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Unraveling Knowledge-Based Chatbot Adoption Intention in Enhancing Species Literacy

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ABSTRACT

Aim/Purpose	This research investigated the determinant factors influencing the adoption intentions of Chatsicum, a Knowledge-Based Chatbot (KBC) aimed at enhancing the species literacy of biodiversity students.
Background	This research was conducted to bridge the gap between technology, education, and biodiversity conservation. Innovative solutions are needed to empower individuals with knowledge, particularly species knowledge, in preserving the natural world.
Methodology	The study employed a quantitative approach using the Partial Least Square Structural Equation Modeling (PLS-SEM) and sampled 145 university students as respondents. The research model combined the Task-Technology Fit (TTF) framework with elements from the Diffusion of Innovation (DOI), including relative advantage, compatibility, complexity, and observability. Also, the model introduced perceived trust as an independent variable. The primary dependent variable under examination was the intention to use the KBC.
Contribution	The findings of this research contribute to a deeper understanding of the critical factors affecting the adoption of the KBC in biodiversity education and outreach, as studies in this context are limited. This study provides valuable insights for developers, educators, and policymakers interested in promoting species literacy and leveraging innovative technologies by analyzing the interplay of TTF and DOI constructs alongside perceived trust. Ultimately, this research aims to foster more effective and accessible biodiversity education strategies.
Findings	TTF influenced all DOI variables, such as relative advantage, compatibility, observability, and trust positively and complexity negatively. In conclusion, TTF strongly affected usage intention indirectly. However, relative advantage, complexity, and observability insignificantly influenced the intention to use. Meanwhile, compatibility and trust strongly affected the use intention.
Recommendations for Practitioners	Developers should prioritize building and maintaining chatbots that are aligned with the tasks, needs, and goals of the target users, as well as establishing trust through the assurance of information accuracy. Educators could develop tailored educational interventions that resonate with the values and preferences of diverse learners and are aligned closely with students' learning needs, preferences, and curriculum while ensuring seamless integration with the existing educational context. Conservation organizations and policymakers could also utilize the findings of this study to enhance their outreach strategies, as the KBC is intended for students and biodiversity laypeople.
Recommendations for Researchers	Researchers should explore the nuances of relationships between TTF and DOI, as well as trust, and consider the potential influence of mediating and moderating variables to advance the field of technology adoption in educational contexts. Researchers could also explore why relative advantage, complexity, and observability did not significantly impact the usage intention and whether specific user segments or contextual factors influence these relationships.

Impact on Society	This research has significant societal impacts by improving species literacy, advancing technology in education, and promoting conservation efforts. Species knowledge could raise awareness regarding biodiversity and the importance of conservation, thereby leading to more informed and responsible citizens.
Future Research	Future works should address the challenges and opportunities presented by KBCs in the context of species literacy enhancement, for example, interventions or experiments to influence the non-significant factors. Furthermore, longitudinal studies should investigate whether user behavior evolves. Ultimately, examining the correlation between species literacy, specifically when augmented by chatbots, and tangible conservation practices is an imperative domain in the future. It may entail evaluating the extent to which enhanced knowledge leads to concrete measures promoting biodiversity preservation.

Keywords task-technology fit, diffusion of innovation, knowledge-based system, chatbot, trust, biodiversity, species literacy

INTRODUCTION

Biodiversity, the remarkable tapestry of life on Earth, faces unprecedented challenges in the 21st century. As human activities continue to alter ecosystems and threaten the survival of countless species, it becomes increasingly vital for society to cultivate a deeper understanding of biodiversity and conservation efforts (Colli et al., 2020). The ongoing threats posed by habitat destruction, climate change, and overexploitation demand an informed and engaged citizenry to participate in conservation efforts (Agduma et al., 2023). In this context, innovative technologies, such as satellite-based remote sensing, cameras, acoustic recording devices, and environmental DNA, offer promising avenues to monitor biodiversity and its conservation (Stephenson, 2020). However, these technologies are expensive and complicated enough for widespread use.

One inexpensive technology is a knowledge-based chatbot (KBC), which is supported by one or more domain-specific knowledge bases that produce instant responses to user questions (Ait-Mlouk & Jiang, 2020). Multiple sectors have adopted the technology, including e-commerce sales and marketing (Ngai et al., 2021), healthcare service (Chung & Park, 2019), and insurance industry (Nuruzzaman & Hussain, 2020). In order to provide a more dynamic and successful conversation, a KBC system should be able to retrieve useful and relevant information from its knowledge bases. Unsuccessful conversions could affect users' intention to adopt the technology.

In the educational sector for biodiversity literacy, a KBC, namely Chatsicum, has been developed to engage and educate species literacy among students, laypeople, and the general public (Manik et al., 2021). The KBC, cheap and easy enough for broad use, represents a novel approach to fostering species literacy by providing accessible, interactive, and user-friendly access to biodiversity knowledge. Enzensberger et al. (2022) found a strong influence of species literacy on acting proactively for biodiversity conservation, for instance, donating money to conservation funding.

Nevertheless, technological and innovative solutions are counterproductive if not used as intended. This research paper delves into the determinant factors that influence the intention to use the KBC, shedding light on the dynamics of its adoption within the broader context of technology-assisted biodiversity education. To comprehensively examine these adoption dynamics, this study draws on two well-established theoretical frameworks: Task-Technology Fit (TTF) and Diffusion of Innovation (DOI).

The TTF framework elucidates the interactions between task characteristics, technology characteristics, and the alignment (or misalignment) between the two, known as task-technology fit. Additionally, DOI principles, encompassing relative advantage, compatibility, complexity, and observability, are incorporated to assess how KBC's innovative features and functionalities impact its adoption. In recognition of the central role of trust in technology adoption, this research also incorporates perceived trust as an independent variable. These factors, rooted in user perception and trustworthiness, are expected to play a pivotal role in shaping individuals' intentions to use the KBC as a knowledge enhancement tool.

By combining these diverse theoretical constructs and employing a quantitative approach, this study offers a nuanced understanding of the factors driving the adoption intentions of the KBC. In doing so, it aims to provide valuable insights for developers, educators, and policymakers tasked with leveraging technology to advance species literacy and conservation awareness. Ultimately, this research contributes to the broader discourse on the intersection of technology, education, and biodiversity conservation in an increasingly interconnected world.

The subsequent sections of this paper delve into a detailed literature review, discussing prior research related to species literacy. Following the literature review, the relevant theories are explained. Then, the subsequent section presents the development of the hypotheses. The methodology section describes the research design, data collection methods, and analytical approaches used in this study. The results section presents the findings, highlighting the factors impacting KBC adoption. The discussion section interprets the results, and the subsequent section draws implications for research and practice. The last section concludes the paper and offers recommendations for further study.

LITERATURE REVIEW

The foundation of any effective biodiversity conservation strategy lies in enhancing the general public's biodiversity literacy (Lundberg et al., 2019). Biodiversity literacy encompasses knowledge, understanding, and appreciation of the various dimensions of biological diversity, including species richness. Hooykaas et al. (2019) found that the level of species literacy, also called knowledge about species, is significantly lower among general people than professionals. Non-experts, especially youngsters in school, encounter challenges when recognizing prevalent and easily noticeable indigenous species. This knowledge gap between laypeople and professionals indicates a potential separation between humans and the natural environment, which could impede future endeavors to conserve biodiversity. Several studies have found that species knowledge strongly influences understanding nature and connecting people with nature (Cox & Gaston, 2015; Skarstein & Skarstein, 2020; Wolff & Skarstein, 2020).

Although many studies have shown that species knowledge is essential for biodiversity conservation efforts, studies to investigate the determinants of species literacy are minimal. Randler and Heil (2021) found that specialization was the most influential predictor, followed by species-related interest/activity. In addition, personal expectations on test performance, the school, favorite playing area, and gender were significant determinants of students' species knowledge (Gerl et al., 2021). Meanwhile, Palmberg et al. (2019) found that outdoor teaching and learning about species knowledge were more efficient than indoor methods.

