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Why College Students Prefer Typing Over Speech Input: The Dual Perspective

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ABSTRACT With the development of technology, the accuracy of speech input has vastly improved and the speed of speech input has surpassed that of typing. However, college students still refuse to switch to speech input as their primary compositional tool. To better understanding this phenomenon, this study investigates the preferences of 593 college students using PLS-SEM for structural model analysis. On the basis of innovation resistance theory (IRT) and technology acceptance model (TAM), this study explores the preference of college students for keyboard typing over speech input for document processing. Results showed that functional barriers (i.e., usage, value, and risk barriers) and psychological barriers (i.e., tradition and image barriers) positively affect users' resistance to change. Perceived ease of use and perceived usefulness influence the intention to adopt speech input, which is consistent with TAM. Resistance to change was proven to negatively affect users' intention to adopt speech input. Academically, results confirm that although barriers to speech input currently exist, users still consider speech input as easy and useful and plan to adopt the technology. In practice, speech recognition system companies can significantly enhance users' adoption intentions by reducing barriers and increasing their perception of ease of use and usefulness of speech input.

INDEX TERMS Speech input, innovation resistance theory (IRT), resistance to change, technology acceptance model (TAM), functional barrier, psychological barrier.

I. INTRODUCTION

Speech is a natural and efficient way to communicate between people. Since the 1960s, computer scientists have been developing ways for computers to translate and understand human speech in an attempt to make speech input the interface for human–machine interaction [1]. Speech input mainly has two forms, speech recognition and speaker recognition. Speech recognition seeks to identify the content of speech, and speaker recognition aims to recognize speakers [2]. Given that speech recognition can transform speech into text, it greatly improves the productivity of office work. Speech recognition also replaces the touch-tone for implementing instructions through speech input [3]. In recent years, speech recognition systems have been widely used in many practical fields, such as vehicle systems [4], smart home appliances [5], and language learning [6]. The application of speech recognition system, in addition to the use of human–computer interface, also has the word processing function, transcribing from speech to text. Transcription also has various applications. For medical purposes, speech recognition technology automatically completes transcription into an electronic health record (EHR) [7]. The doctor initially begins the consultation and then obtains the integrated EHR content through the whole process of speech command. Smartphones are also commonly associated with a speech recognition function called intelligent personal assistants. The popularity of voice assistants and smart speaker devices have led people to believe that speech will change the way people communicate with their electronic devices. By speaking out what users want to do, smart devices will perform the function under the users' instructions. Speech input is undoubtedly the most potential tool to replace keyboard. Although speech recognition has been experimentally proven to be more efficient [8], users are still comfortable with keyboard typing for quite a period of time.

This bizarre phenomenon makes one wonder why speech input has not completely replaced keyboard typing. However, previous studies on speech input and keyboard typing have mostly focused on the comparison of efficiency, such as input words per minute [9], time saving [10], or accuracy rate [11]. Researches have discussed that users rarely prefer keyboard

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than speech input in processing paperwork. Therefore, this study attempts to explore the reasons why users do not want to adopt speech input from the perspective of resistance to change. Resistance to innovative technology adoption has long been a significant issue in the study of information systems.

Innovation resistance is a kind of psychological conflict caused by consumer dissatisfaction with innovative technology because of potential changes from the status quo [12], [13]. On the basis of previous studies, innovation resistance theory (IRT) is the most frequently used in explaining users' resistance to change behavior. Most of the previous studies [5], [23], [44] still focus on revealing the ways to motivate consumers to accept and diffuse innovation. However, the factors influencing consumer resistance to innovation should be highly considered [14]. Only when consumers remove the barriers to innovation resistance will they be able to accept innovative technologies [12]. Understanding why consumers reject to adopt innovative technology is equally important as distinguishing between those who are more receptive to innovation [15]. Exploring the factors of consumer resistance to innovation can assist to improve new product development and design and can also significantly reduce the failure rate of innovative technologies [12].

Moreover, this study aims to understand users' intention to adopt speech input from a positive perspective. Therefore, an evaluation to explore user acceptance of this innovative technology should be implemented. Davis [16] constructed a technology acceptance model (TAM) to understand users' acceptance of information systems, and this model is broadly regarded as a reasonable explanation for the adoption of information technology [17]. Previous studies using the extended TAM to investigate the acceptance of information technology and e-learning also confirmed the effectiveness and significance of this model in predicting user's adoption behavior [18]–[20]. TAM has been widely used to measure the acceptance of software or systems to potential users, such as software measurement programs [21], e-learning platform [22], mobile library application [23], and business management software [24]. In the related research of speech recognition software or systems, Goette [25] based on the perspective of task-technology fit, discussed the key acceptance factors for the adoption of speech recognition system by the members of the organization and interviewed the successful and non-successful acceptors. Blackley *et al.* [7] targeted 10 doctors to compare speech recognition and keyboard typing in clinical documents. They used observations and interviews to evaluate the differences between the two input techniques in a qualitative method. Simon and Paper [26] implemented an experimental survey method, in which a ship's crew inputted a set of code into a naval voice interactive device. The participants were recruited voluntarily from navy shipboard members and were trained before using the equipment. The authors believed that the findings of experimental purposes may not applicable in practice. Summing up the preceding literature of speech recognition system, most studies were experimental, used qualitative survey method, and had a specific purpose. Therefore, a quantitative survey must be conducted to evaluate the general usage of speech recognition system.

