Supporting schools to use face recognition systems: a continuance intention perspective of elementary school parents in China

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Abstract
A great deal of attention has been focused on technological innovation, for example, face recognition, which has been used in some countries in various fields. Nonetheless, there has been little attention paid to parents’ acceptance of the use of face recognition systems on campus. To address this gap in the literature, this study examined how different degrees of technological innovativeness and dangerous beliefs in the virtual world (DBVW) influence parents’ perceived value of using and intention to continue supporting schools’ use of face recognition systems. This study adopted snowball sampling to collect data through questionnaires, and received 380 valid responses from parents living in Xuzhou, China. Confirmatory factor analysis and structural equation modeling were used to analyze the data, with results indicating that: (1) DBVW was negatively related to perceived value; (2) technological innovativeness was positively related to perceived value; and (3) perceived value was positively related to continuance intention to use face recognition systems. The results suggest that parents support the use of face recognition systems in elementary school; thus, such systems can be adopted by other elementary schools in other areas.

Keywords Face recognition verification · Technological innovativeness · Perceived value · Intention to use

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1 Introduction

In recent years face recognition has become a hot biometric technology. It is not only the concern of large scientific and technological enterprises, but also has an important impact on the fields of finance, retail, medical treatment, and security in enterprises and government units. The frequent application of face recognition will further affect existing lifestyles and change the economic system and industries (Burt, 2019). Face recognition technology entered school campuses in China in 2006 (Liu, 2007) and has spread rapidly with the development of 5G since 2019. When a child passes through the school gate with an installed face recognition system, a notice will be sent to the parents’ mobile phones (Li, 2019), and students’ behaviors including violations on campus may also be reported to teachers or parents (Kong, 2019). The general public have concerns about whether this technology will infringe on human rights, resulting in racism and sexism (Dunn, 2020), due to the collection of individuals’ most private biometrics, and the inability to determine the threats that it brings (Baragchizadeh et al., 2017; Quinn, 2015). Particularly, the public still has negative views on face recognition systems when they are applied to control access to campuses. Some parents have claimed that they violate the students’ privacy; some worry about the leakage of students’ personal information; and others are worried about insufficient funds and unclear usage standards (Qiu, 2017). In order to know how to obtain the trust and support of parents when implementing campus face recognition access control systems, it is necessary to explore the main influencing factors of parents’ intention to use them.

The Dual Process Attitude Model proposes two distinct types of attitude: the first is implicit attitude which is a stable evaluation formed a-priori, that is stored in special fast-access memory (Rydell & McConnell, 2006). The second is explicit attitude which is constructed through thoughtful processes; relevant information is deliberately accessed in the individual’s memory, and an evaluation of a device or object is developed within the current context (Serenko & Turel, 2019). As belief can be automatically activated as a response to environmental cues, has many features of implicit attitude, and is stored in associative memory (Greenwald & Banaji, 1995), implicit attitude as beliefs stems from one’s ways of viewing the world (Clay, 2016). Additionally, people who view the world as being highly competitive and threatening might support novel actions which give them an advantage over others (Clay, 2016). Human values are defined as motivational goals and are guided by attitude that influences individual behaviors (Ihemezie et al., 2021). Given that attitudes toward the use of face-recognition systems may be campus-dependent, there is some justification for examining the attitude-value-behavior (Reser & Bentrupperbaumer, 2005) aspect of parents’ perspectives; thus, this study applied dangerous belief and technological innovativeness to explore the formation of continuous intention mediated by value perception.

The “attitude–behavior gap” appears in the context of information system adoption. That is, the information system depends strongly on its value, and there is thus a need for more specific concern about the adoption process of information systems (El-Haddadeh et al., 2019). The Value-based Adoption Model (VAM) was proposed to explain the adoption of the Internet (Kim et al., 2007). In the research on VAM,
perceived value is usually used to explain the behaviors of using a new technology, and is determined by people’s perception of the cost and benefit when using the new technology. VAM can be used to explain both the initial adoption intention (Kim et al., 2017) and post-adopter behaviors (Wang et al., 2020) as users need to keep considering the value while making continuance decisions (Wang et al., 2020). In line with this, VAM is useful for explaining the relationship between relative value advantage and continuance intention; thus, a model of Parents’ Acceptance of Face Recognition Technology in Campus Access Control was constructed in this study to address the research questions listed as follows:

1. Is there a relationship between parents’ dangerous beliefs in the virtual world (DBVW) and their perceived value of face recognition use on campuses?
2. Is there a relationship between parents’ technological innovativeness and their perceived value of face recognition use on campuses?
3. Is there a relationship between parents’ perceived value of face recognition and their continuance intention to use the technology as a campus control approach?

