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Abstract

Purpose: The purpose of the study was to examine the influence of behavioural intention (BI) predictors on the intention to use artificial intelligence (AI) technology, PictureThis, for plant identification by undergraduate students in public universities in Uganda.

Materials and Method: The study was carried out using a correlational, cross-sectional survey method based on a research instrument developed from the extended unified theory of acceptance and use of technology (UTAUT2).

Findings: The findings of the study show that five BI predictors namely, performance expectancy ($\beta = 0.278$, $p = 0.000 < 0.05$), effort expectancy ($\beta = 0.118$, $p = 0.006 < 0.05$), social influence ($\beta = 0.104$, $p = 0.009 < 0.05$), hedonic motivation ($\beta = 0.292$, $p = 0.000 < 0.05$) and habit ($\beta = 0.106$, $p = 0.011 < 0.05$) positively and significantly influence intention to use PictureThis AI by undergraduate students in Uganda's public universities.

Unique Contribution to Theory, Practice and Policy: The study was informed by UTAUT2 which posits that use behaviour of technology is influenced by behavioural intention, coupled with habit and facilitating conditions. To the university management, we suggest that appropriate facilities should be put in their institutions to enhance AI's contribution to performance expectancy, effort expectancy, hedonic motivation, social influence and price value in order to improve students' behavioural intention and ultimately use behaviour of AI technology for better learning experiences and improved learning outcomes. To the student community pursuing biological and agricultural sciences, we recommend the adoption of PictureThis AI as a learning tool for use during plant identification.

Keywords: *Predictors, Behavioural intention PictureThis AI, Plant identification, UTAUT2*

JEL Codes of Classification: *03 (Innovation; Research and Development; Technological Change; Intellectual Property Rights), 121 (Analysis of Education), 123 (Higher Education and Research Institutions).*

1.0 INTRODUCTION

Many enthusiasts in botanical studies face a major challenge of inadequate expertise to identify plant species encountered in the field (Abengmeneng et al., 2023). Incorrect naming and identification failures of organisms characterize the inexperienced botany and agriculture students' engagement with plant identification (Treibergs et al., 2023). Traditionally, plant identification follows a process that employs conventional tools such as field guides and identification keys that are perceived by users to be labour-intensive, lengthy and time consuming (Malik et al., 2022). Researchers and students involved in field botany work (in National Parks, forest reserves, botanical gardens, etc.) are interested in using more convenient methods which provide quick and correct plant identities so that the rest of their time is devoted to the broader goals of their studies (Canuto, 2023; Keivani et al., 2020). Technical assistance to learn faster plant identification techniques is, however, frustrated by inadequate taxonomic expertise and the lengthy processes involved in traditional methods (Malik et al., 2022; Rouhan & Gaudeul, 2021). Thus, many students desist from majoring in botanical studies in general, and plant taxonomy/identification in particular, due to the perception of the field of study being difficult and complex (Uno, 2009). The need for more efficient and convenient approaches to the identification of plants therefore remains paramount in botanical studies.

While there is increased ownership of smartphones and other digital devices (Atas & Çelik, 2019) and emerging artificial intelligence (AI) technology apps for leveraging to learn quick plant identification processes (Hill, 2024; Malik et al., 2022; Schmidt et al., 2023), there is still limited knowledge of the behavioural aspects of AI adoption in educational contexts in low-resource countries such as Uganda. Artificial intelligence (AI) apps exist in varying types and performance levels which results in varying behavioural aspects of their adoption among the users. Most of these apps such as Flora Incognita, PlantNet, PlantSnap, PictureThis, LeafSnap, Seek, PlantNet, Google Lens and many others operate with good internet connectivity (Bilyk et al., 2020; Canuto, 2023), resulting in differences in affordability, usability, ease of use and similar beliefs and attitudes.

Many studies on the adoption of AI plant ID apps (such as, Bawingan et al., 2024; Canuto, 2023; Hart et al., 2023) have focused more on comparative evaluation of their performance and student experiences of using them rather than behavioural aspects of AI adoption in educational contexts. For example, Bawingan et al. (2024) studied the use of four plant identification mobile apps namely, LeafSnap, PictureThis, PlantNet, and PlantSnap; and found that students perceived the use of mobile apps as interesting, enjoyable, and very useful, and that their use could add to knowledge of plants and connection with nature. The study did not address the behavioural aspects such as students' intention to use the apps for plant identification.

Canuto (2023) explored users perceptions of using three plant identification apps namely, PlantNet, PictureThis, and LeafSnap, as potential educational tools; and found that participants strongly perceived the apps as engaging, helpful in plant identification, easy to browse, providing details, effective as emerging tools, and significant for scientific literacy, except for consistency of results. Hart et al. (2023) tested the accuracy and correctness of five popular and free identification applications for plants and established that a large proportion of images were identified correctly in the top five suggestions, and many of them were correct with the first suggestion. The apps performed well, with at least one of the three best- performing apps identifying 96% of images correctly as their first suggestion. Hill (2024) evaluated the identification accuracy of fourteen online AI-based plant ID apps for six consecutive years (2018 – 2023), and found out that PictureThis AI was consistently very accurate in identifying plants for all the years of study.

Relatedly, some technology adoption studies (such as, Barbosa et al., 2021; Frank & Milković, 2018; García de Blanes et al., 2024; Gupta & Dogra, 2017; Khurana & Jain, 2019) have focused on behavioral aspects of adoption of non-AI-based apps in non-educational contexts in developed countries. For example, Barbosa et al. (2021) identified six factors with a positive impact on BI to use analysed the intention to use fitness apps in Portugal. These were performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation and habit. Frank and Milković (2018) identified two main factors namely, user's habit and users' perception of the electronic guide as a source of high-quality information as the motivators of intention to use the electronic programme guide (EPG) service in the Republic of Croatia. García de Blanes et al. (2024) showed that performance expectancy and word-of-mouth influenced the adoption of digital travel and restaurant platforms (TRPs) for reservation of travel and leisure services. Gupta and Dogra (2017) indicated that habit, facilitating conditions, performance expectancy and hedonic motivation were the most significant antecedents of BI to use mapping apps by tourists travelling in India. Effort expectancy, social influence and price value had no significant effects on the tourist's intentions to use the apps. Khurana and Jain (2019) found that except effort expectancy and social influence; performance expectancy, facilitating conditions, hedonic motivation, habit and price value significantly influenced BI to use m-shopping fashion apps in Delhi, National Capital Region (NCR) in India.

The studies above demonstrate that behavioural aspects of AI technology adoption (such as behavioural intention) in low-resource countries such as Uganda particularly focusing on the use AI plant identification apps like PictureThis in educational settings, are not yet fully understood. Thus, the current study examined the predictors of BI to use PictureThis AI which is currently regarded as the top-performing and most accurate AI plant ID app (Hill, 2024; Schmidt et al., 2023). The study was guided by seven specific objectives namely; to examine the effect of performance expectancy on BI to use PictureThis AI for plant identification, to examine the effect of effort expectancy on BI to use PictureThis AI, to examine the effect of social influence on BI to use PictureThis AI, to examine the effect of facilitating conditions on BI to use PictureThis AI, to examine the effect of hedonic motivation on BI to use PictureThis AI, to examine the effect of habit on BI to use PictureThis AI, and to examine the effect of price value on BI to use PictureThis AI for plant identification. The study was also guided by the following research questions: How does performance expectancy influence BI to use PictureThis AI for plant identification? How does effort expectancy influence BI to use PictureThis AI? How does social influence BI to use PictureThis AI? How does facilitating conditions influence BI to use PictureThis AI? How does hedonic motivation influence BI to use PictureThis AI? How does habit influence BI to use PictureThis AI? How does price value influence BI to use PictureThis AI for plant identification?

1.1 Problem Statement

Technology adoption in higher education is greatly influenced by behavioural aspects such as students' attitudes towards using the technology, the perception of people around the user, knowledge of using the tools, and beliefs about the educational value of the technology towards improved learning outcomes (Valle et al., 2024). One of the reasons for the rapid adoption of AI technology in higher education is its importance in learning difficult concepts such as plant identification which requires critical thinking in biological and agricultural sciences (Kuleto et al., 2021; Papaneophytou & Nicolaou, 2025). Understanding the behavioural aspects of AI technology adoption, particularly behavioural intention to use AI apps, is necessary to understand the predictors of students' intention to use this technology for improved academic productivity. While various AI-based apps for plant identification are available, PictureThis leads all others in terms of its performance and identification accuracy (Canuto, 2023; Hill, 2024; Schmidt et al., 2023). The need to examine students' behavioural intention to use PictureThis AI results from persistent learning challenges associated with the use of traditional plant identification tools like field guides and scientific keys (Treibergs et al., 2023). With the limited taxonomic expertise, lengthy processes and inaccuracies/incorrect plant identifications of traditional plant identification tools (Malik et al., 2022; Rouhan & Gaudeul, 2021), it is believed that knowledge of BI predictors to use PictureThis AI for plant identification might enable also educators to develop appropriate learning environments for enhancement of AI technology adoption in higher education in low-resource countries such as Uganda.