Nowadays, college students are referred to as "digital natives" or the "Net Generation" [27] grew up in the environment full of innovative technology, and for whom the operation of digital technology is instinctual [28]. Therefore, why college students forgo the more rapid speech input and still prefer typing methods is an interesting issue worth exploring. Most previous studies examined the influential factors for user adoption or non-adoption in a single perspective, such as user resistance to innovative technology [29], [30] or acceptance behavior [31], [32]. However, users are influenced by dual factors when evaluating a new information technology [33]. Users will also consider the positive benefits such as convenience [34]. Users can also be affected by negative impacts such as the risk of using technology [35]. By comprehensively considering the barriers and advantages, the users' real thoughts can be more completely revealed. In the current study, five barriers of IRT were used as antecedents of resistance to use and as negative effects, and the PU and PEOU of TAM were regarded as positive effects on intention to use. In prior research, resistance to use has been examined in relation to its impact on the user's intention to use [36]–[38]. Nevertheless, the direct impact of resistance to use on intention to use has not been discussed in the integration model of IRT and TAM and is a feature which has not been explored in the past investigations. Furthermore, the Net generation is familiar with the operation of converting speech into text, but they do not apply it in academic work. These issues have not been addressed by the previous research. Therefore, examining these influencing factors is highly necessary and also highlights the core value of this study. Accordingly, dual perspectives are introduced into the research model. The present study adopts the barriers of innovation resistance to validate user resistance to change from a negative point of view. This study also utilizes TAM to test users' intention to accept speech input as a positive viewpoint. Finally, the influence of user resistance to change on their adoption of speech input is discussed, and the framework of this study is formed based on the above arguments.

II. LITERATURE REVIEW

A. TECHNOLOGY ACCEPTANCE MODEL (TAM)

User acceptance is regarded as a critical factor in the successful implementation of information systems. The theory of reasoned action (TRA) was developed by social psychologists to identify the determinants of behavior [39]. TRA asserts that individuals' attitude and subjective norms influence their behavioral intentions, which, in turn, influence the actual behavior toward a specific issue. Davis [40] modified TRA and established TAM, which is based on the interaction between users and technology, to analyze the direct or indirect influence of users' intentions and behaviors toward new information technology. TAM proposes that perceived usefulness (PU) and perceived ease of use (PEOU) are two constructs that mainly affect users' behavioral intention and conjointly to explain users' adoption intention and subsequent behavior. PU is the degree to which users consider that the use of a specific system can improve their work performance, whereas PEOU is the level to which users perceive that the use of such information technology can save their physical or mental effort. TAM has been widely used in various information system adoption, such as Internet-based course management system [41] and object-oriented systems [42]. Empirical results have also demonstrated that the model is particularly suitable for predicting and interpreting users' adoption intentions in information technology [43]. More recently, TAM has also expanded into information devices, such as virtual reality devices [44] and voice-activated smart home appliances [5].

B. USER RESISTANCE TO CHANGE

Resistance to change has been discussed in numerous academic fields, and in information systems research, resistance to change is often regarded as the fundamental reason of failure in implementing new information systems in an organization [45], [46]. Generally, resistance to change is any action taken by the user to maintain the status quo under the pressure of change [47]. The degree of resistance to change usually depends on the perceptions of threat by change [12]. Resistance to change refers to the construct that individuals have difficulty in breaking habitual behaviors and that they generate emotional pressure in the face of change [48]. Therefore, resistance to change should be considered as an inhibiting factor; it will have a negative effect on individuals' acceptance of specified technologies [49]. Resistance to change has been adopted as a construct in a number of information system studies. For example, in the operation of in-vehicle infotainment system, people are reluctant to switch from the touch-based user interface to the voice user interface [4]. Patients attending hospital for treatment are reluctant to change from the preceding healthcare system to big data analytics system in healthcare [50]. User resistance to change applied in information system refers to actions or responses taken by the user against the new information system to perform [45].

C. INNOVATION RESISTANCE THEORY (IRT)

Ram and Sheth [13] proposed that innovation resistance is divided into functional and psychological barriers. Functional barriers originate from the cognitive barriers caused by consumers in adopting innovation, including usage, value, and risk barriers. Psychological barriers are derived from previous beliefs toward accepting innovative technology, including tradition and image barriers. The first obstacle when introducing innovation is the usage barrier. The habits and routines developed by consumers form the use pattern [13]. When innovative technology leads to inconvenience or discomfort in use, resistance will be generated from inconvenient situations and cause more problems [14]. Value barrier refers to benefits that induce consumers to change. The value created by innovative technology must be higher than that of the present value system [30]. Otherwise, consumers will doubt the value created by innovation when they have spent time and effort but get nothing in return [51]. If innovation exists, then uncertainty will create risk barriers [52]. Judging from limited information, such as product performance, functional complexity, and possible harm, consumers will not accept innovative products until they obtain sufficient information to reduce risk perception [53]. Tradition barriers occur when consumers perceive innovation will change and conflict with the existing state [54]. When consumers feel that the use of innovative products will break routines and norms, resistance will be generated [53]. If consumers are accustomed to the existing patterns and are satisfied with the present status quo, then they are unwilling to accept the change [55]. Product image is a critical indicator for consumers to evaluate innovative products or services [53]. When consumers have an unfavorable impression on the brand, quality, or the country of origin of the product, image barrier will occur [54], which usually indicates that the negative impression on innovation comes from the change in nature or image of the product [56]. Above all, this theory has been broadly applied to various innovation resistance research on information systems, such as learning management systems [57], digital payment systems [58], and infotainment system [4]. Therefore, this theory is suitable to apply to the proposed research model of the current study.

III. MODEL AND HYPOTHESIS DEVELOPMENT

On the basis of IRT and TAM, this study integrates IRT and TAM to explore and predict the intention to use (ITU) of college students about speech input. For the research purposes, the researcher developed the following hypotheses.