2 Literature review

2.1 Face Recognition Systems in the context of China

Biometric recognition is based on physiological or behavioral features which are shared by all human beings but which differ from each other (Nie & Li, 2020). Face recognition has a high evaluation speed (Angadi & Kagawade, 2017). The principle of the technology is recognition of the human bone structure, so even if someone’s face is camouflaged, it is still difficult to fake. Compared with handwriting, voice, fingerprint, action, and other biometric recognition methods, face recognition has its own advantages, such as being non-contact, simple acquisition, having stable characteristics, and a low repetition rate (Wang & Ran, 2019). In 2019, the “Smart campus AI face one stop solution” developed by Baidu was adopted by nearly 1,000 primary and secondary schools. These schools started face recognition intelligent attendance (Sina, 2020).

In 2020, COVID-19 promoted schools in China to increase the use of face recognition so as to access a temperature measurement function for managing incoming and outgoing personnel, making the application of face recognition system campus access even more common (Feng & Chen, 2020). Researchers found that face recognition system campus access had impact on students’ sense of school identity and school belonging (Wang et al., 2022). As face recognition is increasingly widely used on campuses, the issue of personal privacy protection is attracting more attention (Li & Fu, 2019). In 2020, China formulated a “personal information protection law” and “data security law” to protect citizens’ personal information (Zhonghua Network, 2020). As the public holds diverse views on face recognition systems, what factors affect the usage of this technology was examined in this study.
2.2 Dangerous beliefs in the virtual world

Dangerous World Beliefs (DWB) were defined by Altemeyer (1988) as considering the world to be dangerous and threatening. The risk worldview stimulates the goals of safety and control, which are usually achieved through other forms of social conservatism. There are two views on the security of the Internet: (1) the positive belief that trusts the virtual world, and (2) the opposite perspective that holds dangerous beliefs of the virtual world (DBVW). Trust is needed in uncertain situations, because it is accompanied by risks and is vulnerable to the influence of the trustors (Dhaggara et al., 2020). On the other hand, DBVW is pervasive in the information Internet world. For example, in the public free wireless Internet, malicious access points or free hot spots in public places will cause a high degree of DBVW among many users (Hong et al., 2015). In line with this, this study considered that DBVW was closely related to new technologies.

Regarding the usage of new technology, continued use of information systems showed the importance of risk belief in explaining and predicting human behavior (Kim et al., 2007). For example, Singh & Sinha (2020) reviewed the perception and adoption of wallet services and found that perceived trust had a positive effect on the influence of perceived value on predicting merchants’ intentions. Moon et al., (2020) studied public support for a carbon capture and storage (CCS) policy and found the hidden effects of risk perception of technology which affected support for the CCS policy. From the above research, it can be seen that if a school implements the face recognition approach and forbids entrance to and exit from the school, parents may have DBVW related to the face recognition system. Thus, the role that DBVW plays in parents’ attitudes towards face recognition in elementary schools was explored in this study.

2.3 Technological Innovativeness

According to Rogers (2016), innovativeness refers to the degree to which one is early in adopting new devices, while Agarwal & Prasad (1998) defined personal innovativeness as certain individuals’ tendency to take risks. The relevant theory of technological innovativeness is Innovation Diffusion Theory (IDT) (Rogers & Everett, 2016) which indicated that innovative people need to make less cognitive effort in order to understand and accept new products. Thus, innovation can be regarded as a psychological trait (Prasad, 1998). With this trait, such individuals are happy to take chances and try out new things, and can more easily cope with a high degree of uncertainty (Bruner, 2005). Technological innovativeness refers to the willingness to try out new technology (Wang & Lee, 2020). Therefore, whether face recognition systems are closely related to parents’ awareness of technology advantages, compatibility, and testability of the system (Frennert et al., 2013) was explored in this study.

Previous studies have shown that technological innovativeness may have a high impact on people’s acceptance and use of a new technology. For example, technological innovativeness would influence students’ acceptance of learning via Moodle (Zwain, 2019). In the Asian context, some researchers have found that technology innovativeness influences smartphone use (Wang & Lee, 2020). However, few stud-
ies have extended technological innovativeness to the use of face recognition systems. Thus, how technological innovativeness is related to parents’ attitude towards face recognition in elementary schools was explored in this study.