2.0 LITERATURE REVIEW

Comparative App Performance: Evaluation of Picture This versus Other AI-based Plant Identification Apps

Developed by a Chinese Artificial Intelligence (AI) Glorify Global Group Limited, Picture This AI (https://www.picturethisai.com/) consists of a database of over 10,000 plant species which include the trees, weeds, vegetables, toxic plants, flowers, succulents, flowers, and leaf plants (Hill, 2024). Comparative studies of the performance of AI plant ID apps in different parts of the world (such as, Bawingan et al., 2024; Canuto, 2023; Hart et al., 2023; Hill, 2024; Long et al., 2023; Michels, 2024; Otter et al., 2021; Schmidt et al., 2023; Xu et al. nd) suggest that PictureThis supersedes many other apps in terms of plant identification accuracy. Bawingan et al. (2024) studied the use of four plant identification mobile apps namely, LeafSnap, PictureThis, PlantNet, and PlantSnap; and found that the use of mobile apps was perceived as interesting, enjoyable, and very useful, and that their use could add to knowledge of plants and connection with nature. Canuto (2023) explored users' perceptions of using three plant identification apps namely, PlantNet, PictureThis, and LeafSnap, as potential educational tools; and found that participants strongly perceived the apps as engaging, helpful in plant identification, easy to browse, providing details, effective as emerging tools, and significant for scientific literacy, except for consistency of results.

Hart et al. (2023) tested five popular and free identification applications for plants using 857 professionally identified images of 277 species from 204 genera; and established that 85% of images were identified correctly in the top five suggestions, and 69% were correct with the first suggestion. Plant type (woody, forbs, grasses, rushes/sedges, ferns/horsetails) was a significant determinant of identification performance for each application. The apps performed well, with at least one of the three best- performing apps identifying 96% of images correctly as their first suggestion. Hill (2024), in a study conducted with her students at Michigan State University Weed Science Laboratory, and evaluated the identification accuracy of fourteen online mobile apps from the W. J. Beal Botanical Garden for four consecutive years, 2018 – 2021 and then six consecutive years (2018 – 2023). She found out that PictureThis was consistently very accurate in identifying plants for all the six consecutive years of study.

While examining the reliability of common smartphone apps for identification (ID) of toxic and edible plants in the Midwestern United States, Long et al. (2023) established that PictureThis had the highest accuracy in identifying potential toxic plants up to the genus and species level compared to LeafSnap, PlantNet and PlantSnap. Otter et al. (2021) compared the accuracy of three iPhone plant ID apps - PictureThis (PT), PlantSnap (PS), and PlantNet (PN) and showed that PictureThis had the best performance with 10/17 (59% [36 to 78]) plant species identified 100% correctly. Hart et al. (2023) tested five popular and free identification applications for plants using 857 professionally identified images of 277 species from 204 genera and found that the apps performed well, with at least one of the three best- performing applications identifying 96% of images correctly as their first suggestion. Schmidt et al. (2022) used PictureThis to identify 440 photographs of leaves and barks of 55 common tree species in the state of New Jersey in Northeastern United States and noted that the app had a high correct identification of 81.36% genus and 67.84% of species of combined leaf and bark structures among 55 tree species. In a comparative study of the performance of plant identifier apps, Xu et al. (n.d.) employed the DNA bar coding technique to analyse the identification accuracy of the apps using 56 samples ranging from plants to animals. The researchers found that PictureThis had the best identification accuracy for plants up to genus and species level and this was verified by the DNA barcoding technique.

This AI provides a detailed output, including sections of a full description of the plant, toxicity explanations, scientific classification, informative videos, popular cultivars and a people-often-ask section (The New York Times Wirecutter [NYTW], 2025). The app has got a lot of other interesting features such as "diagnose" which helps one to learn about the plant's ailments (NYTW, 2025). Despite the usefulness of PictureThis AI, there is still limited knowledge about behavioural intention (BI) to use the technology. According to Venkatesh et al. (2012), BI is a major antecedent of use behaviour (UB) which is vital for understanding the patterns of user engagement with technology, perceptions of its usefulness and consequences (both negative and positive) of using the technology (Berges-Puyo et al., 2024). From an educational perspective, these aspects are important to educators and policy makers in the design of effective and supportive technology-driven study environments which might enhance students' learning experiences and outcomes (Berges-Puyo et al., 2024).

2.1 Theoretical Review

The study was underpinned by the extended unified theory of acceptance and use of technology (UTAUT2) (Figure 1) which was proposed by Venkatesh and his colleagues (Venkatesh et al., 2012).

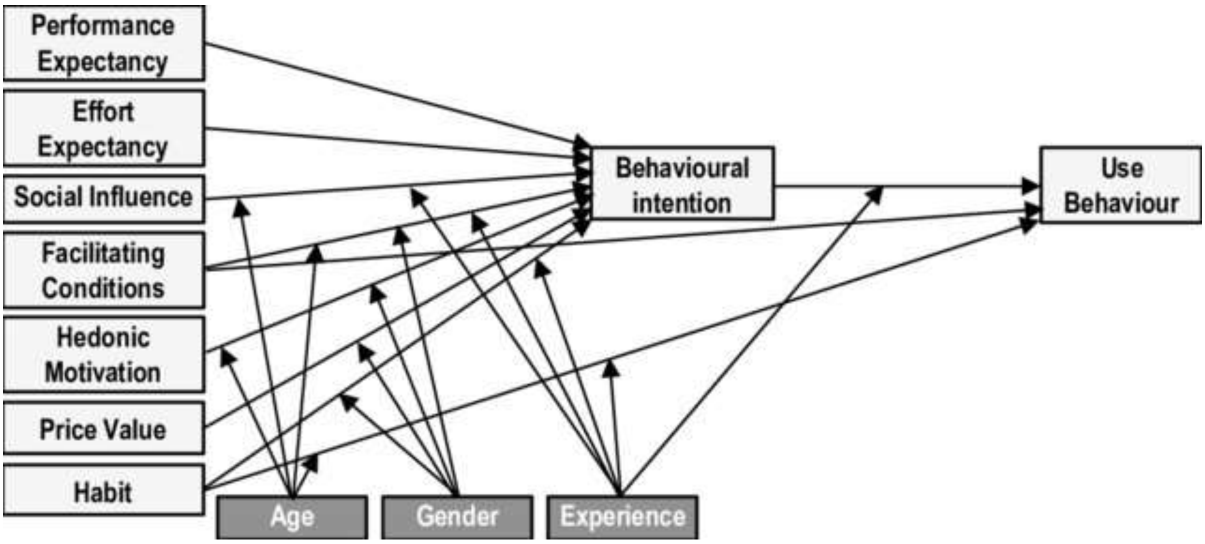

Figure 1: The Extended Unified Theory of Acceptance and Use of Technology, UTAUT2. (Source: Venkatesh et al., 2012).

The UTAUT2 consists of seven constructs (IVs) which are related to BI and use behaviour (UB). These include performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), hedonic motivation (HM), habit (HBT) and price value (PV). All the seven independent variables (IVs) have direct relationship with behavioural intention (BI) to use technology. The influence of five IVs in UTAUT2 on use behaviour (PE, EE, SI, HM, and PV) is mediated by BI, while two variables (FC and HBT) also affect use behaviour directly. As a theoretical basis of the study, UTAUT2 was preferred over other technology adoption models such as technology acceptance model (TAM) and UTAUT due to its more comprehensive approach which integrates intrinsic, individual technology consumer-based factors (such as hedonic motivation and habit), organisational factors (such as facilitating conditions and social influence) and technology-based factors (such as effort expectancy and performance expectancy) (Tamilmani et al., 2020). The completeness of the model was believed to provide a more comprehensive examination of the predictors of BI to use PictureThis AI plant identification app. Nevertheless, some scholars (such as, Choi, 2016) think that UTAUT2 includes some predictors such as hedonic motivation whose source of enjoyment is not well articulated while others think that the model should be combined with others in investing technology adoption phenomena (Tamilmani et al., 2020). In low-resource contexts such as developing countries like Uganda, however, some constructs in UTAUT2 such as price value might not applicable as many technology consumers prefer to use organisational facilities such as free internet connection (like campus-based WiFi) thereby avoiding any money expenses of using technology.

A Review Some Studies which Employed UTAUT2 as the Theoretical Basis

Barbosa et al. (2021) analysed the intention of using fitness app made available by the fitness centre to its members and their relationship with overall customer satisfaction in Portugal. The quantitative study employed the extended unified theory of acceptance and use of technology (UTAUT2) as the base theoretical model. Data were collected from 1676 fitness consumers and all the hypothesised relationships were tested through partial least square structural equation modeling (PLS-SEM). The findings of the study showed that performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation and habit had a positive impact on BI to use the fitness app.

Frank and Milković (2018) investigated ways in which consumers receive information on television programme schedule and what motivated them to use the electronic programme guide (EPG) service in the Republic of Croatia. The data was collected using interviews and survey method. The total sample (234) included 130 interviews conducted by phone among active and potential evotv users, 61 respondents who completed the internet-based survey and 43 face-to-face interviews involving all age groups. The findings showed that intention to use the EPG was driven mainly by the user's habit with more than 50% of influence on the BI, followed by the users' perception that the EPG as a solution gave them high quality information which was quickly retrievable, it was easy and free to use.