Another finding showed that remote learning could achieve higher species literacy levels than face-to-face expert-led workshops (Perry et al., 2021). This approach offers the advantages of reduced resource demands and increased engagement. However, aside from that, other studies on technology and innovation, like e-learning, to increase laypeople's species literacy are minimal. One is the Flora Incognita mobile app, developed by Mäder et al. (2021), used to help users interactively identify species. Including an intuitive user interface and supplemental instructional resources gives users advantages. When designing online species identification tools used by citizen scientists, Sharma et al.

(2019) also found that the type of interface, the difficulty of the specimen on the image being identified, and the interaction between the interface type and 'image difficulty' were essential determinants of the species knowledge learning quality.

As one of the efforts, we also have developed a knowledge-based chatbot (KBC) that students and laypeople can use to query and ask about species-related information (Akbar et al., 2020; Manik et al., 2021). A KBC refers to computer software designed to respond to users' queries or questions using information stored in a knowledge base (KB). One notable benefit is that a chatbot undergoes training using a KB, which serves as a pre-existing repository of organized and structured information. While the chatbot has a simple user interface, it is expected to replace the experts. We named the KBC Chatsicum, as we only have a KB of *Capsicum Sp.* at the current state acquired by Akbar et al. (2021). Nevertheless, the KBC can be utilized for other biodiversity species as long as the KBs of the particular species are stored in the system.

This study bridges the research gap between technology and biodiversity education, particularly species literacy, by investigating factors that influence technology and innovation adoption, such as a KBC, to improve laypeople's species knowledge. Innovative solutions, such as KBC, that offer knowledge of species could be potent tools to empower individuals. A biodiverse literate society is more likely to appreciate the significance of biodiversity conservation, make informed choices, and support conservation initiatives. This research contribution fosters more effective and accessible biodiversity education strategies in an increasingly digital world.

THEORETICAL FOUNDATION

Technology innovation has long been recognized as a transformative educational force. In the context of biodiversity education, technological and innovative tools can overcome traditional barriers to learning, such as geographic constraints, limited resources, and accessibility issues. Several technologies have been explored in this context, including mobile applications and online courses. However, one of the most promising innovations is using chatbots, like KBC, as interactive and personalized educational agents. This section explains theories used as the foundation of research on utilizing technology and adopting innovation.

A recent literature review revealed that the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) are theories that are primarily utilized in adoption studies of chatbot usage intention (Gatzioufa & Saprikis, 2022). Accordingly, native variables of TAM, such as perceived ease of use and usefulness, as well as native variables of UTAUT, such as effort and performance expectancy, are mainly used in these studies. Meanwhile, TTF was utilized instead of TAM and UTAUT in this study because our primary concern was assessing the suitability of chatbot technology for specific tasks, particularly species literacy-related tasks.

Gatzioufa and Saprikis (2022) also found that customer service, tourism, mobile commerce, and banking are among the industries that most regularly adopt chatbot technologies. Therefore, TAM and UTAUT are better choices for understanding the factors that influence chatbot adoption and use at a broader level in these industries. Meanwhile, chatbots are rarely implemented as education tools, particularly in biodiversity education. Fryer et al. (2019) studied why chatbots were not yet a substantial instrument for learning engagement/practice and found that participants who had a qualitative experience of having gained more knowledge from interacting with chatbots displayed a significant correlation with their interest in the task even when they encountered communication difficulties. Thus, we argued that TTF was the most suitable theory in this emerging context. By integrating with DOI, we also would like to assess whether TTF could influence the spread of the technology and, eventually, usage intention.

Task-Technology Fit (TTF)

The TTF framework, developed by Goodhue and Thompson (1995), offers a comprehensive lens for examining the alignment between technological solutions and specific tasks or objectives. TTF posits that individual performances and technology utilizations are contingent upon the compatibility of the technology with the task at hand and the technology's inherent characteristics. TTF is crucial for achieving effective and efficient performance in organizations. A good fit between the technology and its support task can lead to increased productivity, improved user satisfaction, and better outcomes.

TTF has been integrated with the abovementioned theories, such as TAM and UTAUT. The findings have shown that TTF indirectly influenced the successful adoption and utilization of technologies via perceived ease of use, such as for wearable devices (Chang et al., 2016) and knowledge management systems (Kuo & Lee, 2011), as well as through perceived usefulness (Ong et al., 2022). On the other hand, TTF indirectly influenced the usage intention of smart home healthcare services positively via performance expectancy (Kang et al., 2022) and affected effort expectancy in a learning management system (Sharif et al., 2019).

Diffusion of Innovation (DOI)

Rogers (2003) introduced the DOI to explain how innovations are adopted and spread within society. DOI posits that the rate of adoption of an innovation is influenced by several innovation attributes, including relative advantage (the perceived superiority of the innovation over existing alternatives), compatibility (the degree to which the innovation aligns with existing values and needs), complexity (the perceived difficulty of using and understanding the innovation), and observability (the perceived visibility of benefits and capabilities of the innovation). While trialability (the degree to which the innovation can be experimented on a limited basis before committing to its full use) is also one of the attributes, the variable was not included in this study because the research was conducted during a provisional period of the KBC. Therefore, trialability was not applicable in this study.

Several studies have applied DOI to examine the dissemination of innovation within various cases in many disciplines. For example, the relative advantage positively influenced the intention to use mobile learning (Kim et al., 2017). Furthermore, Yuen et al. (2018) found that compatibility positively affected the intention to use self-service technology and relative advantage. Moreover, Sanni et al. (2013) revealed complexity as a significant contributor to the e-journal adoption rate negatively. Besides relative advantage and compatibility, observability positively influenced mobile banking adoption (Al-Jabri & Sohail, 2012).

While studies of integrated TTF and DOI are limited, the combination of TTF and DOI can be performed in various ways. For example, when Deng et al. (2009) investigated the adoption of enterprise short message services, the study found that TTF positively influenced the relative advantage and negatively affected the complexity. Furthermore, relative advantage and compatibility influenced the usage intention positively and complexity negatively. Nevertheless, other studies evaluated whether compatibility, relative advantage, and complexity influenced the TTF when investigating the smartwatch and smart speaker adoption intention (Hsiao, 2017; Ling et al., 2021). Either way, the combined model might be more effective than DOI or TTF alone (Deng et al., 2009).

Relative advantage is an interchangeable term with the perceived usefulness of TAM or the performance expectancy of UTAUT, and complexity is opposite to the TAM's perceived ease of use or UTAUT's effort expectancy (Hernandez & Mazzon, 2007; Mandari & Chong, 2018). Therefore, this study covered DOI, TAM, and partly UTAUT models. The hypotheses were also derived from previous studies that utilized TAM and UTAUT. Accordingly, this research paper touches on both theories a lot.

TRUST IN TECHNOLOGY AND INNOVATION

The role of trust, such as credibility and perceived trustworthiness, in utilizing technology and adopting innovation has been extensively explored in various contexts. Particularly in the chatbot context, Gatzioufa and Saprikis (2022) found that trust is one of the essential variables influencing technology acceptance besides the native variables of theories used in chatbot adoption studies. In the context of educational technology, users are more likely to use and engage with platforms they trust as credible and trustworthy. Trust is influenced by various factors, such as the accuracy of information, the expertise of the knowledge source, and the technology's reliability. These factors are essential when assessing the intentions of biodiversity students, laypeople, and the general public to use KBC.

HYPOTHESES DEVELOPMENT

The research model is shown in Figure 1.