2.4 Perceived Value

Perceived value is usually defined as one’s total evaluation of utility according to the relevant gains and sacrifices (Kim et al., 2007) from the perspective of rational choice theory and decision making theory in the economics field (Bérubé & Henri, 2010). A rational person tends to realize value maximization under the cost-benefit paradigm (Giesbrecht et al., 2017). The cost-benefit paradigm, which developed from the behavioral decision theory (Johnson & Payne, 1985), helps to explain the choices people make in a variety of decision-making strategies and the cognitive trade-offs between the perceived usefulness of the decisions they make (Mclean et al., 2018). In online technology systems, usefulness refers to how useful a technology is for users when performing a certain task (Madan et al., 2018). Accordingly, cognitive trade-off in perceiving value of face recognition was examined in this study.

Regarding value perception of using new technology, in El-Haddadeh et al.’s (2019) study, it was found that the perceived value of information systems (e.g., IoT) was strongly influenced by empowerment, while privacy-related issues significantly affected intentions to continue using the systems. Wang & Teo (2020) extended the updated information system success model to measure the success of mobile government. Their results indicated that information quality and online service quality, but not system quality, had positive associations with citizen satisfaction, which in turn had a positive association with their perceived value. However, the connotation of perceived value of face recognition as one type of new technology, and parents’ perceptions of the value of the access control system for face recognition, which refers to the trade-off between expectancy and value returned (Jamal & Sharifuddin, 2015) have not been extensively studied. Thus, how parents’ perceived value is related to their attitude towards face recognition in elementary schools was explored in this study.

2.5 Continuance intention to Use

Intention is usually defined as “a measure of the likelihood that a person will engage in a given behavior which may be termed behavioral intention” (Ajzen & Fishbein, 1980). Continuance intention to use (CIU) refers to the degree of willingness of users to use a certain service or a specific system (Savage & Waldman, 2015). Researchers have found that users are more willing to continue with a behavior when they can benefit from it (Bhattacherjee, 2001). Therefore, after referring to and integrating relevant theories and definitions, this study defined the factor named intention to use as “the intention of parents to use or understand the services and systems related to face recognition verification for campus access control.” Bhattacherjee (2001) argued that the initial acceptance of IS plays a significant role in IS success, but its long-term viability is determined by its continued use.
Moreover, Gao et al., (2015) argued that acquiring new customers and promoting usage is only the first step; after that, companies need to retain their users and ensure that they continue to make purchases. In the usage of new technology, resistance to change negatively influences intention (Liebana-Cabanillas at al., 2020). For example, when it comes to the mobile context, there is a relationship between the perceived security of the technology and the user’s intention to use mobile cloud storage services (Arpaci, 2016; Wu et al., 2020). It was also shown in previous studies that persistent intention plays a key and positive role in the success of virtual communities (Hong et al., 2017). Thus, this study explored what degree of continuance intention parents have regarding the use of face recognition systems on campus.

3 Research Model and Hypotheses

Drawing on the VAM (Kim et al., 2007), a conceptual research model of face recognition system continuance usage was developed. In view of the fact that face recognition access control systems essentially improve the security and convenience of identity recognition for students entering and leaving campus, it is natural that students’ parents would have perceptual value of using face recognition systems that would promote their acceptance. Therefore, in order to verify the research model, the research framework shown in Fig. 1 was proposed.

3.1 DBVW and Perceived Value

In practice, trust is considered to be a prerequisite of interaction in an uncertain environment (Ba & Pavlou, 2002). It has been proved that trust can affect user behavior in the process of technology adoption (Dhaggara et al., 2020). In this case, it is possible to reduce the confidence of consumers as service providers cannot guarantee the safety of the virtual world, which raises the reluctance to use service systems (Dhaggara et al., 2020). If the consumer lacks trust in the service, it is impossible for the consumer to perceive that the value provided is of any use (Singh & Sinha, 2020). At the same time, DBVW in the service system will reduce the workload required to monitor and control the interaction between services (Hong et al., 2015). Nevertheless, there has been little research exploring the relationship between DBVW and

Fig. 1 Research Model
perceived value in the context of face recognition systems. This study thus examined technological innovativeness to interpret the relationship of using face recognition systems by parents. In line with the existing literature, the present study explored how DBVW is related to the perceived value of face recognition systems, which was hypothesized as follows:

H1: DBVW is negatively related to perceived value.

3.2 Technological Innovativeness and Perceived Value

Researchers have found a positive relationship between consumer innovativeness and perceived value and the intention to continue using a smartwatch (Hong et al., 2015). A previous study found that innovation has a significant association with perceived usefulness (Liebana-Cabanillas et al., 2020; Lewis & Sambamurthy, 2003; Lee, 2013) explored the relationship between e-book use intention and personal innovation, and found that personal innovativeness was positively associated with perceived usefulness, and also had a higher use intention (Lee, 2013). Other researchers have found that consumers were more likely to feel the value of smartphones if they had high innovativeness about technology (Hong et al., 2017), while technological innovativeness was found to influence the perceived value of mobile payment services (Liebana-Cabanillas et al., 2020). However, little research has studied the relationship between technological innovativeness and perceived value in the context of face recognition systems. This study thus examined technological innovativeness to interpret the relationship of parents’ perceived value of using face recognition systems. In line with this, this study proposed the following research hypothesis:

H2: Technological innovativeness is positively related to perceived value.