García de Blanes et al. (2024) studied the use of digital travel and restaurant platforms (TRPs) for reservation of travel and leisure services in order to establish the main factors influencing their adoption. The researchers added to the theoretical model (UTAUT2) two new factors: trust and word-of-mouth. A theoretical model was based on the extended Unified Theory of Acceptance and Use of Technology (UTAUT2). Data collection was conducted through an online survey, in which 331 responses were compilated. The data obtained were analysed using structural equation modeling (SEM) with AMOS v27 software. The results showed that performance expectancy and word-of-mouth had a significant impact on the adoption of travel and restaurant platforms. However, it was found that effort expectancy, social influence, facilitating conditions, trust and price value were not significant variables.

Gupta and Dogra's (2017) study aimed at identifying factors affecting tourist's intentions to use mapping apps while travelling. Mapping apps are location-based travel apps used for navigation and routing. The quantitative study was based on the UTAUT2 as the theoretical framework. The data was collected from 284 travelers in India using a structured questionnaire.

The data was analyzed using PLS-SEM approach. The results indicated that the most significant antecedents of BI to use mapping apps were habit, facilitating conditions, performance expectancy and hedonic motivation. It was observed that the actual usage behavior was influenced by travellers' intentions and habit to use the technology (mapping apps). However, it was noted that effort expectancy, social influence and price value had no significant effects on the tourist's intentions to use mapping apps while travelling.

Khurana and Jain (2019) studied the factors that affect the adoption of m-shopping fashion apps from the consumer perspective in Delhi, National Capital Region (NCR) in India. The researchers employed UTAUT2 model with additional constructs to develop an instrument for use find out consumers' experience and satisfaction level after adopting the mobile shopping (m-shopping) fashion apps. In addition to UTAUT2 variables, new variables such as perceived risk and post-purchase behaviour were added. Data collection was done using the structured online survey on the sample of 557 mobile app young users aged between 18 and 25 years. The quantitative data was analysed using PLS-SEM. The findings revealed that except effort expectancy and social influence, all the remaining UTAUT2 factors significantly influenced BI to use m-shopping fashion apps.

The above review of previous studies employing UTAUT2 as the theoretical framework, with BI as a dependent variable influenced by seven predictors reveals that the major research focus for UTAUT2-based empirical studies has been on adoption of other online technologies other than AI technology such as PictureThis AI app.

Effect of Performance Expectancy on BI to Use Technology

Performance expectancy (PE) influences an individual's BI to use technology and use behaviour positively according to the UTAUT2 theories (Venkatesh et al., 2012). Some researchers (e.g. Hong et al., 2023, Moya, & Engotoit, 2017) have conducted studies on the influence of PE on UB and BI to use mobile/online technology. Hong et al. (2023) examined the determinants of customer purchase intention toward online food delivery services. The results showed that PE positively affected customers' purchase intention towards online food delivery services.

Moya and Engotoit (2017) examined the mediating role of behavioural intentions to use on performance expectancy and adoption of mobile communication technologies by commercial farmers in Uganda. The findings revealed a partial mediating effect of behavioural intentions to use on the relationship between performance expectancy and adoption, significant positive relationship between PE and BI, PE and adoption, and BI and adoption. Thus, contextual gaps exist for example, the PE studies focused on non-educational use intentions such as online food delivery and farming. This calls for more studies in another context where undergraduate students' use is the focus of the study in their use of PictureThis AI to investigate whether the following hypothesis is true:

H1: PE positively influences BI to use PictureThis for plant identification.

Effect of Effort Expectancy on BI to Use Technology

Effort expectancy (EE) is suggested to have an effect on UB and BI to use online/mobile technology according to the UTAUT and UTAUT2 theories (Venkatesh et al., 2012; 2003). Some researchers (e.g. Dagnoush, & Khalifa, 2021; Tang et al., 2021) have conducted studies on the influence of EE on UB and BI to use mobile technology, with BI serving as the mediating variable between EE and UB. Dagnoush and Khalifa (2021) examined the relationship between EE and BI to use m-commerce in Libya. The findings showed that EE had a positive influence on users' BI intention to use m-commerce.

Tang et al. (2021) examined the mediating effect of EE, PE and trust in the context of m-payment usage intention in the banking industry in the Malaysian state of Selangor and Klang Valley in the centre of Kuala Lumpur and Putrajaya territories. The results showed that EE had a significant positive relationship with m-payment usage intention. Thus, contextual gaps exist for example, the EE studies were conducted in Malaysia and Libya in North Africa, and none in East Africa. They focused on m-commerce and banking industry, not on higher education and emerging technologies such as AI. This calls for more studies in another context such as in Uganda in a university setting focusing on PictureThis AI use to investigate whether the following hypothesis is true:

H2: EE positively influences BI to use PictureThis for plant identification.

Effect of Social Influence on BI to Use Technology

Social influence (SI) directly influences an individual's BI to use technology according to the UTAUT and UTAUT2 theories (Venkatesh et al., 2012; 2003). Some researchers (e.g. Latif & Zakariah, 2020; Nassar et al., 2019) have conducted studies to support the influence of SI on BI and UB of mobile/online technology. For example, Latif and Zakaria (2020) studied the factors that determine the BI to use Blockchain technology in the Malaysian Public Sector. The results showed that SI positively and significantly influenced BI of government officers to use Blockchain technology.

Nassar et al. (2019) studied the impact of SI on ICT adoption with BI as the mediator and age as the moderator in Palestinian Ministry of Higher Education (MOHE). The results indicated that BI positively mediated between SI influence on ICT adoption, while age negatively moderated the relationship between SI and BI. Thus, contextual and methodological gaps exist for example, qualitative study methods were employed in Jordan which is also a developed country in the Middle East, and the studies were all outside university settings employing other online technologies other than AI. This calls for more studies in another context such as one employing quantitative research approaches in a university setting in a developing country like Uganda focusing on PictureThis AI to investigate whether the following hypothesis is true:

H3: SI positively influences BI to use PictureThis for plant identification.

Effect of Facilitating Conditions on BI to Use Technology

Facilitating conditions have a direct influence on an individual's BI and UB according to UTAUT2 (Venkatesh et al., 2012). Some researchers (e.g. Chen, & Chen, 2021; Huang, 2023; Khalid et al., 2021) have conducted studies on the influence of FC on BI and UB of mobile/online technology. For example, Chen and Chen (2021) conducted a study on the use behaviour of a mobile news platform in Taiwan known as Line Today in 2018. The findings showed that FC had positive impacts on BI. BI and HBT had positive impacts on UB, and BI mediated the association of FC and UB.

Huang (2023) analysed the factors that drive the elderly's mobile phone shopping behavior in China. The results showed that FC directly impacted the older persons' BI to engage in mobile shopping. Khalid et al. (2021) investigated the factors influencing the BI to use massive open online courses (MOOCs) in Thailand and Pakistan. The results showed that FC significantly influenced students' BI to use MOOCs. Thus, the above studies show that contextual gaps exist, for example, the studies were conducted in developed countries such as China, Taiwan and South Africa, outside university settings and involving other mobile technologies other than AI tools. Such gaps call for more studies in other use contexts such as the use of PictureThis AI for plant identification to investigate whether the following hypothesis is true:

H4: FC positively influences BI to use PictureThis for plant identification.

Effect of Hedonic Motivation on BI to Use Technology

Hedonic motivation (HM) directly influences an individual's BI to use technology positively according to the UTAUT2 (Venkatesh et al., 2012). Some researchers (e.g. Akbar et al., 2018; Athambawa et al., 2023; Hartelina et al., 2021) have conducted studies on the influence of HM on BI. For example, Akbar et al. (2018) examined the determinants of purchase behaviour in online mobile game in Indonesia. The findings revealed that HM had a positive effect on purchase intention, and the intention also had a positive effect on actual purchase. However, it was found that EE and SI did not have significant effect on purchase intention.

Hartelina et al. (2021) determined how HM could influence decisions to use online learning services among users of online learning apps in Indonesia. The results showed that HM had a positive and significant effect on BI to use online learning apps. These studies reveal a contextual gap as they focused on the use of other technologies such as online mobile games and online learning apps rather than AI apps such as PictureThis. They also focused on areas outside Africa such as Indonesia. This calls for more studies in other contexts such as in Uganda in a university setting with a focus on PictureThis AI use to investigate whether the following hypothesis is true:

H5: HM positively influences BI to use PictureThis for plant identification.

Effect of Habit on BI to Use Technology

Habit (HBT) is a predictor of an individual's BI to use with a positive influence, according to the UTAUT2 theory (Venkatesh et al., 2012). Some researchers (e.g. Gharaibeh et al., 2020; Huang, 2023) have conducted studies on the influence of HBT on BI. For example, Gharaibeh et al. (2020) studied the predictors that influenced consumer expectation and intention to adopt mobile commerce in Jordan. The results showed that habit significantly affected Jordanian consumer intention to adopt mobile commerce.

Huang's (2023) study on the drivers of the elderly's mobile phone shopping behavior in China involving 389 Chinese elderly people revealed that HBT directly impacted the older persons' intention to engage in mobile shopping in addition to other factors such as anxiety, trust, PE, EE, SI and FC. Thus, contextual gaps such as focus on Spain in Europe, Myanmar in Asia and Jordan in the Middle East leaves no such studies of the influence of habit on BI and UB of online/mobile technologies conducted in Africa. Besides, the studies address BI and UB for other technologies (such as m-commerce and mobile apps for restaurant searches and/or reservations) which are outside higher education/university settings. These gaps call for more studies in other contexts such as Uganda with a focus on the use of PictureThis AI for plant identification, to investigate whether the following hypothesis is true:

H6: HBT positively influences BI to use PictureThis for plant identification.