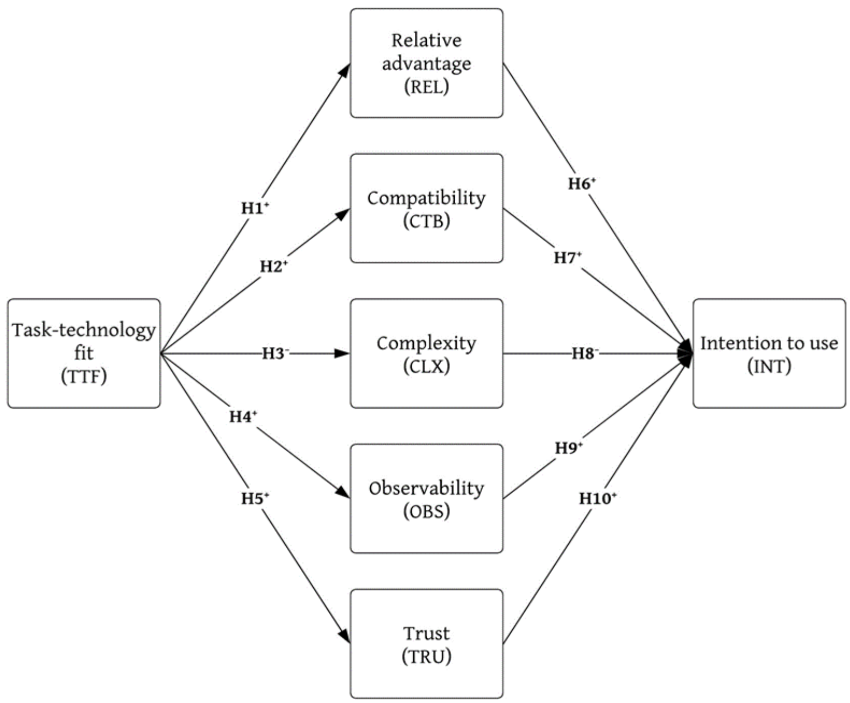

Figure 1. Research model

TTF and relative advantage are two distinct concepts, with TTF focusing on aligning a technology with a specific task. In contrast, relative advantage is a component of the DOI that pertains to how a new technology is perceived as better than existing alternatives. However, TTF could positively influence the perceived relative advantage of technology in several ways. For example, in the context of species literacy-related tasks, when the KBC is well-suited to replace the experts in helping users identify a particular Capsicum species, users would be more likely to perceive it as advantageous. This alignment could make the technology appear more efficient and effective, contributing to a higher perceived relative advantage. Several studies in other various contexts found that TTF indeed influenced relative advantage (Deng et al., 2009), perceived usefulness (Chang et al., 2016), as well as performance expectancy (Kang et al., 2022; Sharif et al., 2019), and we hypothesized the same.

H1: *Task-technology fit positively affects the relative advantage.*

TTF and compatibility are related concepts within the context of technology adoption. Compatibility is a component of the DOI that addresses how well a new technology aligns with existing practices and systems. For example, if the KBC could be accessed anywhere and anytime, it would be more likely to align with and complement existing learning processes and students' study practices, where students commonly use online learning or digital devices in the current era. This alignment might enhance compatibility, as the technology fits seamlessly into the current workflow. Furthermore, technologies that fit well with the task tend to cause less disruption to existing practices. Users might perceive such technology as compatible because it could be integrated into their daily routines without significant changes or adjustments. Following Kuo and Lee (2011), we also hypothesized that TTF affected compatibility positively.

H2: *Task-technology fit positively influences the compatibility.*

TTF and complexity are closely related to technology adoption and the DOI. A high TTF implies that the technology aligns well with the specific task, making it more straightforward. This alignment might reduce the perceived complexity as users could find it easier to accomplish their tasks. In species literacy, when KBC could replace experts to help users answer inquiries regarding the morphology of various species, the cognitive load on users tends to be reduced. Moreover, technologies with a high TTF associated with functionalities matching the task's requirements would often be less complex. Several studies in various contexts also found that TTF positively influenced perceived ease of use (Chang et al., 2016), effort expectancy (Kang et al., 2022; Sharif et al., 2019), as well as negatively affected complexity (Deng et al., 2009), and we hypothesized the same.

H3: *Task-technology fit negatively influences the complexity.*

Although we did not find literature that supports the subsequent hypothesis, we argued that TTF could influence the perceived observability of technology in several ways. For example, high TTF technologies typically contribute to more straightforward and more predictable task outcomes. If users could get the same replies when querying the KBC questions or information related to species literacy as they do when asking the experts, it would enhance the observability of the chatbot's impact. Furthermore, the alignment between technology and the task could make the benefits of the technology more visible. When users can see the advantages of using the technology in the context of their task, it might strengthen the perceived observability.

H4: *Task-technology fit positively affects the observability.*

Although trust is a big issue when adopting several technologies, including chatbots, limited studies have investigated the influence of TTF on perceived trust. Lippert and Forman (2006) and Shanshan and Wenfei (2022) investigated the influence of TTF on perceived trust in the context of supply chain and online learning, respectively. Both studies have indicated that TTF benefits perceived trust and our hypothesis is aligned with these findings. In the context of our study, KBC with good TTF could help students complete their homework or exams to minimize the likelihood of errors and mistakes. Users would trust the technology that could help them avoid errors and inaccuracies in their tasks, contributing to higher perceived trust. Furthermore, high TTF often results in predictable and expected outcomes. Users could anticipate how the technology would behave and what results they could achieve, enhancing their trust in its predictability.

H5: *Task-technology fit positively affects the trust.*

Relative advantage refers to the perceived superiority of innovative technology over existing or traditional learning methods, in this case, the KBC. Students would be more likely to use the KBC when they believe it is more effective than conventional learning methods. Furthermore, if the KBC is considered a time-saving and efficient tool for learning about species, students could be likelier to adopt it. When students perceive that using the KBC offers clear benefits regarding species literacy enhancement, they might be more likely to have a positive intention to use it. Several studies found the relative advantage positively influenced the usage intention (Al-Jabri & Sohail, 2012; Deng et al., 2009; Kim et al., 2017; Yuen et al., 2018), and we hypothesized the same.

H6: *Relative advantage positively influences the intention to use.*

Compatibility refers to the degree to which an innovation aligns with the existing values, experiences, and needs of potential users. For example, compatibility with students' preferred learning styles is essential. Furthermore, compatibility with the curriculum and learning materials is crucial in the classroom environment. Multiple studies have indicated that compatibility benefits the intention to use (Al-Jabri & Sohail, 2012; Deng et al., 2009; Kuo & Lee, 2011; Yuen et al., 2018), and our hypothesis was aligned with these findings.

H7: *Compatibility positively affects the intention to use.*

High complexity implies that using the KBC would require significant time to learn how to use it effectively. If students perceive the KBC as too complex, with a steep learning curve or overwhelming information, it might lead to cognitive overload. Furthermore, complex user interfaces, confusing navigation, or unclear instructions could frustrate users. If students believe using the KBC is complex or requires advanced technical skills, they might perceive it as beyond their abilities. It could lead to a lack of confidence and reduced intention to use the KBC. Several studies found that complexity negatively influenced the usage intention (Deng et al., 2009; Sanni et al., 2013), and we hypothesized the same.

H8: *Complexity negatively influences the intention to use.*

Observability refers to the extent to which the outcomes or benefits of an innovation are visible and can be easily observed by potential users. When students can visibly see the positive learning outcomes associated with using the KBC, such as improved species knowledge or greater engagement in species-related topics, they could explain how to use the KBC, describe the process of using the KBC, as well as tell the benefit of using the KBC to others, they would be more likely to have a positive intention to use it. As mentioned in the previous section, Al-Jabri and Sohail (2012) indicated that observability positively influenced the intention to use. Therefore, our hypothesis was aligned with this finding.

H9: *Observability positively affects the intention to use.*

Students who perceive the KBC as reliable and accurate in providing credible species-related information could be likelier to trust it. Furthermore, if students trust the KBC's knowledge more than theirs, they would be more likely to have a positive intention to use it. Several studies found that perceived trust positively influenced usage intention in various contexts (Lippert & Forman, 2006; Shanshan & Wenfei, 2022), and we hypothesized the same. Trust could be a fundamental factor in positively influencing the intention to use the KBC for enhancing students' species literacy.

H10: *Trust positively influences the intention to use.*

METHODOLOGY

The research employed a series of questionnaires as the primary data collection instrument adhered to the research model depicted in Figure 1. The questions were partitioned into two sections. The first section comprised inquiries regarding the participants' demographic information, while in the second section, participants were presented with statements equipped with a five-point Likert scale. This scale ranged from one to five, with one depicting 'strongly disagree,' two representing 'disagree,' three depicting 'neutral,' four representing 'agree,' and five depicting 'strongly agree.' In order to assess the constructs, 21 items presented in Table 1 were selected from existing literature in various education settings and subsequently modified by incorporating insights from case studies.