3.3 Perceived Value and Continuance Intention to Use

The literature reports that perceived value positively impacts CIU (Chen & Chen, 2010). For example, Singh & Sinha (2020) found that perceived usefulness can predict people’s CIU for a certain merchant. Moreover, perceived value was found to significantly affect users’ intentions (Li et al., 2018; Wang, 2014). Previous research indicated that the greater value users perceive in their initial usage of technology, the higher continuance intention they would have (Wang, 2014). It has also been confirmed that perceived value has a mediating effect on the impact of innovative characteristics on behavioral intention (Plouffe et al., 2001; Liebana-Cabanillas et al., 2020) analyzed the intention to use mobile payment services in an emerging market and found that perceived value could predict the intention to use the services. Moreover, Wang & Teo (2020) argued that information quality and online service quality are positively associated with continuance intention and satisfaction, which have a positive association with perceived value. However, the literature provides little evidence of the relationship between perceived value and continued use intentions in the face recognition systems context. This study thus examined the role of perceived value in predicting the use of face recognition systems and parents continued use intentions. Considering this, how parents’ perceptions of the value of using face recognition systems affect their CIU was hypothesized as follows:
H3: Perceived value is positively related to continuance intention.

3.4 DBVW, Technological Innovativeness, and Continuance Intention

Implicit and explicit attitudes are different, but they can both influence one’s behaviors, with explicit attitude influencing behavior by triggering behavioral responses, while implicit attitude can affect the habituation of behaviors (Serenko & Turel, 2019). Moreover, those people with strong explicit attitudes have a greater tendency to engage in increasingly costly behavior (Kaiser & Lange, 2021) and individuals’ attitudes can predict the value perception before performing a behavior (Kaiser et al., 2021). Drawing on the attitude-value-behavior model (Reser & Bentrupperbaumer, 2005), the continuous intention to use face recognition systems was explored. Thus, to understand how parents’ DBVW and technological innovativeness related to continuous intention mediated by value perception was hypothesized as follows:

H4: DBVW and technological innovativeness are significantly related to continuous intention.

4 Method

The purpose of this study was to explore whether parents can accept the adoption of face recognition systems for the efficiency and convenience of identity verification when using the technology as a campus access control approach. The data were collected using “Questionnaire Star,” a widely used online survey platform in mainland China. The questionnaire was modified according to the operational definition of the variables. Finally, the hypotheses were verified by structural equation modeling (SEM).

4.1 Procedure

In order to collect a large number of samples, the online questionnaire survey method was used. Representative samples were selected according to the feasibility principle of snowball sampling (Sekaran & Bougie, 2013). The questionnaire was distributed from January 7 to 17, 2020 by emailing members of three Elementary School Parent Associations and asking them to mail the questionnaire link to acquainted parents to deliver it to other parents with children studying at elementary schools. After that, we analyzed the data and wrote the results. The whole research flowchart was shown in Fig. 2.

4.2 Participants

The participants were parents of elementary students from Xuzhou, China. A total of 394 valid data were collected. The proportion of male and female respondents accounted for 41.6% and 58.4% respectively, with slightly more females. Most were between 21 and 30 years old and 31–40 years old, accounting for 79.2%.
4.3 Instrument

In this study, the questionnaire items were adapted from the relevant literature. The BDVW measurement was adapted from Aurigemma & Mattson (2017), the technological innovativeness measurement was adapted from Albertsen et al., (2020), and the perceived value measurement and the continuance intention to use measurement were both adapted from Wang et al., (2020).

Then, the content validity was examined by three domain experts. If the semantic meaning of the questionnaire items was not clear, they were revised or deleted. The questionnaire used a 5-point Likert scale, with options “strongly disagree,” “disagree,” “neutral,” “agree,” and “strongly agree.” The higher the score, the higher the degree of agreement. After data collection, this study tested the reliability and validity of the questionnaire items and constructs for subsequent structural equation modelling. Reminded items are listed as Appendix 1.
5 Data Analysis

In confirmatory (also called hypothesis-testing) research, the researcher has a specific idea about the relationship between the variables under investigation and is trying to see if hypotheses are supported by data (Butler, 2014). Based on the requirement of confirmatory research, after invalid questionnaires were excluded, the present study tested the construct reliability and validity. Then, AMOS 20.0 was performed to verify research model.