Influence of Price Value on BI to Use Technology

Venkatesh et al. (2012) defined price value (PV) as the consumer's awareness of the trade-off between the perceived benefits of the application and the monetary cost of using the application. The PV construct is a direct determinant of BI and UB of technology. Some researchers (e.g. Athambawa et al., 2023; Hungilo, & Setyohadi, 2020; Ismail et al., 2020) have conducted studies on the influence of PV on BI and UB of digital technology. For example, Athambawa et al.'s (2023) studied the factors affecting behavioural intention (BI) to adopt cloud computing (CC) and actual adoption of CC in Sri Lanka among the small and medium enterprises. The findings showed that while relative advantage, compatibility, and complexity significantly influence BI to adopt cloud computing. Hungilo and Setyohadi (2020) explored the factors influencing Tanzanians' purchase behaviour of goods and services online to provide a behavioural use context for a developing country (Tanzania). The findings showed that PV significantly influenced BI to purchase online.

Ismail et al. (2020) applied exploratory factor analysis (EFA) to assess the determinants of customer acceptance and usage of mobile hotel reservation apps (MHRA) in Malaysia. The findings showed that PV positively and significantly affected customers' intention to adopt MHRA. Thus, contextual gaps exist, for example the Tanzanian study focused on purchase behaviour online and the Malaysian study was focusing on MHRA applications which operate differently from AI plant identification apps like PictureThis. Such gaps call for more studies in a different context such as a university to explore the use PictureThis AI in order to investigate whether the following hypothesis is true:

H7: PV positively influences BI to use PictureThis for plant identification.

2.2 Conceptual Framework

Figure 2 is the framework relating the variables in the study.

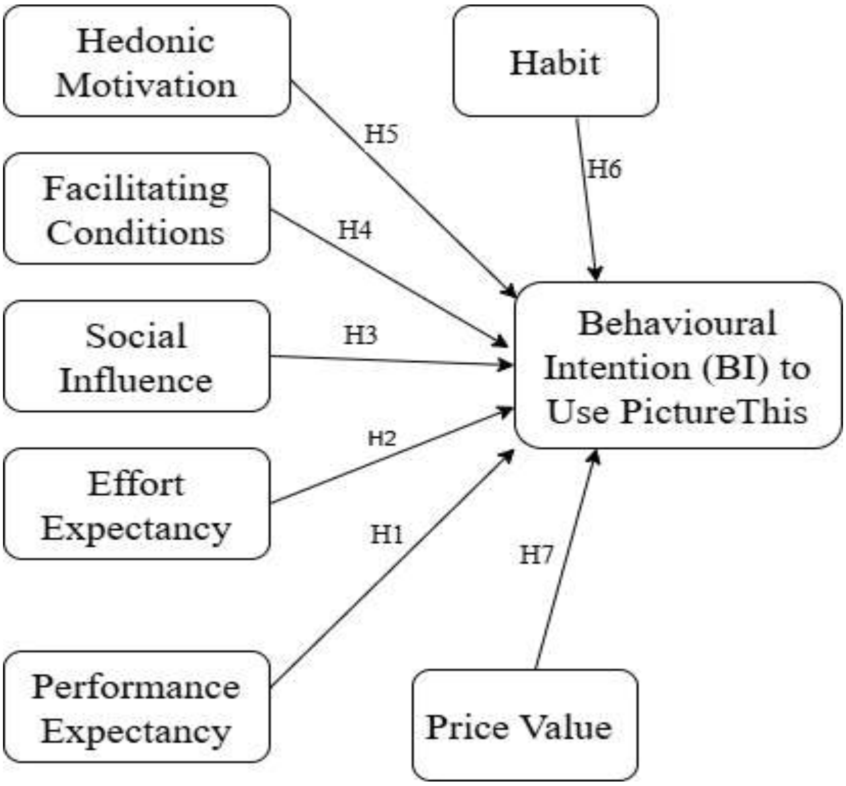

Figure 2: The Conceptual Framework Postulating that Behavioural intention is Dependent on Seven Predictors. Adapted from Venkatesh et al. (2012).

The framework in Figure 2 suggests that the dependent variable, BI to use PictureThis is predicted by seven independent variables (IVs). The seven independent variables include facilitating conditions (FC), social influence (SI), performance expectancy (PE), effort expectancy (EE), hedonic motivation (HM), habit (HBT) and price value (PV). Each IV is related to BI and the relationships can be shown as PE -> BI to Use PictureThis, EE -> BI to Use PictureThis, SI -> BI to Use PictureThis, FC -> BI to Use PictureThis, HM -> BI to Use PictureThis, HBT -> BI to Use PictureThis, and PV -> BI to Use PictureThis.

2.3 Research Gaps

The reviewed studies were conducted in more developed countries outside Africa, including Portugal, Croatia, India, Malaysia, Bangladesh, Spain, and Australia. Absence of similar studies in Africa makes the study on BI to use PictureThis AI technology in Uganda very timely. While the methodology employed in some of the reviewed studies involved qualitative and mixed-methods approaches (such as, Frank, & Milković, 2018), the current positivist study will adopt a quantitative research approach, employing face-to-face survey and self-administered questionnaires (rather than online survey) to collect data from 477 study participants using PictureThis AI technology distributed in urban and rural-based universities across the different regions of Uganda. In terms of the breadth of data collection, while many of the reviewed studies collected data from a smaller section of the country, this study focuses on all major geographical regions with varying cultures, socio-economic backgrounds and internet connection efficiency across Uganda.

3.0 MATERIALS AND METHODS

Study Design

The study adopted the positivist world view which applies to surveys and generation of causal relationships (Park et al., 2025). The research design was a correlational cross-sectional survey. The study was correlational due to causal relationships, where explanatory associations between IVs (PE, EE, FC, SI, HM, PV, HBT) and BI were examined.

Study Location

The study was conducted in four public universities distributed in the four major geographical regions of Uganda. The study participants were based in Gulu University in the north, Busitema University in the east, Kabale University in the west and Makerere University in the central region.

Population

The target population was all the undergraduate students in public universities in Uganda numbering 82,547 and these were distributed across the ten public universities in Uganda (National Council for Higher Education [NCHE], 2022). These universities were selected because they offer more undergraduate study programmes in biological and agricultural sciences which provided an opportunity of interacting with undergraduate students from diverse backgrounds, both rural and urban.

Sample and Sampling

The sample size was determined using Krejcie and Morgan's (1970) method of sample size estimation (Krejcie & Morgan, 1970) and in total 477 students were selected for the study using multistage sampling. The survey was the data collection method, which enabled the researchers to cover a large number of respondents spread in different universities across the country quickly and with limited costs.

Data Collection

The data collection instrument was a self-administered questionnaire developed by adapting items from UTAUT2-based instruments previously used by other scholars. The use of tools used in earlier studies was based on the premise that their validities and reliabilities could be taken to be true before data collection (Table 1). Tavakol and Dennick (2011) contend that the guarantee of validities is grounded on the fact that an instrument cannot be valid unless it is reliable. The study was divided into two phases; that is phase one and phase two. In the first phase, study participants who were undergraduate students enrolled on academic programmes in biological and agricultural sciences were identified and trained in downloading and installing PictureThis AI from Google Play Store for Android devices and the Apple App store onto their iPhones and iPads. They were supported to use the app for plant identification for one week and thereafter given a self-administered questionnaire to fill. Filled forms were collected from 477 study participants immediately after filling.

Table 1: Variables, Constructs, Number of Items Adapted, Their Sources and Their Reliabilities in the Research Instrument

Variable	Construct	Number of items adapted	Source of instrument, number of items and their reliability (α)
BI Predictors (IV)	Performance expectancy	4	Dhingra & Gupta, 2020 (4 items; α = 0.897)
	Effort expectancy	3	Dhingra & Gupta, 2020 (3 items; α = 0.802)
	Facilitating conditions	4	Dhingra & Gupta, 2020 (4 items; α = 0.827)
	Social influence	4	Dhingra & Gupta, 2020 (4 items; α = 0.806)
	Hedonic motivation	4	Dhingra & Gupta, 2020; (4 items; α = 0.902)
	Habit	5	Dhiman et al., 2020 (3 items; α = 0.811) Dhingra & Gupta, 2020; (4 items; α = 0.902)
	Price Value	5	Dhingra & Gupta, 2020 (4 items; α = 0.846)
Behavioural intention (BI)	BI	11	McCaffrey et al., 2021(8 items; α = 0.973); Dhingra & Gupta, 2020 (3 items; α = 0.905)

Statistical Analysis

Descriptive analysis and validity plus reliability analyses were done using IBM-SPSS software, version 27. Inferential analysis, was conducted using partial least squares structural equation modeling (PLS-SEM) with the aid of SmartPLS 4 software. Assessment of the structural models included identification of path coefficients, coefficients of determination (R^2 values and Adjusted R^2 values), t-statistics, and significance values for the hypothesised path relationships. This information was used to decide whether to accept (support) or reject the research hypotheses.