A. USER INNOVATION RESISTANCE

Ram and Sheth [13] divided user innovation resistance into functional and psychological barriers, among which functional barriers include usage, value, and risk barriers. Psychological barriers are tradition and image barriers. Ram and Sheth [13] also identified that user resistance to innovation results from the expected changes of contented status quo or from conflicts in their previous beliefs. Similar concept can be applied in the study of information systems. Resistance to change can be interpreted as a reverse reaction to possible changes. User resistance to change ranges from mild to strong; whether overt or hidden resistance, it will reduce the performance of the system implementation [59]. High levels of innovation may significantly reduce the familiarity of customers with existing technology, resulting in psychological and functional barriers. In the development of innovations, obstacles and unfamiliarity of innovation usage must be solved through redesign [60]. In this study, user resistance to change is identified as the user resistance to changing the status quo of keyboard input and unwillingness to utilize speech input as a typing method.

1) USAGE BARRIERS

When innovation is not compatible with the existing system, especially contradicting the usage habits and norms, it will cause users to feel uncomfortable and resist changes, which can be called usage barriers [13]. The complexity of use and the inconvenience of the operation process may also make users reluctant to adopt innovation [61]. For first-time or inexperienced users of speech input, there may be usage barriers, such as personal accents, frequent interruptions, and time-taking to adapt [62]. Previous studies have also shown that usage barriers are associated with resistance to adopting new systems. Chen *et al.* [63] studied consumer resistance to brand mobile applications (apps) and found that consumers who must download apps, input data independently, and change their habits to adapt to the new interface would be psychologically resistant and will not want to use the apps. Kim *et al.* [64] compared e-book users and non-users in South Korea and confirmed that when using e-book reading, users must install software and use computers, thereby making them perceive e-books as inconvenient and uncomfortable and causing corresponding usage barriers. Mani and Chouk [65] explored the main resistance factors of consumers as regards the practical application of the Internet of Things. The results illustrated that when consumers suffer the complexity of the operation when using smart services and encounter difficulties in using them, this situation will generate use barriers for consumers. Therefore, usage barriers of speech input will affect user resistance to change. Thus, the following hypothesis is inferred:

H1: Usage barriers have a positive effect on resistance to use speech input.

2) VALUE BARRIERS

The value of innovation includes financial and effort benefits. When innovation fails to deliver superior performance relative to the current product, value barrier will arise [13]. Although speech input can yield the benefits of speech-to-text, people with cognitive delays on language or slow processing of language may need additional time to solve word retrieval problems [66]. Previous empirical studies on information systems have also confirmed that value barriers positively affect user resistance to adopting new information system. After investigating e-book readers, Kim *et al.* [64] found that when users could perceive the convenience of a new style reading, their resistance to adopting e-book would be reduced. The belief that paper books have advantages will result in the resistance of e-books among users. Mani and Chouk [65] identified consumers' viewpoints about innovative technologies and verified that the need to pay higher prices for smart services may lead to resistance to the adoption of new technologies. Chaouali and Souiden [29] consider that new technology should provide additional value and flexibility, such that if elderly consumers fail to realize that the benefits brought about by mobile banking are superior to other banking channels such as physical banks and ATMs, then they will resist this innovative technology. Therefore, this study proposes the following hypothesis:

H2: Value barriers have a positive effect on resistance to use speech input.

3) RISK BARRIERS

Innovations are inherently subject to some degree of uncertainty and are viewed as a risk barrier [13]. The higher the perceived risk of new products is, the higher the innovation resistance will be [67]. When users are aware of the risks caused by uncertainty, they tend to postpone the adoption of innovations until they have a sufficient understanding of the product [13]. Users usually hold a negative attitude toward risks with innovative products [14]. Recognition accuracy will vary due to individual speech quality; people with thick accents may cause lower recognition rate. Moreover, the use of speech input systems in public context may result in privacy leakage risks [68]. Previous studies have also obtained positive correlation results in exploring risk barriers and users' innovation resistance. Kim *et al.* [64] concluded from the evaluation of e-books by readers that they do not fully comprehend e-books, so unknown risks existed. Moreover, the installation and download of software before reading complicates the process, thereby causing reader resistance to e-book usage. Mani and Chouk [65] argued that consumers will evaluate smart services in terms of security and health risks, and that negative perceptions of losing control of private information or the possibility of physical or health damage when using the technology can lead to resistance to the adoption of smart technology. Chaouali and Souiden [29] discovered from a survey on the adoption of mobile banking that perceived performance, financial, and security risks in the use of mobile banking from the perspective of elders would generate uncertainty about the operation of this technology and thus create resistance to mobile banking usage in that group. Thus, the following hypothesis is proposed in this study:

H3: Risk barriers have a positive effect on resistance to use speech input.

4) TRADITION BARRIERS

Due to the need to maintain social relations, people tend to evaluate their behavior with the behavior of others they pay attention to and subject to the restrictions of tradition and norms [69]. In comparison, they feel the pressure to behave the same way as others, and tradition barriers thus occur [70]. When a new technology is not widely used by the public, users will perceive the invisible pressure and resist to adopt the new technology. The resistance of users to the new technology leads to tradition barriers [61]. Speech input is not a common input method. Keyboard typing is still the mainstream input method, and users may feel social pressure in adopting speech input. Preceding information system literature also confirms the positive relationship between tradition barriers and resistance to change. On the basis of reader response to e-book adoption, Kim *et al.* [64] established that users will hesitate to use the new technology when they realize that such an adoption entails social pressure. If the innovative technology is not accepted by the public at present, then users are more likely to resist using the technology. Chaouali and Souiden [29] confirm that the elderly prefer the traditional communication mode of face-to-face interaction, thereby making them less able to realize the benefits from mobile banking and resulting in resistance to this new fintech. Mani and Chouk [65] suggested that some individuals prefer direct human interaction to machine interaction, and as smart services often require the autonomous execution of tasks, these people may have negative perceptions of the operation methods and thus resist the adoption of this innovative technology. Hence, the following hypothesis is proposed:

H4: Tradition barriers have a positive effect on resistance to use speech input.

