Edge computing	*IoT*: Thermal Sensor / IR Temperature sensor for checking the temperature of human sensor while spraying alcohol. *Mobile*: GPS Sensor to determine the location.
Demo Link	https://youtu.be/1Ywpe74ymOY

B. SMART TRASH BIN



Physical object	It could open/close the cover automatically if a hand is near the cover.
Edge computing	*IoT:*Motion Sensor to count the person in front of the trash bin and to check whether the human need to remember the cleaning. *Mobile:*GPS Sensor to determine the location.
Demo Link	https://youtu.be/fy309LwPrZ0

C. SMART VITAMIN BOTTLE



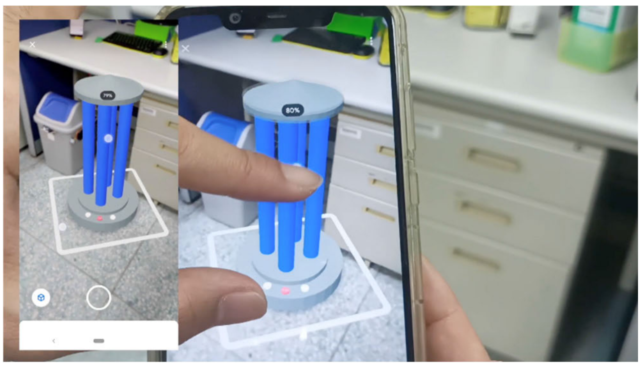
Physical object	It could keep the vitamin in the clean area.
Edge computing	*IoT:*Dust Sensor for checking the clean environment in the surrounding bottle to put the Vitamin. *Mobile:*GPS Sensor to determine the location.
Demo Link	https://youtu.be/87zTaNVeyVo

APPENDIX B
SMARTTHINGS: SMART DIGITAL OBJECTS

A. SMART AIR PURIFIER

Digital object	It displayed the 3D NFT of the Air Purifier with augmented reality technology.
Edge computing	*IoT*: -
	Mobile: Air Quality Index (AQI) to determine the air quality of surroundings device. It uses a GPS Sensor to recognize the Location and then retrieves the AQI index from internet.
Demo Link	https://youtu.be/uDbVeztN2Pg

B. SMART UVC LIGHT



Digital object	It can display the 3D NFT of the UVC Light using augmented reality technology.
Edge computing	*IoT*: -
	Mobile: Air Quality Index (AQI) to determine the air quality of surroundings device. It uses a GPS Sensor to recognize the Location and then retrieves the AQI index from internet.
Demo Link	https://youtu.be/1HCoqwAUaJE

DECLARATION OF CONFLICTING INTEREST

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

INFORMED CONSENT STATEMENT

Informed consent was obtained from all subjects involved in the study.

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