4.0 FINDINGS

Background Characteristics

The background characteristics of the respondents covered were age group, gender, university name, sponsorship scheme, highest academic qualification, study programme name, year of study, mode of study and most-used social media app. These were the basis for assessing the level of use behaviour of PictureThis for plant identification by undergraduate students in public universities in Uganda measured against the independent variables of the study. The results follow in Table 2.

Table 2: Background Characteristics

Variable	Categories	Frequency	Percent
Gender	Male	342	71.9
	Female	134	28.1
Name of university	Busitema	117	24.5
	Kabale	79	16.6
	Makerere	189	39.6
	Gulu	92	19.3
Study programme	Biological sciences	266	55.8
	Agricultural sciences	211	44.2
Year of study	First	225	47.2
	Second	109	22.9
	Third	132	27.7
	Fourth	11	2.3
Sponsorship scheme	Private	137	28.7
	Government	316	66.2
	Loan scheme	24	5.0
Study mode	Day, full time	431	90.4
	Distance learning	46	9.6
Highest qualification	A level	433	90.8
	Diploma	34	7.1
	Degree	10	2.1
Age group (in years)	19 – 23	245	51.4
	24 – 28	201	42.1
	29 – 33	17	3.6
	34 – 38	14	2.9
Most-used social media	WhatsApp	227	47.6
	Tiktok	107	22.4
	YouTube	89	18.7
	X (formerly Twitter)	41	8.6
	Others	3	0.4

The results in Table 2 on gender indicate that there were more males (71.9%) than the females (28.1%) who offered the responses. Thus, the findings indicate that a bigger number of male undergraduate students participated in this study than the females. More study participants (93.5%) were 28 years and below, with only 6.5% aged between 29 - 38 years. There were more respondents (66.2%) on government sponsorship compared to those on private sponsorship (28.7%), with very few of them on loan scheme (5.0%) and this is in line with the government's Vision 2040 of promoting skills-based academic programmes (Rwendeire, 2012). There were more respondents directly from advanced level (90.8%) than the diploma holders (7.1%) and bachelor's degree holders (2.1 %). A larger percentage of respondents (39.6 %) studied at Makerere, Busitema (24.5%) and Gulu (19.0%) universities, with the least (16.5%) studying at Kabale University which reflected the differences in student enrolment in biological and agricultural science programmes for the different universities.

Biological science programmes had a larger proportion of respondents (55.8%) compared to the agricultural sciences (44.2%). More students (90.4%) studied during day with only 9.6% on distance learning. There were more respondents in first year (47.2%), third year (27.7%), second year (22.9%) and fourth years were the least (2.3%). Most respondents (47.6%) used

WhatsApp, TikTok (22.4%), YouTube (18.7%), X (8.6%) and the Learning Management System, LMS (2.1%) was the least used social media.

Descriptive Results

Items measuring all the variables in this study were scaled using the five-point Likert scale where 1 = strongly disagree, 2 = disagree, 3 = undecided, 4 = agree, and 5 = strongly agree.

Description of Behavioural Intention to Use PictureThis AI

Behavioural intention (BI) to use PictureThis AI for plant identification was studied as a dependent variable influenced by seven independent variables (IVs). We present our findings, starting with descriptive analysis, followed by inferential analysis (path analysis). The descriptive results namely, frequencies, percentages and means of the items on BI to use PictureThis AI, according to the respondents, are presented in Table 3.

Table 3: Frequencies, Percentages and Means on Items of BI to Use PictureThis AI

Item	SD Count (%)	D Count (%)	U Count (%)	A Count (%)	SA Count (%)	Mean	Overall rating
BI1: I would consider using PictureThis AI more than once	13 (2.7)	21 (4.4)	59 (12.4)	238 (49.9)	146 (30.6)	4.01	Agree
BI12: I expect to use PictureThis AI regularly in my studies	07 (1.5)	37 (7.8)	60 (12.6)	220 (46.1)	153 (32.1)	4.00	Agree
BI3: It is likely that I will use PictureThis AI in the next six months	16 (3.4)	28 (5.9)	80 (16.8)	195 (40.9)	158 (33.1)	3.95	Agree
BI4: PictureThis AI will be my tool for use in plant identification in the next thirty days	11 (2.3)	47 (9.9)	97 (20.3)	186 (39.0)	136 (28.5)	3.82	Agree
BI5: I intend to continue using PictureThis AI in the future	10 (2.1)	20 (4.2)	88 (18.4)	199 (41.7)	160 (33.5)	4.00	Agree
BI6: I predict that I will continue using PictureThis AI the following semester	15 (3.1)	25 (5.2)	97 (20.3)	190 (39.8)	150 (31.4)	3.92	Agree
BI7: I plan to use PictureThis AI continuously the following academic year and even after graduation	14 (2.9)	24 (5.0)	93 (19.5)	191 (40.0)	155 (32.5)	3.94	Agree
BI8: I will recommend others to use PictureThis AI for plant identification	12 (2.5)	11 (2.3)	59 (12.4)	215 (45.1)	180 (37.7)	4.13	Agree

BI9: I plan to switch gradually from using traditional tools/methods of plant identification to PictureThis AI	17 (3.6)	30 (6.3)	82 (17.2)	209 (43.8)	139 (29.1)	3.89	Agree
BI10: I plan to switch to PictureThis AI as a complete replacement of all previously used traditional methods of plant identification	17 (3.6)	41 (8.6)	86 (18.0)	207 (43.4)	126 (26.4)	3.81	Agree
BI11: I intend to switch to PictureThis AI in six months' time	15 (3.1)	42 (8.8)	96 (20.1)	202 (42.3)	122 (25.6)	3.78	Agree

The results in Table 3 show that for all items measuring BI to use PictureThis AI, cumulatively the majority percentage of the respondents agreed with each item while a smaller percentage disagreed. The means for each item being close to code 4 on the scale which corresponded to agree meant that the respondents considered using PictureThis AI more than once, expected to use PictureThis AI regularly in their studies, were likely to use PictureThis AI in the next six months, regarded PictureThis AI as a tool for use in plant identification in the next thirty days, intended to continue using PictureThis AI in the future, predicted continuity of using PictureThis AI the following semester, planned to use PictureThis AI continuously the following academic year and even after graduation, would recommend others to use PictureThis AI for plant identification, planned to switch gradually from the use of traditional tools of plant identification to PictureThis AI, planned to switch to PictureThis AI as a complete replacement of all previously used tools of plant identification, and intended to switch to PictureThis AI in six months' time.

Description of Performance Expectancy (PE)

The descriptive results namely, frequencies, percentages and means of the items on PE, according to the respondents, are presented in Table 4.

Table 4: Frequencies, Percentages and Means on Items on PE

Item	SD Count (%)	D Count (%)	U Count (%)	A Count (%)	SA Count (%)	Mean	Overall rating
PE1: I find PictureThis AI very useful in my studies	23 (4.8)	24 (5.0)	54 (11.3)	188 (39.4)	188 (39.4)	4.04	Agree
PE2: Use of PictureThis AI enables me to accomplish learning tasks easily	11 (2.3)	35 (7.3)	63 (13.2)	223 (46.8)	145 (30.4)	3.96	Agree
PE3: Use of PictureThis AI increases the effectiveness of performance of my learning activities	08 (1.7)	31 (6.5)	82 (17.2)	209 (43.8)	147 (30.8)	3.96	Agree
PE4: PictureThis AI enables me to identify plants from anywhere any time	10 (2.1)	36 (7.5)	59 (12.4)	170 (35.6)	202 (42.3)	4.09	Agree

The results in Table 4 show that for all items measuring PE, cumulatively the majority percentage of the respondents agreed with each item while a smaller percentage disagreed. The means for each item being close to code 4 on the scale which corresponded to agree meant that the respondents found PictureThis AI very useful in their studies, agreed that the use of PictureThis AI enabled them to: accomplish learning tasks easily, increase the effectiveness of performance of their learning activities and enabled them to identify plants from anywhere any time.

Description of Effort Expectancy (EE)

The descriptive results namely, frequencies, percentages and means of the items on EE, according to the respondents, are presented in Table 5.

Table 5: Frequencies, Percentages and Means on Items on EE

Item	SD Count (%)	D Count (%)	U Count (%)	A Count (%)	SA Count (%)	Mean	Overall rating
EE1: It is easy for me to become skillful at using PictureThis.	09 (1.9)	27 (5.7)	56 (11.7)	212 (44.4)	173 (36.4)	3.89	Agree
EE2: It is easy for me to learn using PictureThis	(2.3)	35 (7.3)	63 (13.2)	223 (46.8)	145 (30.4)	4.08	Agree
EE3: The use of PictureThis requires minimal effort	23 (4.8)	64 (13.4)	70 (14.7)	196 (41.1)	124 (26.0)	3.70	Agree

The results in Table 5 show that for all items measuring EE, cumulatively the majority percentage of the respondents agreed with each item while a smaller percentage disagreed. The means for each item being close to code 4 on the scale which corresponded to agree meant that the respondents found it easy to become skilful at using PictureThis, learning how to use the app and that the use of the tool required minimal effort.

Description of Social Influence (SI)

The descriptive results namely, frequencies, percentages and means of the items on SI, according to the respondents, are presented in Table 6.