5) IMAGE BARRIERS

The characteristics or functions of innovative products may be difficult to observe, and individuals shape images of new technologies from different forms of information [13]. If users do not like the features of a product, they will have a negative impression of the new product, thereby forming image barriers [13]. Users will receive various types of information sources, including previous stereotypes, conversations of others, or indirect experience, and form their own product image; conversely, negative product image will also cause resistance to use innovation [14]. If there exists a negative awareness in the process of information search, it will cause resistance to adopt speech input. Chen *et al.* [63] found that when companies promoted the download and use of brand apps to users, consumers resisted using them because they had a negative impression towards the brand or apps. Kim *et al.* [64] asserted that for readers considering using e-books, negative perspectives such as unfamiliar operation or eye fatigue would cause negative associations with these technological products. Mani and Chouk [65] investigated consumers' intentions to use smart services and found that negative attitudes persist when users perceive innovative products to be inconsistent with their image. On the basis of previous information system studies, image barrier is positively correlated with resistance to change. Therefore, the following hypothesis is suggested in this study:

H5: Image barriers have a positive effect on resistance to use speech input.

B. RESISTANCE TO CHANGE

Bhattacherjee and Hikmet [33] believed that resistance to change is users' opposition due to the expected negative results originated from change. Therefore, resistance to change is the individual cognition of the potential behavior and can also predict user acceptance of information system. In the process of adopting information technology, when users experience the complexity of the new technology and they think that it is not well-suited with their habits, the change by the new technology will cause users to resist [64]. If the users refuse to switch to the new information technology and want to maintain the existing status, then they prefer to continue using the current information system [69]. Moreover, researchers have examined the influence of RTC on the acceptance of information systems and confirmed that RTC will negatively affect users' adoption intentions to specific information systems. Ferdousi and Levy [71] investigated the use of e-learning system by full-time, part-time, and adjunct instructors of different departments in community colleges and found that if these instructors were unfamiliar with the system operation or did not understand the value of the system, then they would be resistant to using the system and also reduce their intention to use an e-learning system. Hsieh and Lin [72] examined the relationship between PharmaCloud usage intention and resistance and established that physicians would resist using the new system because they did not want to change the patient care process and maintain the existing interaction with medical professionals, thereby reducing their intentions to adopt health information technology. Huang [73] inspected the adoption intentions of college students to use Flickr. Students could use text-based annotations and non-text stickers to diagnose and solve problems with mutual assistance. The results demonstrate that student resistance to the photo-hosting site can negatively affect their adoption intentions. In the present study, the researchers consider that the above inferential relationship can be applied to examine the acceptance of speech input by college students. Thus, the following hypothesis is proposed:

H6: Resistance to change is negatively associated with the ITU of users about speech input.

C. PU AND PEOU

Previous research has proven that PEOU and PU have a positive effect on users' intentions to adopt technology and that PEOU also has a positive effect on PU [74]. Moreover, PEOU can reduce users' doubts about new technology [75]. Past research has also argued that new technology should be considered only if users feel that the system is useful and attractive to them [76], [77]. Therefore, both constructs are imperative factors in the acceptance of new technology by users. In addition, studies have found that PEOU can indirectly influence the ITU of users about new technology through PU [77], which indicates that the relationship between PU and PEOU is significant for the adoption of new technology. When users realize the usefulness and ease of use of an information system, they are more likely to accept the system. Previous research has also shown a causal relationship among PU, PEOU, and ITU [24]. Previous studies have investigated the influencing factors of users in the context of adopting new system. Similar results have been confirmed in technology information system. Al-Rahmi *et al.* [78] revealed the potential factors influencing the use of e-learning systems by Malaysian undergraduate and postgraduate students and confirmed that the usefulness of the new system was perceived only when the students felt that the system was easy to operate. The ease of using the system and the effect of improving learning can increase the intention of college students to adopt e-learning systems. Salloum *et al.* [20] used the extended TAM to explore e-learning acceptance intentions from different departments of five universities. Their findings demonstrate that a user-friendly design will make students perceive the system as easy to use and be beneficial for system usage. In addition, ease of use and usefulness have a positive correlation with the intention to adopt e-learning system by students. Rafique *et al.* [23] examined a mobile library application to identify users with the reasons behind the low acceptance and intention to use the application. The results indicate that the system quality and usage habits have direct effects on the users' perception of ease of use and usefulness, and the ease of use of technology has an impact on user perception of usefulness and the intention to use the system. Consistent with previous studies, this study explores the ITU of users about a speech input system and proposes the following hypotheses:

H7: PEOU has a positive effect on PU.

H8: PEOU has a positive effect on ITU.

H9: PU has a positive effect on ITU.

On the basis of the previous assumptions, the model constructed in this study is shown in Figure 1, which is used to understand and predict the functional and psychological barriers of college students to speech input, taking these factors as the antecedents of RTC. In addition, the current study also measures the influence of user resistance to change on TAM. Moreover, user acceptance toward speech input was tested by the TAM.