Table 1. Questionnaire

VAR	ID	Question	Adopted
TTF	ttf1	Chatsicum can replace experts to help me identify a particular Capsicum species based on its morphology.	Sharif et al. (2019)
	ttf2	Chatsicum can replace experts to help me answer inquiries regarding the morphology of various Capsicum species.	
	ttf3	Chatsicum can enhance my species literacy about Capsicum species because it can be accessed anytime and anywhere.	
REL	rel1	Chatsicum offers more advantages than other means of identifying a particular Capsicum species.	Kim et al. (2017)
	rel2	Chatsicum saves me time in acquiring information regarding the morphology of various Capsicum species.	
	rel3	Chatsicum enables me to have ubiquitous access to improving my species literacy compared to asking experts.	
CTB	ctb1	Chatsicum is compatible with all aspects of my study.	Kuo and Lee (2011)
	ctb2	I think that Chatsicum would fit well with how I study.	
	ctb3	Chatsicum would fit into my study style.	
CLX	clx1	I think that Chatsicum would be very difficult to use.	Kim et al. (2017)
	clx2	I think learning to use Chatsicum would be difficult.	
	clx3	Chatsicum would require a lot of effort to use.	
OBS	obs1	I believe I can explain to others how to use Chatsicum.	Sanni et al. (2013)
	obs2	I would have no difficulty telling others the process of using Chatsicum.	
	obs3	I believe I could communicate the benefits of using Chatsicum to others.	
TRU	tru1	I trust Chatsicum to provide me with accurate identification of particular Capsicum species based on their morphology.	Shanshan and Wenfei (2022)
	tru2	Chatsicum provides me with credible information regarding the morphology of various Capsicum species.	
	tru3	I trust the knowledge of Chatsicum more than mine regarding the morphology of various Capsicum species.	

VAR	ID	Question	Adopted
INT	int1	I intend to use Chatsicum in the future.	Kim et al. (2017)
	int2	I plan to use Chatsicum frequently, enabling me to quickly identify Capsicum species based on particular morphology.	
	int3	I will use Chatsicum, which helps me acquire information regarding the morphology of various Capsicum species.	

In addition, an analysis utilizing structural equation modeling (SEM) was conducted to assess the inner model. This analysis aimed to ascertain the degree of correlation between independent and dependent variables within a given model. SEM is a statistical methodology that encompasses several multivariate methodologies. It enables the concurrent examination of a relatively intricate network of interactions. For instance, the model can ascertain a system that operates through a sequence of path flows, whereby each flow represents the connection between two variables.

The collected data was analyzed using SmartPLS 4. While it can now perform covariance-based SEM (CB-SEM), this study utilized the SEM-based partial least squares (PLS) instead. CB-SEM is a statistical technique to evaluate, validate, or contrast different theoretical frameworks. Meanwhile, this research could be classified as exploratory, as it aimed to expand upon an existing structural theory by predicting the fundamental structures that drive the phenomenon under investigation. Therefore, the utilization of a PLS-SEM was deemed appropriate for this study. Furthermore, PLS-SEM has a specific advantage over CB-SEM regarding data distribution. PLS-SEM is more robust than CB-SEM when dealing with small sample sizes and non-normally distributed data. Unlike CB-SEM, PLS-SEM would be more suitable in this study because it does not require the data to follow a multivariate normal distribution. The data analysis phase encompassed the measurement and structural model. The measurement model assessed latent or composite variables, whereas the structural model employed path analysis to examine all hypothetical relationships.

KBC Implementation

Chatsicum, a KBC, was developed specifically for this study. It was designed to identify and explore *Capsicum Sp.* using its KB. The users can query the morphology of a particular Capsicum species to the Chatsicum. The users can also ask the KBC to identify a particular Capsicum species name by providing its morphology. The chatbot was accessible through a web-based platform and was available to participants throughout the data collection period. The user interface of the KBC is shown in Figure 2.

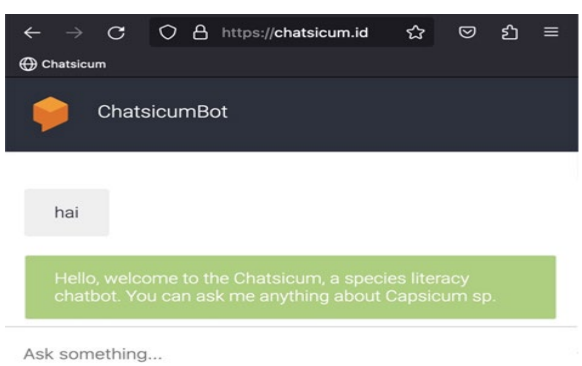

Figure 2. Chatsicum user interface

Sample Size and Data Collection

This study employed purposive sampling to select participants with specific characteristics relevant to the KBC we developed. The sampling population consisted of undergraduate students majoring in botany-related studies at a large university in a metropolitan area. Purposive sampling was chosen to ensure the inclusion of students whose college majors have courses in the plant's study because they must use the KBC to explore *Capsicum Sp.* before responding to the questionnaire. Criteria for participant selection included having experiences using technology or digital devices for studying, varied years of college (aged 18-22), varied backgrounds in biodiversity studies, and varied experiences using chatbots.

The sample size for this study was determined using the apriori approach outlined by Westland (2010). Given the utilization of Structural Equation Modeling (SEM), the necessary sample size can be determined based on several factors. In this case, with seven latent variables, 21 observed items, an anticipated effect size of 0.3 (considered medium), a statistical power level of 0.75, and a probability level of 0.1, the required sample size for detecting effects is 137.

Before collecting the data, we briefly gave the students a tutorial on how to use the KBC. Then, the students had the chance to try to interact with the chatbot. After the trial period, students who voluntarily agreed to participate after being informed about the purpose and objectives of the study gave responses to the questionnaire through a structured online survey. Additionally, participants were assured of the confidentiality and anonymity of their responses to encourage honest and accurate reporting.

Data Analysis

The adequacy of fit criteria in partial least squares (PLS) was evaluated by assessing the outer and inner models during the model measurement analysis phase. Two measurement criteria were utilized to evaluate the outer model in this study. These criteria included validity tests, namely convergent validity, including outer loadings and average variance extracted (AVE), and discriminant validity. The other measurement criteria, which involved examining reliability tests, were also conducted, including composite reliability and Cronbach's alpha.

The validity test is a method used to evaluate the degree of validity exhibited by an instrument. The validity of data collection instruments is determined by their ability to measure the intended variables accurately. Hence, a questionnaire might be deemed legitimate if it is deemed appropriate for assessing the constructs under investigation. The validity test is conducted on the content of an instrument, specifically a questionnaire, to assess its accuracy for use in a research project. The correlation between the indicator and the construct demonstrates convergent validity. An indicator is considered valid if its outer loading value exceeds 0.7 in correlation (Vinzi et al., 2009).

Furthermore, the capacity of the latent variable value to accurately depict the original data score may be assessed by analyzing the Average Variance Extracted (AVE) value, which serves as a measure for evaluating construct validity. There is a positive correlation between proficiency in elucidating the significance of the indicators that assess the underlying variable and the magnitude of the AVE score. The AVE value is used as an indicator of convergent validity, which should be higher than 0.5 since this suggests that the likelihood of an indicator inside a construct influencing another variable is minimal (Hair et al., 2019).

In addition to assessing convergent validity, discriminant validity was employed to evaluate the construct items' validity level. It refers to construct differentiation, the degree to which a particular construct exhibits dissimilarity. It pertains to the lack of a strong correlation between a given construct's indicators and those associated with other constructs. The discriminant validity of the measuring model was evaluated based on cross-loading measurements of constructs using reflecting indicators. The correlation between the construct and the measurement item is assumed to hold greater significance than other constructs' magnitudes. In this particular scenario, the latent construct performs better than other block sizes in predicting block size. According to Hair et al. (2019), each indicator's cross-loading value on a variable inside the construct must exceed 0.7 to establish discriminant validity.