Table 6: Frequencies, Percentages and Means on Items on SI

Item	SD Count (%)	D Count (%)	U Count (%)	A Count (%)	SA Count (%)	Mean	Overall rating
SI1: People who are important to me think that I should use PictureThis	23 (4.8)	40 (8.4)	129 (27.0)	195 (40.9)	90 (18.9)	3.61	Agree
SI2: People who influence me think that I should use PictureThis	24 (5.0)	46 (9.6)	119 (24.9)	203 (42.6)	85 (17.8)	3.58	Agree
SI3: People whose opinion I value think that I should use PictureThis	19 (4.0)	47 (9.9)	126 (26.4)	176 (36.9)	109 (22.9)	3.65	Agree
SI4: Most people surrounding me use PictureThis	84 (17.6)	118 (24.7)	97 (20.3)	116 (24.3)	62 (13.0)	2.90	Unsure

The results in Table 6 show that for three of the four items measuring SI, cumulatively the majority percentage of the respondents agreed with each of the three items while a smaller percentage disagreed. The means for each item being close to code 4 on the scale which corresponded to agree meant that the respondents agreed that people who were important to them thought that they had to use PictureThis AI, people who influenced them thought that they had to use the app and people whose opinion they valued thought that they had to use PictureThis AI. For only one item, cumulatively majority of the respondents (42.3%) disagreed that most people surrounding them used PictureThis AI while 37.3% agreed. The mean (2.90) being close to code 3 on the scale used meant that the respondents were unsure, implying that they were unsure whether most people surrounding them used PictureThis AI.

Description of Facilitating Conditions (FC)

The descriptive results namely, frequencies, percentages and means of the items on FC, according to the respondents, are presented in Table 7.

Table 7: Frequencies, Percentages and Means on Items on FC

Item	SD Count (%)	D Count (%)	U Count (%)	A Count (%)	SA Count (%)	Mean	Overall rating
FC1: I have the resources including the internet connection for using PictureThis	41 (8.6)	105 (22.0)	72 (15.1)	157 (32.9)	102 (21.4)	3.36	Not sure
FC2: I have the knowledge necessary for using PictureThis	21 (4.4)	27 (5.7)	71 (14.9)	202 (42.3)	156 (32.7)	3.93	Agree
FC3: I can get help from others when I encounter difficulties in using PictureThis	13 (2.7)	40 (8.4)	75 (15.7)	218 (45.7)	131 (27.5)	3.87	Agree
FC4: PictureThis is compatible/similar with other apps I use	42 (8.8)	81 (17.0)	116 (24.3)	149 (31.2)	89 (18.7)	3.34	Not sure

The results in Table 7 show that for two of the four items measuring FC, cumulatively the majority percentage of the respondents agreed with each of the two items while a smaller percentage disagreed. The means for each item being close to code 4 on the scale which corresponded to agree meant that the respondents agreed that they had the knowledge necessary for using PictureThis AI, and that they could get help from others when faced with difficulties in using PictureThis AI. On whether the respondents had the resources for using PictureThis AI, cumulatively majority of the respondents (54.3%) agreed while 30.6% disagreed. The mean (3.36) being close to code 3 on the scale used meant that the respondents were unsure, implying that they were unsure whether they had resources for using PictureThis AI. On whether PictureThis AI with other apps they used, cumulatively majority of the respondents (49.9%) agreed while 25.8% disagreed. The mean (3.34) being close to code 3 on the scale used meant that the respondents were unsure, implying that they were unsure whether PictureThis AI was compatible with other apps they used.

Description of Hedonic Motivation (HM)

The descriptive results namely, frequencies, percentages and means of the items on HM, according to the respondents, are presented in Table 8.

Table 8: Frequencies, Percentages and Means on Items on HM

Item	SD Count (%)	D Count (%)	U Count (%)	A Count (%)	SA Count (%)	Mean	Overall rating
HM1: Using PictureThis is fun for me	34 (7.1)	61 (12.8)	57 (11.9)	194 (40.7)	131 (27.5)	3.69	Agree
HM2: Using PictureThis is delightful	17 (3.6)	29 (6.1)	94 (19.7)	224 (47.0)	113 (23.7)	3.81	Agree
HM3: Using PictureThis is exciting	15 (3.1)	27 (5.7)	63 (13.2)	197 (41.3)	175 (36.7)	4.03	Agree
HM4: Using PictureThis is entertaining	23 (4.8)	43 (9.0)	76 (15.9)	190 (39.8)	145 (30.4)	3.82	Agree

The results in Table 8 show that for all items measuring HM, cumulatively the majority percentage of the respondents agreed with each item while a smaller percentage disagreed. The means for each item being close to code 4 on the scale which corresponded to agree meant that the respondents concurred that using PictureThis AI was fun, delightful, exciting and entertaining.

Description of Habit (HBT)

The descriptive results namely, frequencies, percentages and means of the items on HBT, according to the respondents, are presented in Table 9.

Table 9: Frequencies, Percentages and Means on Items on HBT

Item	SD Count (%)	D Count (%)	U Count (%)	A Count (%)	SA Count (%)	Mean	Overall rating
HBT1: It has become my habit to use PictureThis.	27 (5.7)	76 (15.9)	96 (20.1)	167 (35.0)	111 (23.3)	3.54	Agree
HBT2: I use PictureThis on a daily basis	43 (9.0)	143 (30.0)	75 (15.7)	149 (31.2)	67 (14.0)	3.11	Unsure
HBT3: It has become natural for me to use PictureThis	34 (7.1)	93 (19.5)	85 (17.8)	186 (39.0)	79 (16.6)	3.38	Unsure
HBT4: I am addicted to using PictureThis	28 (5.9)	88 (18.4)	92 (19.3)	183 (38.4)	86 (18.0)	3.44	Unsure
HBT5: It has become a must for me to use PictureThis	20 (4.2)	59 (12.4)	92 (19.3)	188 (39.4)	118 (24.7)	3.64	Agree

The results in Table 9 show that for three of the four items measuring habit, cumulatively the majority percentage of the respondents disagreed with each of the three items while a smaller percentage agreed. The means for each item being close to code 3 on the scale which corresponded to unsure meant that the respondents were not sure whether they used PictureThis AI on a daily basis, whether it had become natural for them to use PictureThis AI and whether they were addicted to using the app. Regarding whether it had become a habit for the respondents to use PictureThis AI, a cumulative majority (58.3%) agreed while a smaller percentage (21.6%) disagreed. The mean (3.54) being close to code 4 on the scale meant that the respondents agreed that it had become their habit to use PictureThis AI. On whether it had become a must for the respondents to use PictureThis AI, a cumulative majority (64.1%) agreed while a smaller percentage (16.6%) disagreed. The mean (3.64) being close to code 4 on the scale meant that the respondents agreed that it had become a must for them to use PictureThis AI.

Description of Price Value (PV)

The descriptive results namely, frequencies, percentages and means of the items on PV, according to the respondents, are presented in Table 10.

Table 10: Frequencies, Percentages and Means on Items on PV

Item	SD Count (%)	D Count (%)	U Count (%)	A Count (%)	SA Count (%)	Mean	Overall rating
PV1: PictureThis avails me with free use for a reasonable period of time without paying for subscription	24 (5.0)	48 (10.1)	86 (18.0)	196 (41.1)	123 (25.8)	3.73	Agree
PV2: PictureThis asks for fair prices for continued use	47 (9.9)	64 (13.4)	140 (29.4)	150 (31.4)	76 (15.9)	3.30	Unsure
PV3: The use of PictureThis gives good value for money	35 (7.3)	71 (14.9)	133 (27.9)	164 (34.4)	74 (15.5)	3.36	Unsure
PV4: At the current price, I find PictureThis affordable	35 (7.3)	63 (13.2)	112 (23.5)	179 (37.5)	88 (18.4)	3.47	Unsure

The results in Table 10 show that for three of the four items measuring price value, cumulatively the majority percentage of the respondents disagreed with each of the three items while a smaller percentage agreed. The means for each item being close to code 3 on the scale which corresponded to unsure meant that the respondents were not sure whether PictureThis AI asked for fair prices for continued use, whether the use of PictureThis AI provided good value for money and whether at the current price, they found PictureThis AI affordable. On whether PictureThis AI availed them with free use for a reasonable period of time, a cumulative majority (56.2%) agreed while a smaller percentage (15.1%) disagreed. The means for each item being close to code 4 on the scale which corresponded to agree meant that the respondents agreed that PictureThis AI availed them with free use for a reasonable period of time.

Measurement Model (Validity and Reliability Assessments)

Prior to the running of path relationships, validity was assessed by average variance extracted (AVE) to establish how well the given indicators described the various constructs, and Heterotrait-Monotrait (HTMT) ratios of correlations to establish how independent each of the independent variables (PE, EE, SI, FC, HM, HBT, PV) predicted the dependent variable (BI) (Sarstedt et al., 2021). Table 11 gives the results of these two assessments.