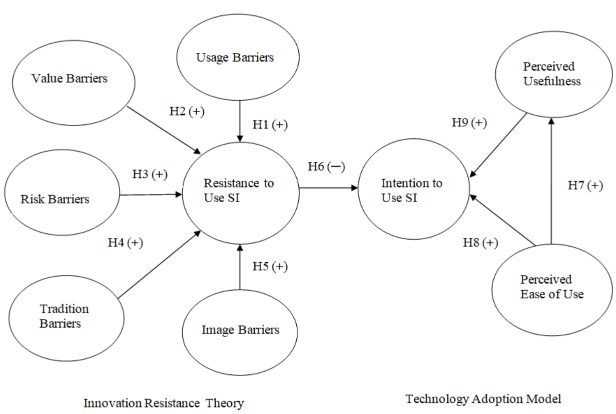

FIGURE 1. Proposed research model.

IV. RESEARCH METHODOLOGY

A. MEASUREMENT DEVELOPMENT

For the questionnaire designed in this study, the items were extracted from a variety of previous studies related to the construct variables. The first part of the questionnaire is the demographic information of the target population. The second part includes the theoretical framework and the variables within the research model, including the variables of TAM (i.e., PU, PEOU, and ITU), functional barriers (i.e., usage, value, and risk barriers) and psychological barriers (i.e., tradition and image barriers). In this study, PU and PEOU were adapted from Davis [40]. ITU was derived from Venkatesh *et al.* [79]. Resistance to change was taken from Kim and Lee [4]. Items for functional barriers were selected from Laukkanen *et al.* [61] and Nel and Boshoff [80]; whereas items for psychological barriers were adopted from Laukkanen *et al.* [61] and Chaouali and Souiden [29]. A Likert's five-point scale was used in this study, from strongly disagree (1) to strongly agree (5). Two pre-tests were conducted to develop the preliminary questionnaire. First, a pilot study was performed with 25 graduate students. After obtaining the feedback from the respondents, the ambiguous and repetitive semantic meanings were amended, and the phrases of the questions were simplified without affecting the content validity, thereby making the narration of the questionnaire readily comprehensible. Next, two researchers in the field of information technology were invited to review the contents of the questions and revisions were performed in line with their suggestions to create a formal questionnaire. The final version of the questionnaire is shown in Table 1.

TABLE 1. Measurement of constructs.

Items	Measures
PU1	Using speech input enables me to accomplish tasks more quickly.
PU2	Using speech input improves my performance.
PU3	Using speech input increases my productivity.
PU4	Using speech input enhances my effectiveness. (Davis, 1989)
PEOU1	I find it easy to use speech input to do what I want.
PEOU2	My interaction with speech input does not require much effort.
PEOU3	It is easy for me to become skillful at using speech input technology.
PEOU4	I have control over speech input technology. (Davis, 1989)
ITU1	I intend to use speech input in the future.
ITU2	I will always try to use speech input in my daily life.
ITU3	I plan to use speech input frequently. (Venkatesh et al, 2012)
UB1	Speech input is difficult to use.
UB2	The use of speech input is inconvenient.
UB3	Speech input is slow to use. (Laukkanen et al., 2008)
VB1	I am quite skeptical about the benefits of speech input.
VB2	Speech input does not offer any advantages compared to keyboard typing.
VB3	The use of speech input will not increase my ability to type my homework. (Nel & Boshoff, 2021)
RB1	I fear using speech input may reduce the confidentiality of my personal information.
RB2	I am unsure whether speech input performs satisfactorily.
RB3	I am not sure whether speech input performs as well as keyboard typing. (Nel & Boshoff, 2021)
IB1	I have a very negative image of speech input.
IB2	New technology is often too complicated to be useful.
IB3	I have such an image that speech input are difficult to use. (Laukkanen et al., 2008)
TB1	I find using speech input less comfortable than keyboard input.
TB2	I prefer to type documents using keyboard input rather than using speech input.
TB3	I am so used to using keyboard input that I find it difficult to move to speech input. (Chaouali & Souiden, 2019)
RTC1	I would not comply with the change to type by speech input.
RTC2	I would not spend time and effort coping with using speech input.
RTC3	I oppose changing to do homework using speech input.
RTC4	I would resist changes to do homework using speech input. (Kim & Lee, 2016)

B. SAMPLE AND DATA COLLECTION

After the questionnaire was developed, the researchers sent it to two public and two private universities for research, but the impact of the pandemic meant that only one public university in southern Taiwan approved the survey. To establish the representativeness of the sample, a stratified sampling method was adopted, for which the researchers selected 15 different representative courses in proportion to the number of students in each of the five colleges of the university. The chosen institution is a medium-sized comprehensive university with a cross-section of disciplines and an enrollment of approximately 10,000 students. Questionnaires were given to students during class with the consent of the course instructor. To let students understand the contents of the survey, the researchers explained the research background approximately and conducted a 10-minute orientation before filling the questionnaire. The collection period lasted from March to April, 2021 (about 6 weeks), with a total of 626 completed questionnaires. After removing incomplete and invalid questionnaires, 593 valid samples were gathered for subsequent analysis. The respondents comprised roughly equal proportions of males (48.6%) and females (51.4%). Generally, the sample was evenly distributed among colleges; each college was approximately 20%. From freshman to senior, the samples of each grade were more than 20%, and the sample size of each grade was approximately equal. In term of typing experience of using speech input for documents, 46.7% of the students had no experience, with the largest portion of the respondents, followed by 31.5% of the users who had used 1–3 times. Hence, although college students have experienced using speech input in mobile phones, only a few students have applied it to type documents. The respondents' profiles are shown in Table 2.