The Fornell-Larcker criterion assessed discriminant validity (Fornell & Larcker, 1981). It involved comparing the correlation coefficient between each construct and other constructs to the square root of the AVE for each construct, hence evaluating the latent variable correlation. If the AVE for each construct exceeds the correlation between the constructs and other constructs, it can be concluded that the model possesses adequate discriminant validity. Following the Fornell-Larcker criterion, it is necessary for each indicator inside a construct to possess a value greater than 0.7 to establish discriminant validity, akin to the concept of cross-loading.

However, it is essential to note that the Fornell-Larcker discriminant validity test has been criticized by Henseler et al. (2014). As a result, an alternative test known as the heterotrait monotrait ratio of correlations (HTMT) test was conducted. An HTMT score below 0.85 indicates the presence of discriminant validity between two reflective notions. Nevertheless, the HTMT value slightly above 0.85 does not necessarily invalidate discriminant validity. It should prompt further scrutiny and exploration of the model's structure and relationships among constructs. As Franke and Sarstedt (2019) suggested, a slightly less conservative threshold, 0.90, was used in this study. When the HTMT value exceeds the conventional threshold of 0.85, indicating potential overlap between constructs, several circumstances, such as theoretical justification or contextual factors, may justify the discriminant validity between constructs despite the higher value. It is essential to consider multiple pieces of evidence, such as the pattern of loadings, cross-loadings, and correlations among constructs, alongside measures like the AVE, to make a comprehensive evaluation when assessing discriminant validity, rather than relying solely on one criterion, such as HTMT.

The reliability test assesses the degree of soundness exhibited by a variable or indicator of a construct. For example, when a participant repeatedly provides the same response to a statement on a survey, it is likely indicative of reliability. Cronbach's alpha is a statistical metric used to assess the internal consistency of a set of items, indicating the degree of interrelatedness among them. The metric is considered to be a measure of scale dependability. Meanwhile, composite reliability, often called construct reliability, is a metric akin to Cronbach's alpha that assesses the internal consistency of scale components. The AVE coefficient quantifies the extent to which shared causes can account for the variance in indicators. Hair et al. (2019) suggest that variables and indicators are dependable when CR and Cronbach's alpha coefficient values are above 0.7.

It was necessary to conduct a collinearity test because many dependent and independent variables were included in the study model per the guidelines provided by Hair et al. (2019). Collinearity refers to the condition that two variables exhibit a nearly perfect linear relationship to be expressed as almost identical linear combinations. The Variance Inflation Factors (VIF) are utilized to quantify the inflationary effect on the parameter estimates of variances due to collinearities among predictors. A VIF value of 1 suggests no association between a predictor variable and the other predictor variables. VIFs over a value of 4 warrant further investigation, while VIFs beyond 10 indicate a significant multicollinearity that necessitates appropriate remedial measures.

Cross-sectional studies are susceptible to common method bias (CMB). The term "bias" describes a potential source of error in the data, which can lead to common method variance and an exaggerated association between variables. The potential origin of this phenomenon may extend beyond the measurements themselves. It could be attributed to self-reported bias when data is gathered from a single source or when both predictors and dependent variables are measured using a shared scale. Therefore, verifying the absence of CMB in the data is imperative. Kock (2015) suggests that a VIF value should be less than 3.3, indicating the absence of CMB.

Furthermore, the normality test was conducted to examine the distributional properties of variables. In this study, Shapiro-Wilk and Kolmogorov-Smirnov tests were performed. The Shapiro-Wilk test is a widely used normality test that assesses whether a dataset comes from a normally distributed population. It calculates a test statistic based on the differences between observed and expected values under the null hypothesis of normality. A significant *p*-value indicates rejection of the null hypothesis, suggesting that the data do not follow a normal distribution. The Kolmogorov-Smirnov test compares the data's empirical cumulative distribution function (ECDF) to the cumulative distribution function (CDF) of a normal distribution. The test statistic is based on the maximum absolute difference between the two distributions. Like the Shapiro-Wilk test, a significant *p*-value indicates a departure from normality.

The association between the independent and dependent variables was investigated using the bootstrapping procedure, which generated 5,000 sub-samples. Examining the strength of the hypothesized correlations among the constructs involved an evaluation of the standardized path coefficients and their associated significance levels, as indicated by *t*-statistic or *p*-value. According to Hair et al. (2019), when testing hypothesized relationships, an empirical *t*-statistic value surpasses the threshold of 2.57, resulting in a *p*-value below the significant level of 0.01 or 1%. Accordingly, a *t*-statistic value greater than 1.96 indicates a *p*-value below the significant level of 0.05 or 5%. A lower *p*-value or a higher *t*-statistic value indicates a more substantial significance level in the association between the two variables.

This study also assessed R^2 and f^2 as significant model fit indicators. The coefficient of determination, denoted as R^2, quantifies the proportion of variance in the endogenous variable that can be accounted for by the exogenous variable(s). According to Chin (1998), it is suggested that R^2 values for endogenous latent variables can be categorized as considerable (0.67), moderate (0.33), and weak (0.19). In a multiple regression model with continuous dependent and independent variables, the measurement of f^2 is utilized to evaluate effect magnitude. As stated by Cohen (1988), an effect size of f^2 greater than or equal to 0.02 is classified as small, an effect size of f^2 greater than or equal to 0.15 is deemed medium, and an effect size of f^2 greater than or equal to 0.35 is categorized as high.

RESULTS

Table 2 presents the demographic characteristics of the respondents. The respondents were 145 Biology students of Syarif Hidayatullah State Islamic University (UIN) in Jakarta, the capital city of Indonesia. According to the UIN Jakarta website, based on data from 19 October 2023, the number of students was around 35,000, and 300 were Biology students. At first, all Biology students were introduced to a brief presentation regarding *Capsicum Sp.* and a short tutorial on how to use Chatsicum. Then, the students were provided direct practical experience in the operation or functioning of Chatsicum, including a quiz game to guide them hands-on. At the end of the trial period, the questionnaires were given to all students, and 145 completed the survey voluntarily. The period of these processes was between October 23 and 31, 2023. The data collected from respondents indicated a predominance of female participants. The sample population for this study comprised 124 female respondents, accounting for 86% of the total, and 21 males, representing 14% of the respondents. Moreover, 84% of the participants often used technology or digital devices for learning, and an almost equal proportion of respondents indicated previous experience using chatbots.

Table 2. Demographics of respondents

Characteristics	Value	Percentage
Gender	Male Female	14.48% 85.52%
Age	18 19	4.83% 35.86%

Characteristics	Value	Percentage
	20 21 >21	27.59% 25.52% 6.21%
Frequency of using technology or digital devices for learning	Rarely Occasionally Often Always	3.45% 2.07% 57.24% 37.24%
Ever used chatbots before	Yes Never	85.52% 14.48%

Measurement Model

Table 3 displays the measurement results of convergent validity, specifically the outer loadings and average variance extracted (AVE). Based on the criterion for validity, it was established that all indicators and variables were deemed legitimate, as indicated by outer loading values exceeding the predetermined threshold of 0.7 and AVE values surpassing 0.5.

Table 3. Outer loadings and AVE

Relations	Outer loadings	Construct	AVE
ttf1←TTF ttf2←TTF ttf3←TTF	0.827 0.787 0.805	TTF	0.651
rel1←REL rel2←REL rel3←REL	0.827 0.883 0.842	REL	0.724
ctb1←CTB ctb2←CTB ctb3←CTB	0.737 0.947 0.935	CTB	0.771
clx1←CLX clx1←CLX clx1←CLX	0.894 0.929 0.885	CLX	0.815
obs1←OBS obs2←OBS obs3←OBS	0.905 0.923 0.946	OBS	0.855
tru1←TRU tru2←TRU tru3←TRU	0.858 0.890 0.806	TRU	0.727
int1←INT int2←INT int3←INT	0.922 0.925 0.908	INT	0.843

Furthermore, the corresponding results of the discriminant validity analysis using cross-loading, Fornell-Larcker, and HTMT tests are displayed in Tables 4, 5, and 6, respectively. It is worth noting that the highest value in each row is highlighted in bold font. According to the data shown in Table 4, it can be observed that the highest values for each variable item were above the predetermined threshold of 0.7. Additionally, the item correlation exhibited a greater value than its correlation with other items. Like the cross-loading test, as depicted in Table 5, all variable items exhibited Fornell-Larcker values above 0.7, and the item correlation was greater than its correlation with others. Moreover, it is evident from the data shown in Table 6 that all HTMT values observed were below the predefined threshold of 0.9. Hence, all variables were deemed valid as the measurement findings satisfied the criteria for discriminant validity.