Table 11: AVE Convergent Validity and Heterotrait HTMT Discriminant Validity Assessments

Construct	AVE	BI	EE	FC	HBT	HM	PE	PV	SI
BI	0.486								
EE	0.614	0.770							
FC	0.482	0.709	0.789						
HBT	0.608	0.630	0.562	0.686					
HM	0.611	0.799	0.749	0.781	0.637				
PE	0.625	0.792	0.864	0.691	0.550	0.718			
PV	0.510	0.610	0.594	0.620	0.725	0.648	0.519		
SI	0.560	0.680	0.679	0.730	0.787	0.683	0.631	0.640	

The results in Table 11 show that AVE values for EE, FC, HBT, HM, PE, PV and SI exceeded 0.50, suggesting that convergent validity was established for these constructs that is, the different indicators described the various constructs appropriately. AVE values for BI and FC were, however, slightly below the recommended 0.50. To establish whether these two could be retained as valid constructs, factor analysis was conducted. The factor loadings for these constructs all exceeded 0.50 which is the minimum validity value recommended for the indicators to be retained as valid measures of the construct (Hair Jr et al., 2021). The results of factor analysis for each construct are presented together with the structural equation models in the next section (Figure 3). HTMT values were all below the minimum of 0.90 and this suggested that the independent variables (PE, EE, SI, FC, HM, HBT and PV) independently predicted the outcome variable of behavioural intention. Reliability, which indicates the internal consistency of the items in measuring the constructs, was established by Cronbach's alpha (α) and composite reliability (CR) assessments (Table 12). Table 12 also gives variance inflation factors (VIF) which establish collinearity among the indicators for the different constructs. According to Kock (2015), VIF values should be below 3.3 for multicollinearity to be considered non-existent.

Table 12: Reliability, Average Variance Extracted and Variance Inflation Factor Assessments

Construct	BI	EE	FC	HBT	HM	PE	PV	SI
Α	0.894	0.684	0.646	0.840	0.789	0.799	0.681	0.736
CR	0.912	0.826	0.786	0.886	0.862	0.869	0.804	0.833
VIF	1.864	1.349	1.252	1.811	1.608	1.686	1.310	1.453

The results in Table 12 indicate that Cronbach's alpha values for BI, HBT, HM, PE and SI were above 0.70 which suggested that reliability of these constructs was established. α values for EE, FC and PV were slightly below 0.70 but well above 0.50 which was an acceptable range (Hair Jr et al., 2020). CR values for all constructs were above 0.70, indicating that construct validity (composite validity) for all constructs was established. VIF values of all constructs were all below 3.30, which indicated that no multicollinearity existed. Having established validity and reliability of the instrument, path relationships were then conducted.

Structural Equation Modeling of Predictors of Behavioural Intention and BI to Use PictureThis AI

To test whether the seven independent variables (PE, EE, SI, FC, HM, HBT, PV) had any positive influence on BI, a structural equation model was developed combining all the seven IVs and the results are shown in Figure 3.

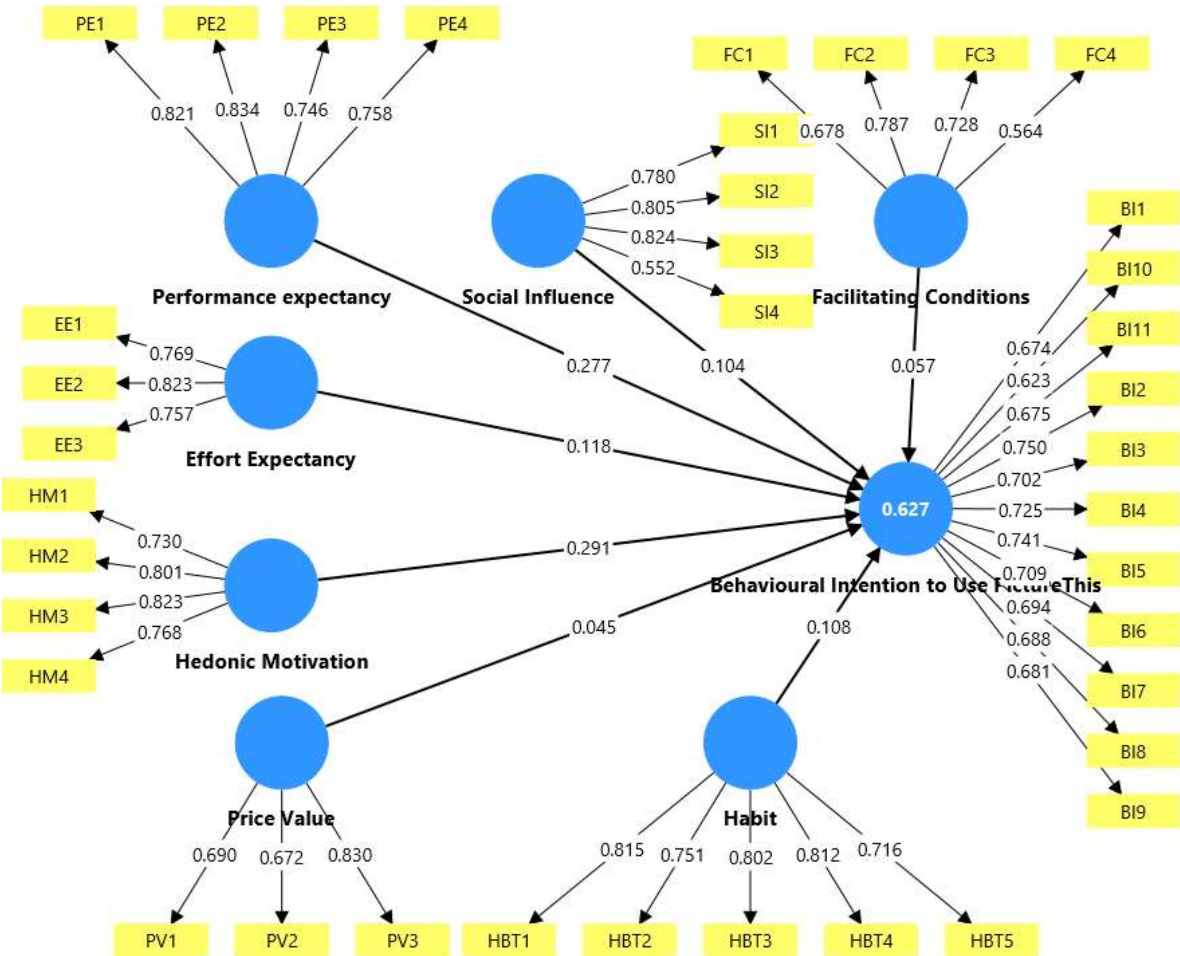

Figure 3: Structural Equation Model for the Predictors of BI and BI to Use PictureThis for Plant Identification

The findings in the structural equation model in Figure 3 suggested that all the indicators for measuring the IVs (PE, EE, SI, FC, HM, HBT and PV) loaded highly above the recommended minimum validity value of 0.50 (Hair Jr et al., 2021) and were thus all retained as valid measures of the different constructs. Similarly, all indicators for measuring BI loaded highly above 0.50 and were retained as valid measures of BI. The path estimates for the relationships between the seven independent variables and BI to use PictureThis AI were computed using the bootstrapping technique in SmartPLS 4 and the results are presented in Table 13.

Table 13: Path Estimates for the Relationships between BI Predictors and BI to Use PictureThis AI

Hypothesis	Path	Path Coefficient (β)	Mean	STD	T	P	Results
H1	PE -> BI to Use	0.278	0.278	0.046	6.011	0.000	H1 supported
H2	EE -> BI to Use	0.118	0.119	0.046	2.541	0.006	H2 supported
H3	SI -> BI to Use	0.104	0.105	0.044	2.358	0.009	H3 supported
H4	FC -> BI to Use	0.058	0.059	0.043	1.341	0.090	H4 not supported
H5	HM -> BI to Use	0.292	0.291	0.050	5.811	0.000	H5 supported
H6	Habit -> BI to Use	0.106	0.104	0.046	2.291	0.011	H6 supported
H7	PV -> BI to Use	0.044	0.046	0.038	1.159	0.123	H7 not supported
	$R^2 = 0.627$ Adjusted $R^2 = 0.624$						

The results in Table 13 and Figure 3 established that five predictors of behavioural intention to PictureThis AI namely, performance expectancy ($\beta = 0.278$, $t = 6.011$, $p = 0.000 < 0.05$), effort expectancy ($\beta = 0.118$, $t = 2.541$, $p = 0.006 < 0.05$), social influence ($\beta = 0.104$, $t = 2.358$, $p = 0.009 < 0.05$), hedonic motivation ($\beta = 0.292$, $t = 5.811$, $p = 0.000 < 0.05$) and habit ($\beta = 0.106$, $t = 2.291$, $p = 0.011 < 0.05$) positively and significantly influenced BI. Only two predictors namely facilitating conditions ($\beta = 0.058$, $t = 1.341$, $p = 0.090 > 0.05$) and price value ($\beta = 0.044$, $t = 1.159$, $p = 0.123 > 0.05$) had a positive but insignificant effect on BI to use PictureThis AI.

The coefficient of determination, expressed as R-squared, revealed that 62.7% ($R^2 = 0.627$) of the variance in BI to use PictureThis AI could be explained by the seven independent variables/predictors (namely, performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, habit and price value). The Adjusted R^2 showed that the significant BI predictors (PE, EE, SI, HM, HBT) contributed 62.4% (0.624) to BI to use PictureThis AI. The coefficient of determination suggested that other factors, other than the in the model, contributed 37.6% of behavioural intention to use PictureThis AI. The findings implied that if undergraduate students in public universities in Uganda could put more emphasis on other BI predictors which are not included in the model, behavioral intention to use PictureThis AI would more likely improve.