TABLE 2. Respondent profile.

Demographic Characteristics		Frequency	Percentage
Gender	Male	288	48.6
	Female	305	51.4
College	Management	115	19.4
	Computer Science	112	18.9
	Education	123	20.7
	Social Science	125	21.1
	Science	118	19.9
Student year	Freshman	159	26.8
	Sophomore	171	28.8
	Junior	135	22.8
	Senior	128	21.6
Speech input usage experience	None	277	46.7
	1–3 times	187	31.5
	4–6 times	51	8.6
	7–9 times	24	4.0
	10–12 times	12	2.0
	Above 12 times	42	7.1

V. RESULTS

The model in this study was tested by using a partial least square (PLS) method and applying SmartPLS 3.2.8 to perform model analysis [81]. PLS is more suitable because it has the minimum limitation considering the sample size and residual distribution [82]. PLS structure model test is conducted in a two-stage procedure [83]. The first stage is the evaluation of the measurement model, verification of the reliability, and checking the convergent and discriminant validity of each construct. The second stage is the evaluation of the structural model and testing the significance between the model variable relationship. A total of 5000 bootstrap replicates were conducted to assess the estimates of the construct variables [84]. As the data in this study were collected using a self-report questionnaire, samples were obtained from similar sources, the independent and dependent variables were from the same respondents, and common method variance (CMV) had to be carefully evaluated. Thus, the researchers performed Harman's single factor test on SPSS 22 to exclude common method bias [85]. A maximum covariance of 43.819% was observed, thereby indicating that CMV did not cause serious problems in the data set [86].

A. MEASUREMENT MODEL

The 30 measurement items in the research model represents reflective indicators to their matching constructs, and confirmatory factor analysis (CFA) using maximum likelihood estimation was applied to check the overall fitness of the measurement model [87]. The study has performed CFA using the AMOS 23 software. The CFA results show that CMIN = 866.327, df = 369, p = 0.000, CMIN/df = 2.348, CFI = 0.969, GFI = 0.909, TLI = 0.964, and RMSEA = 0.048. A good model fit indicates that the theoretical model fits well with the empirical data. Data analysis was performed using SmartPLS 3.2.8 to assess the measurement model and structural model for main effects. On the basis of the results of the measurement model (see Table 3), the outer factor loadings exceeds the threshold value of 0.5 [88], indicating appropriate convergent validity. Bagizzi and Yi [89] suggested that average variance extracted (AVE) of above 0.5 is the acceptable standard. The results showed that the measurement model had the proper construct validity. Reliability analysis was performed by testing two values, which should reach the level of 0.6 [89] in Cronbach's α test, and the composite reliability (C.R.) should be greater than 0.7 [90]. Both results illustrate that the alpha coefficient of all constructs are above 0.843, whereas the coefficients of composite reliability are greater than 0.894. The two tests indicate that the measurement model is reliable. In addition, the Fornell–Larcker criterion [88], which presents the discriminative validity of the construct, was tested by comparing the correlation coefficients of the square root of AVE with the latent variables (see Table 4). The square root of AVE is higher than its correlations with any other construct evaluated in the model, indicating the discriminant validity of the proposed model [91].

B. STRUCTURAL MODEL

According to the assessment results (see Table 5), user resistance to use is significantly influenced by usage barriers

TABLE 3. Measurement model assessment.

Items	Loading	Mean	S.D.	AVE	C.R.	Cronbach's α
PU1	0.919	3.14	0.88	0.845	0.956	0.939
PU2	0.904	2.76	0.88			
PU3	0.923	2.97	0.71			
PU4	0.931	3.00	0.83			
PEOU1	0.813	2.75	0.72	0.678	0.894	0.843
PEOU2	0.806	3.61	0.86			
PEOU3	0.858	3.23	0.82			
PEOU4	0.817	3.33	0.81			
ITU1	0.955	2.99	0.72	0.915	0.970	0.954
ITU2	0.966	3.02	0.84			
ITU3	0.948	2.90	0.71			
UB1	0.904	3.32	0.84	0.820	0.932	0.890
UB2	0.906	3.29	0.84			
UB3	0.907	3.40	0.85			
VB1	0.913	3.88	0.82	0.846	0.943	0.909
VB2	0.921	3.83	0.83			
VB3	0.926	3.73	0.89			
RB1	0.884	3.56	0.82	0.784	0.916	0.862
RB2	0.863	3.41	0.90			
RB3	0.908	3.53	0.89			
IB1	0.906	2.84	0.76	0.804	0.925	0.878
IB2	0.901	2.84	0.78			
IB3	0.883	2.91	0.83			
TB1	0.908	4.00	0.94	0.814	0.929	0.886
TB2	0.905	4.08	0.93			
TB3	0.894	4.06	0.93			
RTC1	0.906	3.39	0.81	0.843	0.956	0.938
RTC2	0.923	3.22	0.82			
RTC3	0.907	3.25	0.87			
RTC4	0.937	3.31	0.84			

TABLE 4. Correlation matrix and square root of the AVE.