Table 4. Cross loadings

	TTF	REL	CTB	CLX	OBS	TRU	INT
ttf1	**0.827**	0.510	0.415	-0.219	0.267	0.502	0.437
ttf2	**0.787**	0.527	0.447	-0.130	0.317	0.519	0.472
ttf3	**0.805**	0.653	0.503	-0.203	0.619	0.542	0.494
rel1	0.678	**0.827**	0.592	-0.342	0.455	0.503	0.482
rel2	0.539	**0.883**	0.587	-0.201	0.577	0.480	0.545
rel3	0.584	**0.842**	0.496	-0.177	0.589	0.516	0.543
ctb1	0.365	0.424	**0.737**	-0.216	0.276	0.326	0.451
ctb2	0.584	0.684	**0.947**	-0.279	0.551	0.540	0.624
ctb3	0.525	0.593	**0.935**	-0.266	0.578	0.545	0.652
clx1	-0.203	-0.311	-0.297	**0.894**	-0.271	-0.260	-0.274
clx2	-0.243	-0.251	-0.245	**0.929**	-0.238	-0.308	-0.204
clx3	-0.175	-0.204	-0.242	**0.885**	-0.228	-0.313	-0.254
obs1	0.463	0.584	0.474	-0.250	**0.905**	0.535	0.564
obs2	0.439	0.586	0.497	-0.221	**0.923**	0.643	0.585
obs3	0.539	0.590	0.555	-0.283	**0.946**	0.696	0.646
tru1	0.518	0.508	0.446	-0.261	0.655	**0.858**	0.613
tru2	0.557	0.513	0.520	-0.256	0.613	**0.890**	0.659
tru3	0.583	0.482	0.432	-0.312	0.468	**0.806**	0.594
int1	0.533	0.594	0.633	-0.263	0.604	0.685	**0.922**
int2	0.538	0.515	0.591	-0.195	0.554	0.646	**0.925**
int3	0.535	0.581	0.603	-0.286	0.626	0.680	**0.908**

Table 5. Fornell-Larcker test results

	TTF	REL	CTB	CLX	OBS	TRU	INT
TTF	**0.807**						
REL	0.709	**0.851**					
CTB	0.570	0.657	**0.878**				

	TTF	REL	CTB	CLX	OBS	TRU	INT
CLX	-0.230	-0.285	-0.291	**0.903**			
OBS	0.522	0.634	0.552	-0.273	**0.925**		
TRU	0.649	0.588	0.548	-0.324	0.679	**0.852**	
INT	0.583	0.614	0.664	-0.271	0.649	0.731	**0.918**

Table 6. HTMT results

	TTF	REL	CTB	CLX	OBS	TRU
REL	**0.899**					
CTB	0.702	**0.781**				
CLX	0.282	0.331	**0.333**			
OBS	0.601	**0.739**	0.605	0.300		
TRU	**0.834**	0.725	0.647	0.384	0.785	
INT	0.708	0.716	0.749	0.300	0.709	**0.851**

Table 7 presents the findings of reliability tests, including Cronbach's alpha and composite reliability. From these findings, it can be concluded that all variables demonstrated a satisfactory level of reliability, as indicated by their values surpassing the predetermined threshold of 0.7. Additionally, the results of the collinearity test are presented in Table 8. All Variance Inflation Factor (VIF) values were below 3.3, indicating a minimal association level between each variable and the absence of Common Method Bias (CMB). Meanwhile, Table 9 presents the results of normality tests. All *p*-values according to the Shapiro-Wilk and Kolmogorov-Smirnov tests are lower than 0.001, indicating the rejection of the null hypothesis. The results suggest that all variables in the data did not follow a normal distribution.

Table 7. Reliability measures

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)
TTF	0.735	0.743	0.848
REL	0.809	0.908	0.887
CTB	0.848	0.891	0.909
CLX	0.887	0.889	0.930
OBS	0.915	0.923	0.947
TRU	0.811	0.812	0.888
INT	0.907	0.908	0.942

Table 8. VIF results

	REL	CTB	CLX	OBS	TRU	INT
TTF	1.000	1.000	1.000	1.000	1.000	
REL						2.234
CTB						1.940
CLX						1.145
OBS						2.231
TRU						2.120

Table 9. Normality tests

	Shapiro-Wilk		Kolmogorov-Smirnov	
	Statistic	Sig.	Statistic	Sig.
ttf1	0.890	<0.001	0.228	<0.001
ttf2	0.874	<0.001	0.258	<0.001
ttf3	0.822	<0.001	0.242	<0.001
rel1	0.857	<0.001	0.238	<0.001
rel2	0.837	<0.001	0.251	<0.001
rel3	0.841	<0.001	0.269	<0.001
ctb1	0.890	<0.001	0.214	<0.001
ctb2	0.863	<0.001	0.227	<0.001
ctb3	0.863	<0.001	0.219	<0.001
clx1	0.899	<0.001	0.166	<0.001
clx2	0.881	<0.001	0.181	<0.001
clx3	0.905	<0.001	0.180	<0.001
obs1	0.814	<0.001	0.245	<0.001
obs2	0.823	<0.001	0.240	<0.001
obs3	0.816	<0.001	0.247	<0.001
tru1	0.848	<0.001	0.256	<0.001
tru2	0.833	<0.001	0.268	<0.001
tru3	0.879	<0.001	0.214	<0.001
int1	0.834	<0.001	0.251	<0.001
int2	0.835	<0.001	0.212	<0.001
int3	0.834	<0.001	0.239	<0.001

Structural Model

The results of the structural model analysis are shown in Figure 3, and the hypothesis test results are presented in Table 10. Of the total ten hypotheses tested, seven were accepted since the relationships between two variables in the hypothesis showed a significant correlation where the *t*-statistic values were higher than 2.57, and the other three were rejected because the *p*-values were higher than the predetermined level of 0.05. Furthermore, the specific indirect effects are presented in Table 11, and values of f^2 are shown in Table 12. The effect estimations were in line with path analysis results.

TTF was found to determine all other variables, positively influencing relative advantage (β=0.709, p<0.001, f^2=1.010), compatibility (β=0.570, p<0.001, f^2=0.481), observability (β=0.522, p<0.001, f^2=0.375), trust (β=0.649, p<0.001, f^2=0727), and negatively affected complexity (β=-0.230, p=0.009, f^2=0.056). TTF also accounted for 49.9%, 32.0%, 4.6%, 26.7%, and 41.7% of the variance in relative advantage, compatibility, complexity, observability, and trust, respectively. The TTF's indirect effect on usage intention through relative advantage, compatibility, complexity, observability, and trust were 0.053, 0.173, -0.004, 0.079, and 0.274, respectively. Conclusively, TTF significantly influenced the intention to use indirectly (β=0.576, p<0.001).

Nevertheless, the relative advantage, complexity, and observability insignificantly influenced the usage intention, where *p*-values yielded 0.419, 0.748, and 0.085, respectively. Meanwhile, compatibility strongly affected the intention to use (β=0.304, p<0.001, f^2=0.137). Furthermore, trust strongly affected the intention to use (β=0.423, p<0.001, f^2=0.241). Lastly, the determinants explained 63.8% of the usage intention variance.