Discussion

Performance Expectancy and BI to Use PictureThis AI

The first hypothesis of the study postulated that PE positively influenced BI to use PictureThis. The study found out that PE positively influenced BI to use PictureThis, and accordingly hypothesis one (H1) to the effect that, PE positively influenced BI to use PictureThis, was supported. In the Ugandan context where students find hardship in using traditional tools such as field guides of plants to identify plants in the field, consistent use of AI plant ID tools with high identification accuracy could improve student performance in the field and botany class assignments. The finding agreed with Funmilola et al. (2019) who showed that PE significantly influenced BI to use mobile technologies for instruction by secondary school teachers in Kaduna State of Nigeria. Hendrajaya et al. (2024) also found that PE had a significant effect on intention to use social commerce in Indonesia. Hong et al. (2023) found that performance expectancy was a significant predictor of customers' purchase intention towards online food delivery services. On the contrary, Dingra and Gupta (2020) found an insignificant impact of PE on behavioural intention to use mobile banking. Similar contradictions were reported by Merhi et al. (2019) that PE did not significantly influence Lebanese and British consumers' intention to use mobile banking. Additionally, the study on internet banking adoption by Rahi et al. (2019) established that PE was not a predictor but instead a mediator of the relationship between EE and intention to use internet banking.

Effort Expectancy and BI to Use PictureThis AI

The second hypothesis postulated that EE positively influenced BI to use PictureThis. The study found out that EE positively influenced BI to use PictureThis, and accordingly hypothesis two (H2) to the effect that, EE positively influenced BI to use PictureThis, was supported. In the Ugandan context, EE is relevant in that given the generally low digital literacy rates in the country especially among the rural students, AI plant ID apps with a lower learning curve might gain higher adoption rates than those with higher learning curves. This finding concurred with the study by Admassu and Gorems (2024) which reported a significant effect of ease of use of e-health systems on employees' intention to use the e-health services in Southwestern Ethiopia. Catherine et al. (2017) also showed that effort expectancy had a significant influence on BI to use ATMs with fingerprint authentication in Ugandan banks. Dagnoush and Khalifa (2021) agreed that EE had a significant influence on behavioural intention to use m-commerce by users in Libya. Funmilola et al. (2019) showed that EE significantly affected secondary school teachers' BI to use mobile technologies for instruction in Nigeria. Hendrajaya et al. (2024) reported a significant effect of EE on intention to use social commerce. Tang et al. (2021) also contended that effort expectancy was positively and significant influential on m-payment usage intention by mobile device users in Malaysia. On the contrary, Dingra and Gupta et al. (2020) found that EE did not have a significant effect on intention to use mobile banking among Indian customers. Latif and Zakaria (2020) also showed that EE did not have a significant impact on BI to use Blockchain technology. Moorthy et al. (2019) indicated that EE did not have a significant effect on BI to use digital library services in Malaysian private universities.

Social Influence and BI to Use PictureThis AI

The third hypothesis postulated that SI positively influenced BI to use PictureThis. The study found out that SI positively influenced BI to use PictureThis, and accordingly the third hypothesis (H3) to the effect that, SI positively influenced BI to use PictureThis, was supported. In the Ugandan context, given the high-dependence rate on colleagues, peers, teachers, sponsors, friends and parents for survival, the decision to adopt a given technology as an educational tool will be greatly influenced by others. This finding was consistent with the study by Cioc et al. (2023) which found a significant impact of social influence in predicting BI to use energy efficiency smart solutions (EESS) by Romanian energy consumers with PE and HM playing mediating roles. Dingra and Gupta (2020) found that SI had a positive and significant impact on BI to use mobile banking in the city of New Delhi in India. On the contrary, Hendrajaya et al. (2024) reported that SI was not a significant predictor of intention to use social commerce. Merhi et al. (2019) also found that SI was not a significant antecedent in predicting intention to use mobile banking between Lebanese and British consumers. Susilowati's (2021) revealed that the effect of SI on intention to use digital wellness apps by the Finish elderly was not statistically significant. Tang et al.'s (2021) study in Kuala Lumpur and Putrajaya territories of Malaysia, it was established that SI was not a significant factor influencing m-payment usage intention in the banking industry.

Facilitating Conditions and BI to Use PictureThis AI

The fourth hypothesis that FC positively influenced BI to use PictureThis was not supported. The study revealed that FC positively but insignificantly influenced BI to use PictureThis and thus, hypothesis four (H4) to the effect that, FC positively influenced BI to use PictureThis was not supported. In a country such as Uganda where most students own smartphones and with internet connectivity everywhere on university campuses, facilitating conditions might not be a major determinant of students' intention to use or not to use PictureThis AI for plant identification. In agreement with the finding, Latif and Zakaria (2020) reported that FC did not have a significant effect on BI of government officers to use Blockchain technology. The finding is, however, inconsistent with the study by Chatterjee and Bhattacharjee (2020) which assessed the adoption of AI in higher education and revealed that FC influenced intention to use AI in higher education. Huang (2023) found that FC directly impacted the older persons' intention to engage in mobile shopping. Musakwa and Petersen (2023) also revealed that FC had a significant effect on intention to use of mobile delivery applications. FC was also reported by Khalid et al. (2021) to significantly affect BI to use massive open online courses (MOOCS). FC also had a significant impact on BI to use Line Today in a study conducted by Chen and Chen (2021) in Taiwan.

Hedonic Motivation and BI to Use PictureThis AI

The fifth hypothesis postulated that HM positively influenced BI to use PictureThis. This study established that HM positively influenced BI to use PictureThis, for which reason hypothesis five (H5) to the effect that, hedonic motivation positively influenced BI to use PictureThis, was supported. In the Ugandan context, students frequently use smartphone apps such as WhatsApp which are compatible and similar with PictureThis AI. This would imply that Ugandan students generally enjoy using PictureThis app and would consider/intend using it as their plant identification tool. The finding agrees with the study by Akbar et al. (2018) which found a significant influence of HM on purchase intention in online mobile game in Indonesia. It was also consistent with Dingra and Gupta (2020) who showed that HM had a significant but negative impact on customers' intention to adopt m-banking. Hartelina et al. (2021) found a positive and significant impact on BI to use online learning services among users of online learning apps.

Habit and BI to Use PictureThis AI

The sixth hypothesis postulated that habit positively influenced behavioral intention (BI) to use PictureThis. The study revealed that habit positively influenced BI to use PictureThis and thus, hypothesis six (H6) to the effect that, habit positively influenced BI to use PictureThis was supported. Since Ugandan students spend much of their time using smartphone tools like TikTok, YouTube and WhatsApp, habit would be expected to greatly influence their intention to use PictureThis AI which is a smartphone-based app. This finding was consistent with many other studies such as Barbosa et al. (2021) who found out that habit had a positive impact on BI to use the fitness app. Frank and Milković (2018) also found out that the intention to use the electronic programme guide in the Republic of Croatia was driven mainly by the user's habit with more than 50% of influence on BI.

Price Value and BI to Use PictureThis AI

The seventh hypothesis postulated that price value influenced behavioral intention (BI) to use PictureThis. The study revealed that PV positively but insignificantly influenced BI to use PictureThis and thus, hypothesis seven (H7) to the effect that, price value positively influenced BI to use PictureThis, was not supported. Use of online apps for learning in the field for students in a developing country like Uganda comes with a cost of paying for internet connection. While students grapple with other costs of education such as tuition fees, feeding and accommodation, it becomes increasingly difficult for them to pay for the internet in order to access and use internet-based AI apps such as PictureThis AI especially when they have moved to distant upcountry areas away from university campuses. The implication is that the price value of using AI apps is high and many students would forego this service and simply use traditional, free tools such as field plant guides. In agreement with the finding, Gharaibeh et al. (2020) found out that PV did not have significant influence on Jordanian customers' intention to use m-commerce. On the contrary, the finding disagrees with the study by Lin and Theingi (2019) who found out that price value had a positive and significant effect on BI to use mobile commerce. Hungilo and Setyohadi (2020) also found out that PV significantly influenced BI to purchase goods and services online in Tanzania. The study by Ismail et al. (2020) also established that that PV positively and significantly affected customers' intention to use mobile hotel reservation apps.

5.0 CONCLUSION AND RECOMMENDATIONS

Conclusion

Five BI predictors (PE, EE, SI, HM and HBT) positively influence behavioural intention to use PictureThis AI for plant identification. FC and PV have insignificant influence on BI to use PictureThis AI.

Recommendations

The study was informed by UTAUT2 which posits that use behaviour of technology is influenced by behavioural intention, coupled with habit and facilitating conditions. University information and communication technology (ICT) units such as DICTS (Directorate of Information and Communication Technology) at Makerere University should ensure compatibility of institutional devices and networks with AI learning tools such as PictureThis. For lecturers, the use of PictureThis should be integrated into field-based assignments to reinforce habitual use. Finally, app developers should consider integrating local language support and offline access in order to enhance usability of PictureThis AI plant identification app in low-connectivity areas or parts of the country with poor internet connectivity.

Acknowledgments and Conflicts of Interest Declaration

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Conflict of Interest

The authors declare that they have no competing interests.

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