Construct	IB	ITU	PEOU	PU	RTC	RB	TB	UB	VB
IB	0.897								
ITU	−0.269	0.957							
PEOU	−0.180	0.670	0.824						
PU	−0.223	0.716	0.744	0.919					
RTC	0.803	−0.352	−0.225	−0.286	0.918				
RB	0.589	−0.310	−0.241	−0.279	0.770	0.885			
TB	0.678	−0.280	−0.180	−0.219	0.806	0.645	0.902		
UB	0.652	−0.417	−0.289	−0.357	0.828	0.746	0.678	0.906	
VB	0.496	−0.390	−0.252	−0.342	0.573	0.492	0.469	0.548	0.920

($\beta = 0.285$, $P < 0.001$), value barriers ($\beta = 0.052$, $P < 0.01$), risk barriers ($\beta = 0.183$, $P < 0.001$), tradition barriers ($\beta = 0.264$, $P < 0.001$), and image barriers ($\beta = 0.304$, $P < 0.001$), which confirms H1–H5. User resistance to use is found to negatively influence ITU ($\beta = -0.156$, $P < 0.001$). Hence, H6 is supported. PEOU is proven to have a positive relationship with PU, thereby supporting H7. PEOU ($\beta = 0.304$, $P < 0.001$) and PU ($\beta = 0.446$, $P < 0.001$) are found to affect ITU. Therefore, H8 and H9 are also supported.

Although R^2 represents the level of the predictive accuracy of constructs in the research model, a value of R^2 below 0.25 is weak, between 0.25 and 0.75 is moderate, and above 0.75 is considered strong (Hair *et al.*, 2011). The research model can explain 86.4% in resistance to use, which presents strong explanatory power; 57.8% of the variance in ITU, and 55.3% of the variance in PU, which shows moderate explanatory power (see Figure 2).

TABLE 5. Summary of hypothesis results.

Relationship (Hypothesis)	Path Coefficient	T Statistics	Significance	Support?
UB → RTU (H1)	0.285	9.102	$p < 0.001$	Yes
VB → RTU (H2)	0.052	2.829	$p < 0.01$	Yes
RB → RTU (H3)	0.183	7.065	$p < 0.001$	Yes
TB → RTU (H4)	0.264	10.475	$p < 0.001$	Yes
IB → RTU (H5)	0.304	12.684	$p < 0.001$	Yes
RTU → ITU (H6)	−0.156	5.297	$p < 0.001$	Yes
PEOU → PU (H7)	0.744	38.660	$p < 0.001$	Yes
PEOU → ITU (H8)	0.304	7.120	$p < 0.001$	Yes
PU → ITU (H9)	0.446	9.747	$p < 0.001$	Yes

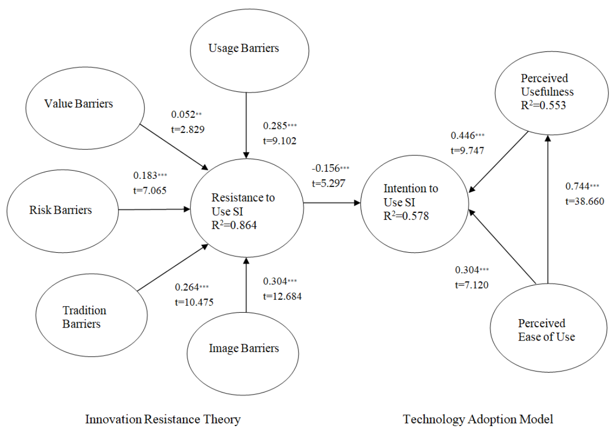

FIGURE 2. Results of the structural model.

VI. DISCUSSION AND CONCLUSION

A. DISCUSSION OF RESULTS

This study aims to reveal both the barrier factors for college students not to accept speech input and probe the influence factors of adopting speech input. Therefore, this study reviews the previous literature on IRT and resistance to change to identify the various barriers for not adopting speech input. Furthermore, this study examines the TAM literature on innovation technology to investigate users' intention to adopt this input method. In addition, the relationship between resistance to change and TAM is discussed. The results show that the barriers of speech input, namely, usage, value, risk, tradition, and image barriers, can highly influence college students not to utilize speech input as their major typing method. The outcome also echoes the findings of previous research, indicating that innovative technologies do not necessarily replace traditional ones directly. For example, e-books still cannot replace paper books [45], which means that people who prefer paper books are against adopting e-books. Another innovation technology study shows that although the Internet of Things created the possibility of smart services, most people still have not prepare to adopt smart technology [46]. In short, the results provide evidence that college students have significant barriers to adopting speech input as major typing method and are thus resistant to using it. Furthermore, the results show that college students' resistance to the adoption of speech input has a negative influence on their usage intentions. This finding coincides with previous studies on the adoption of new technologies [54]–[56]. In TAM, this study finds that PU and PEOU affect users' intention to adopt for speech input. Moreover, PEOU indirectly influences their intentions through PU, on behalf of the user to experience speech input of easy to operate, and will affect them to perceive the usefulness of this input method. These findings are also consistent with previous literature on TAM [57], [61], [62]. To sum up the above results, when users perceive that speech input is easy to use, they will consider the usefulness of the input method, which will also affect the ITU of users about this technology. Despite the barriers, users still consider speech input as an easy and useful tool and will have ITU. The results illustrate that when users evaluate the acceptance of new technologies, they will assess the barriers and risks between new technologies and traditional technologies and consider the value and benefits of adopting new technologies. Users may encounter some uncertainty when switching from keyboard typing to speech input, and changing their habitual interfaces may be risky for users [4]. Although the speed of speech input is faster than keyboard typing [8], subsequent editing may take more time, such that the efficiency of document processing is reduced [92]. Whether speech input creates risks or barriers for users depend on the users, context, and device [93]. Examples include the user encountering execution errors and the input device may experience recognition errors [94]. In addition, the user's utterance ability and familiarity with the input device may influence the effectiveness of speech recognition [66], [95]. Interference, such as background sound and noise during input [96], [97], and a complex word processing task [98] may result in lower accuracy of speech input.