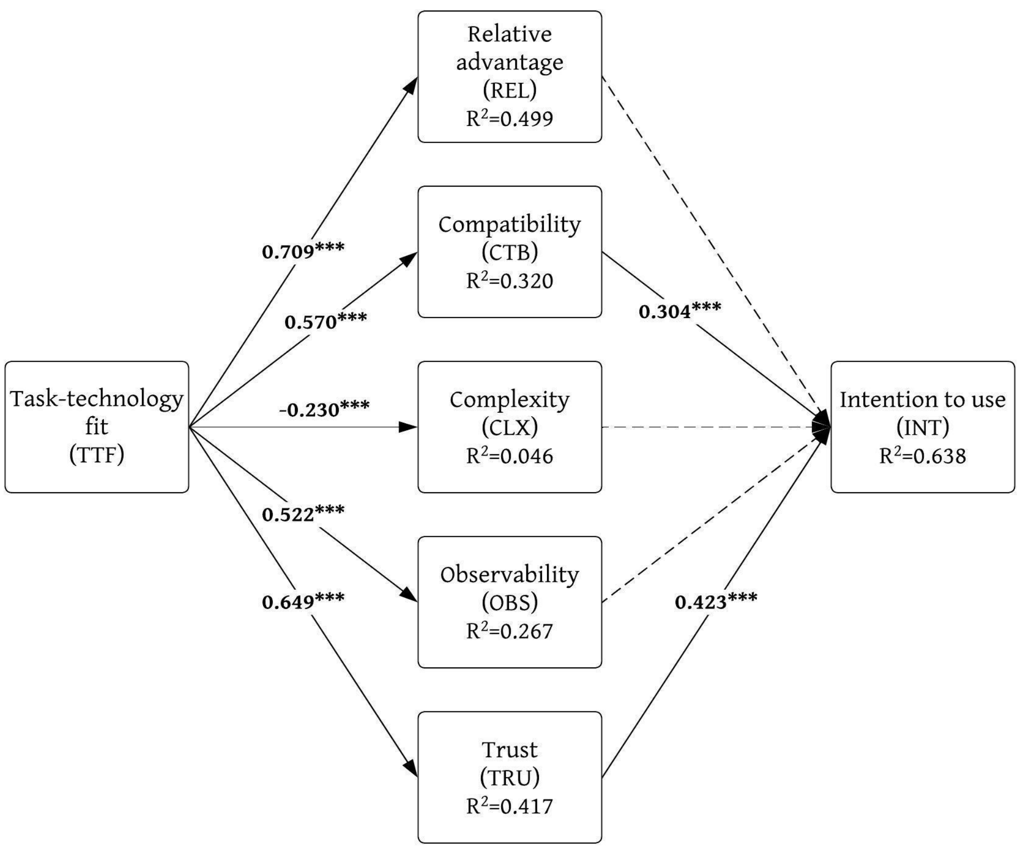

Figure 3. Hypotheses paths analysis

Table 10. Hypotheses testing results

Hypothesis	Relation	Path coefficient (β)	*t*-Statistics	*p*-Values	Results
H 1	TTF→REL	***0.709	17.205	<0.001	Supported
H 2	TTF→CTB	***0.570	9.464	<0.001	Supported
H 3	TTF→CLX	***-0.230	2.617	0.009	Supported
H 4	TTF→OBS	***0.522	8.986	<0.001	Supported
H 5	TTF→TRU	***0.649	11.726	<0.001	Supported
H 6	REL→INT	0.075	0.808	0.419	Not supported
H 7	CTB→INT	***0.304	3.906	<0.001	Supported
H 8	CLX→INT	0.016	0.322	0.748	Not supported
H 9	OBS→INT	0.151	1.745	0.081	Not supported
H 10	TRU→INT	***0.432	4.223	<0.001	Supported

Notes: ***Significant at 1% level, $p<0.01$; *Significant at 5% level, $p<0.05$

Table 11. Specific indirect effects

Relation	Path coefficient (β)	*T*-Statistics	*P*-Values	Results
TTF→REL→INT	0.053	0.805	0.421	Not supported
TTF→CTB→INT	***0.173	3.548	<0.001	Supported
TTF→CLX→INT	-0.004	0.284	0.776	Not supported
TTF→OBS→INT	0.079	1.724	0.085	Not supported
TTF→TRU→INT	***0.274	3.880	<0.001	Supported

Notes: ***Significant at 1% level, $p<0.01$; *Significant at 5% level, $p<0.05$

Table 12. f^2 results

	REL	CTB	CLX	OBS	TRU	INT
TTF	1.010	0.481	0.056	0.375	0.727	
REL						0.007
CTB						0.137
CLX						0.001

	REL	CTB	CLX	OBS	TRU	INT
OBS						0.029
TRU						0.241

DISCUSSION

Technologies that align well with users' needs and tasks tend to be perceived more favorably regarding relative advantage, compatibility, observability, and trust. These perceptions collectively contribute to users' intention to adopt and use the technology. Task-technology fit (TTF) was the most vital determinant for students to adopt KBC in enhancing their species literacy, followed by trust and compatibility. This finding suggests that TTF is pivotal in shaping users' perceptions and intentions regarding adopting and using the KBC.

The positive influence of TTF on the relative advantage could be explained by a high level of TTF experienced by the participants, leading to perceived advantages over alternative methods. This result corroborates with Kuo and Lee's (2011). The capability of the KBC to replace subject matter experts might meet the participants' needs better than if the experts were asked directly. Nevertheless, the relative advantage did not determine whether students use KBC. Although surprising and not aligned with most studies, the finding is in line with Sanni et al. (2013) and Wu and Wu (2005). Furthermore, this result also aligns with several TAM and UTAUT studies where the perceived usefulness and performance expectancy have not always affected the intention to use (Ong et al., 2022; Sharif et al., 2019). One plausible reason could be the measurement timing. The data was collected before participants could fully engage with the KBC. Therefore, their perception of relative advantage might not be well-formed, affecting the relationship with intention to use. Moreover, users might prefer alternative technology options for species literacy enhancement despite the fact that the proposed technology fits the tasks.

The TTF influenced compatibility positively, and the compatibility affected the intention of use significantly, which aligns with several studies (Al-Jabri & Sohail, 2012; Deng et al., 2009; Kuo & Lee, 2011; Yuen et al., 2018). Based on the data collected in this study, it could be deduced that the participants were digital natives, where more than 84% of the participants used technology or digital devices for their learning routines. Therefore, participants might find that the KBC fits well with their existing working methods and technology interaction, making them less confused. Moreover, the participants have used chatbots before. They might find the KBC compatible with their existing systems, tools, and processes, resulting in less effort required to incorporate it into their workflows. The reduced perceived effort would make users more inclined to adopt and use the KBC as it aligns seamlessly with their current practices.

The negative effect of TTF on the complexity could be elucidated by a high level of TTF experienced by the participants, contributing to a KBC that might be easy-to-use, intuitive, and less complex. This result is in line with Deng et al. (2009). Nevertheless, it should be noted that TTF reduced perceived complexity but only contributed 5% of the complexity's variance. Most of the variance remains unexplained, and some likely other factors or variables might contribute to the complexity experienced by users. For example, in several TAM studies, social interaction, enjoyment, and usability positively influenced perceived ease of use (Manik et al., 2023; Wilis & Manik, 2022). Future studies could investigate whether these factors influence complexity since perceived ease of use and complexity are interchangeable terms (Hernandez & Mazzon, 2007; Mandari & Chong, 2018).

Moreover, the complexity was not a determinant for students adopting a KBC. Although surprising, this result aligns with several studies (Al-Jabri & Sohail, 2012; Kim et al., 2017; Yuen et al., 2018).

Like our argument on the reason for the positive influence of TTF on compatibility, the demographics of respondents could also be a plausible reason for this negative result. The particular demographic attribute implies that these participants are more likely to exhibit a greater inclination toward utilizing KBC with relative proficiency. Therefore, one might argue that the perceived level of complexity did not significantly impact students' decision-making process when it came to either accepting or rejecting the use of KBC. As a result of their increased exposure to emerging innovations, young folks have acquired a more extensive array of experiences with various technologies. Consequently, they have developed a strong foundation of knowledge that enables them to utilize and engage with the KBC effectively. Another possible reason could be that participants might not have had sufficient exposure to the KBC to evaluate its complexity accurately. Familiarity with the technology and its features could influence users' perceptions of the complexity.

The positive influence of TTF on observability could be justified by direct benefits and outcomes that participants might obtain from the KBC. However, the observability did not significantly affect the intention to use. Although this result does not align with Al-Jabri and Sohail (2012), it corroborates with Sanni et al. (2013) and Yuen et al. (2018). Users might acknowledge the benefits without feeling strongly motivated to use the technology.