B. IMPLICATIONS FOR RESEARCH AND PRACTICE

The insights presented in the current study contribute to the academic and practical aspects. First, most of the past studies on speech input have focused on professionals, such as physicians' use of speech input to record the patients' diagnosis and treatment [62]. Conversely, the present work discussed the application of speech input in general word processing. In addition, previous studies have compared speech and keyboard input in terms of efficiency (e.g., time, word number, or error rate), but they have not revealed factors that influence users' attitudes and psychological traits. The present study guides a pioneer direction to the field of general use of speech input and discovers the related factors that affect users' behavior intention. Second, past studies have only considered user resistance to change and the barriers that cause user resistance to adopt new technologies [65], [29], [53]. Some other studies have used TAM to explore users' intentions to accept innovative technologies [74], [76], [77]. However, these one-way inferential studies on user acceptance or resistance fail to provide details on users' influencing factors. A unilateral examination of user acceptance obviously has some drawbacks. This study adopts a dualistic view, using negative IRT combined with positive TAM, to explore the aspects for users' adoption or non-adoption. This integrated model is the first to adopt dual perspectives. Third, the results indicate that at this stage, users do not intend to adopt speech input as a textual working method for their documents. However, the results also show that users perceive this input tool to be easy and useful and intend to adopt speech input. This interesting finding suggests that although users know that speech input is a great tool, functional and psychological barriers still exist and must be overcome. Previous research found that although digital natives have ample experience and skills with various knowledge of the Internet, a large proportion of them are not seeking effective or purposed-oriented usage of technology [99]. The Net Generation will apply technology for academic purposes, only when they perceive tangible results, enjoy using technology, and are under appropriate social influence [100].

The existing barriers do not imply that innovative technology cannot be accepted eternally. This result also indicates that users should have a single state of acceptance or rejection. This conclusion is similar to the concept of symbolic adoption proposed by Wolverton and Cenfetelli [101]. Symbolic adopters are users who accept the idea of the technology but have not considered using it. College students still have functional and psychological barriers to be surmounted. Thus, this input method has not been adopted at this moment. Vinodan and Meera [102] further distinguished the acceptance of technology into symbolic and intended adoption. Relevant studies on information systems also confirm the existence of symbolic adoption [103], [104]. In addition, the results demonstrate the practical contributions. Practitioners of speech recognition system can dedicate their efforts in two directions. For example, they can help users overcome their uncertainties about speech input functions by resolving the diversity recognition rate between different accents [68] and reducing environmental constraints, such as noise interference [105]. In terms of breaking through the psychological barriers of users, speech recognition systems companies may consider cooperating with computer manufacturers to include speech input in typing options, such that users can notice the existence of such input method. As long as they are willing to try, they might accept such input tool in the future. When users consider that speech input is easy, they will recognize its usefulness and be more eager to adopt it.

Compared with keyboard typing, speech input is more difficult to learn, and the complexity of the speech input process will affect the adoption intention of users. To make it easier for first-time users to try speech input, system manufacturers could consider increasing the ease of use of speech input by designing user friendly, intuitive, and simple interfaces. Enhancing transcribing functions may be implemented, such as by adding an extensive dictionary, introducing contextual judgment, and adding automatic punctuation to improve the accuracy and efficiency of speech-to-text conversion. Editing functions should be considered. Note that when transcribing from speech to text, possible words could show up on the screen for real time, such that the user can just click on a check-box to improve the efficiency of editing. This feature will make recognition system more useful. Moreover, integrating a speech input system with innovative technologies such as artificial intelligence could be considered to achieve a better match between speech and text, thereby allowing users to perceive more effort-saving and encourage them to benefit from speech input. Manipulating the input system usually requires time to train and practice for users to become proficient in terms of input speed and sentence pauses. To satisfy the user's expectation, system manufacturers could improve system recognition rapidity to provide transcription under the natural speaking speed so as to reduce the resistance of existing users or potential users toward speech input.

VII. LIMITATION AND FUTURE RESEARCH

Although this study has some insights and contributions to the literature, some limitations must be noted. First, this study did not deliberately classify the usage experience among the respondents. Previous research on technology acceptance [106] shows that people who lack experience in using technology may have difficulty evaluating the benefits of adopting technology. Future research can distinguish users as initial and experienced users, which will help comprehend the influence of experience on the adoption of speech input. Second, this study was based on a sample of college students with high homogeneity. For the findings to be generalized to all users or other innovative technology, further examination is needed to support the results. Future research can include more diverse users, such as administrators, counter staff, or customer service staff, to provide future prospects of speech input toward replacing the keyboard. In addition to usage experience, adopters and non-adopters may present diverse factors that cause their resistance to speech input. The non-adopters' barriers to speech input may differ from the factors that adopters consider. Therefore, future research can distinguish the influencing factors that lead to the resistance or acceptance of these users. This study confirmed the positive effects of psychological barriers (tradition and image barriers) and functional barriers (usage, value, and risk barriers) on user resistance to speech input. Previous studies have explored the influence of psychological barriers on functional barriers [29]. The impact of image, value, risk, and tradition barriers on the usage barrier were also discussed [107]. Future studies can examine the influential relationship among these barriers to acquire a better understanding of user barriers. Although the conceptual model includes the influence of the PEOU and PU on user intention to accept speech input, the antecedents of these two factors and other external determinants that affect adoption intentions should also be identified. Examples of features that should be investigated include the human–machine interaction interface, perceived compatibility and adaptability of users, and privacy concerns. Future investigations that include these factors will provide a more complete and richer perspective of the barriers and adoption factors for use of speech input.

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