Furthermore, the influences of TTF on trust and trust on intention to use are expected and in line with several studies (Lippert & Forman, 2006; Shanshan & Wenfei, 2022). The different characteristics of KBC and other types of generative chatbots powered by large language models (LLM), like ChatGPT, rely on the knowledge behind them. ChatGPT and its variants generate human-like text responses by learning from vast text data, enabling them to respond to various topics. Some studies reported a need for more trust in chatbots because sometimes they generate hallucinated responses (Alkaissi & McFarlane, 2023; Ji et al., 2023). Meanwhile, KBCs rely on predefined knowledge bases, excelling in providing accurate responses within their predefined domain or subject matter. Therefore, the KBC characteristics in our study might explain why the participants strongly trusted the Chatsicum because it performed as expected and provided accurate and reliable information. It could reduce the perceived risk of errors or negative consequences, encouraging users to use the KBC.

However, it should be noted that the analysis results were performed on non-normally distributed data. There are implications for this issue to consider. PLS-SEM aims to estimate the parameters of a structural model by maximizing the explained variance in the dependent variables. Non-normally distributed data can affect the accuracy of parameter estimates, potentially leading to biased estimates of path coefficients and latent variable correlations. This issue can compromise the validity of the structural model and the interpretations of relationships between constructs. Nevertheless, PLS-SEM was still a better choice than CB-SEM in this regard because PLS-SEM is more robust than CB-SEM when dealing with datasets with small sample sizes that do not follow a multivariate normal distribution.

IMPLICATIONS

The findings of this research hold several critical theoretical implications for the fields of biodiversity education, technology adoption, and the intersection of the two.

THEORETICAL IMPLICATIONS

By integrating TTF, DOI, and trust constructs into the investigation of Chatsicum's adoption, this study contributes to a deeper theoretical understanding of how innovative technological solutions are adopted in biodiversity education, particularly in the context of species literacy. We identified that other than trust, TTF and compatibility were the key determinants influencing students' intentions to use KBC in improving their species knowledge. Researchers could delve deeper into the significant factors of these determinants, investigate the nuances, mechanisms, and specific aspects that might influence these factors in driving usage intention, and explore why TTF, compatibility, and trust were enormously significant in influencing intention to use while relative advantage, complexity, and observability were not. For example, researchers could explore whether specific user segments or contextual factors influence these relationships.

One of the results of this study that found relative advantage insignificantly affected the intention to use suggests a need for deeper investigation. For example, researchers could compare KBC with alternative technology or educational methods to understand the relative advantages and disadvantages. Moreover, factors mediating relative advantage's effect on the usage intention would be worth investigating. For instance, Wu and Wu (2005) found that relative advantage influenced the intention to use indirectly through an attitude variable, which implied that users would need some time to digest the advantages of the KBC that lead to usage intention. Furthermore, the insignificance of complexity affecting the intention to use is noteworthy because we thought the KBC was already simple enough. Researchers should examine whether simplifying the technology further or providing more training and support could change this relationship. Understanding the reasons for these insignificances would guide design improvements.

Since TTF was found to influence the intention to use through several DOI variables indirectly, it would be essential to explore the specific mediating mechanisms through which TTF affects these variables. It could involve conducting mediation analyses to understand the sequential relationships between these factors. Moreover, observability did not influence the intention to use positively, but TTF affected observability, which was a promising finding. Research can further explore enhancing observability and its relationship with KBC's alignment regarding species literacy-related tasks to maximize its impact on user intentions. It may involve designing features that make the benefits more visible and quantifiable.

Furthermore, the strong influence of compatibility on the intention to use underscores its importance. Researchers could investigate strategies to enhance the compatibility. Finally, this study integrated trust as an essential variable in technology adoption. It highlights its significance in shaping user intentions, shedding light on the multifaceted nature of trust in educational technology. Researchers could investigate methods to improve trust-building elements within technology.

Practical Implications

The practical implications of this research offer actionable insights for developers, educators, conservationists, and policymakers seeking to leverage the KBC to enhance biodiversity literacy. Given the indirect solid influence of TTF on usage intention, developers of educational chatbots should prioritize designing and implementing chatbots that align closely with the tasks, needs, and goals of the target users. Maximizing TTF could involve user-centric design, customization, and usability testing. Furthermore, building and maintaining trust would be essential for the developers, considering the significant direct impact of trust on users' intention to use. Ensuring the accuracy of information could enhance perceived trustworthiness and credibility, thereby increasing the adoption and effectiveness of such tools.

Educators could also benefit from understanding the factors influencing individuals' intentions to use educational chatbots. This knowledge could inform the development of tailored educational interventions that resonate with the values and preferences of diverse learners, ultimately improving species literacy outcomes. KBC might be aligned closely with the student's learning needs, preferences, and curriculum, ensuring seamless integration with the existing educational context. Highlighting the KBC's compatibility with the academic environment and integrating seamlessly with users' current processes and technologies would promote its use, given the solid direct influence of compatibility on usage intention.

CONCLUSION

In an age characterized by unprecedented challenges to biodiversity conservation, knowledge dissemination and awareness-building are pivotal. This research has delved into integrating KBC as an innovative educational technology to enhance species literacy among biodiversity students. By exploring the interaction between TTF, DOI, and trust, this study has offered valuable insights into the factors influencing the adoption and use of the chatbot.

Central to our findings is the pivotal role of Task-Technology Fit (TTF) in driving users' perceptions and intentions regarding adopting and using chatbots. TTF emerged as a powerful determinant, positively influencing users' attitudes towards chatbots and facilitating their acceptance as practical educational tools. The robust positive effects of TTF on various dimensions of the Diffusion of Innovation (DOI) framework underscore its multifaceted impact on technology adoption processes. Furthermore, the intention to use was significantly influenced by trust and compatibility, highlighting its critical role in fostering users' confidence in chatbots and the need for seamless integration. The practical implications of our findings are twofold. Firstly, our results emphasize the need to ensure that chatbots are well-aligned with users' tasks and need to enhance their acceptance and effectiveness as educational tools. Secondly, understanding the nuanced relationship between TTF and DOI variables can inform the design and implementation of chatbot-mediated educational interventions to promote biodiversity conservation efforts effectively.

STUDY LIMITATIONS

While this research offers valuable insights into the factors influencing the intention to use KBC for enhancing species literacy, it is important to acknowledge several limitations that may have affected the findings and should be addressed in future studies. First, this study employed a cross-sectional design, capturing data at a single point in time. Longitudinal studies provide a more comprehensive understanding of the adoption and usage patterns of Chatsicum over time. Moreover, the study's findings were based on the current state of Chatsicum and its features. The findings might become less relevant to future chatbot versions or similar technologies as technology evolves rapidly. Furthermore, the relatively small sample size, with students from only one university, could prevent the generalizability of this study.

FUTURE WORKS

This study opens up several avenues for future research in biodiversity education, technology adoption, and the role of chatbots like Chatsicum. Conducting longitudinal studies to track the usage patterns of Chatsicum over time would provide valuable insights into how adoption intentions translate into real-world behavior, especially regarding task-technology fit, compatibility, and trust. It could reveal such technological innovations' sustainability and long-term impact on species literacy. Moreover, future works will also consider experiments to influence non-significant factors. For example, implementing interventions to improve relative advantage, complexity, and observability, as well as assessing their impact on intention to use, would be worth investigating.

A larger sample size, preferably systematically randomized, would be needed to generate generalizable results with more statistical power in future studies. Furthermore, comparative studies could investigate other educational chatbots to check whether the same results would be acquired. Finally, exploring the relationship between species literacy, as enhanced by chatbots, and actual conservation behaviors might be a critical area for future research. It could involve assessing whether increased knowledge translates into tangible actions that support biodiversity conservation.

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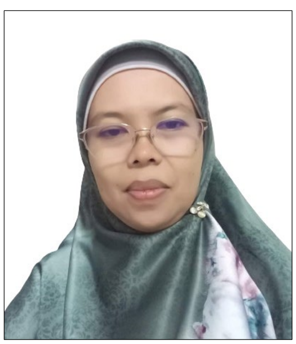

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