6 Results

6.1 Item analysis

In this study, first-order confirmatory factor analysis (CFA) was conducted to test the suitability of the scale items. Table 1 shows the model fit indices of the scale structure by CFA. Based on the analysis, those items with factor loadings lower than 0.5 were deleted. Then, those items with the highest residual values in each construct were deleted until the first-order values met the threshold suggested by Hair et al., (2019). Table 1 shows that the $\chi^2/df$ values of all factors were less than 5, the RMSEA value was less than 0.08, GFI was more than 0.9, and AGFI was greater than 0.9, indicating that the items had good internal validity (Hair et al., 2019). Accordingly, the number of items for BDVW was reduced from eight to six; technological innovativeness was reduced from seven to five; perceived value was reduced from eight to six; and continuance intention to use was reduced from seven to five.

The independent sample t test was used to verify external validity by dividing the scale scores into two groups: a high group (the top 27% of the scale scores) and a low group (the bottom 27% of the scale scores). For a confirmatory study, items with a $t$ value higher than 3 should be retained (Green & Salkind, 2004). As can be seen in Table 1, all $t$-values exceeded 55.732. The retained items, listed in Appendix 1, were then subjected to reliability and validity analysis.

| Indices | Threshold | DBVW  | Technological innovativeness | Perceived value | CIU   |
|---------|-----------|-------|-----------------------------|-----------------|-------|
| $\chi^2/df$ | $< 5$ | 3.382 | 2.668 | 2.383 | 1.708 |
| RMSEA   | $< 0.08$ | 0.079 | 0.066 | 0.060 | 0.043 |
| GFI     | $> 0.8$  | 0.959 | 0.973 | 0.969 | 0.979 |
| AGFI    | $> 0.8$  | 0.927 | 0.947 | 0.944 | 0.961 |
| FL      | $> 0.5$  | 0.816 | 0.813-0.879 | 0.801-0.819 | 0.875 |
| $t$-value | $> 3$ | 0.866 | 55.732–66.148 | 0.880 | 0.875 |
|         |          | 58.695–65.599 | 75.515 | 63.338 |
6.2 Reliability and validity analysis

To measure the reliability of the data and to verify the consistency and stability of the data results, Cronbach’s α coefficient and composite reliability (CR) were calculated using SPSS 20.0, as shown in Table 2. The Cronbach’s α values of the total questionnaire and each factor were all between .870 and .960, and the CR values of the constructs were over .938, as shown in Table 2, exceeding the Cronbach’s α standard of .7 (Fornell & Larcker, 1981), indicating the good reliability of the instrument.

In the convergence validity test, AVE value and construct factor loading are used to calculate the variable explanatory power of each measurement variable for the potential variable, and two types of value should be higher than 0.5 (Fornell & Larcker, 1981). As shown in Table 3, the AVE values of each potential variable in this research model ranged from 0.655 to 0.754, and the values of construct factor loading were over 0.840, which are all higher than 0.5 (Fornell & Larcker, 1981), showing that the variation of potential variables in this study had good convergent validity.

To test the discriminant validity among constructs, the average variation extraction method (Fornell & Larcker, 1981) was used. Table 3 shows that the correlation coefficient absolute values of the four dimensions of the scale were less than the root square value of AVE, indicating good discrimination validity.

6.3 Model Fit Analysis

According to Hair et al., (2019), the GFI can be classified into three categories: (1) Absolute Fit Measures, (2) Incremental Fit Measures, and (3) Parsimonious Adjusted Measures. For the Absolute Fit Measures, four indices were used: (1) Chi-square statistic/df, where a $\chi^2/df$ value less than 3 indicates a good fit; (2) RMSEA, where an RMSEA value less than 0.08 shows a good fit; (3) GFI, where a GFI value over 0.8

| Constructs | DBVW | Technological innovativeness | Perceived value | CIU |
|------------|------|------------------------------|----------------|-----|
| DBVW       | (0.809) |                              |                |     |
| Technological innovativeness | 0.228 | (0.849)                   |                |     |
| Perceived value | 0.392 | 0.499                | (0.849)        |     |
| CIU        | 0.138 | 0.127                     | 0.386          | (0.868) |

*Note: the diagonal reversed part is the mean explanatory variation (AVE square root); the non-diagonal absolute value is the correlation coefficient of each factor
is considered an acceptable fit; and (4) AGFI, where an AGFI value over 0.8 shows an acceptable model fit. Table 4 lists the following Absolute Fit Measures generated from AMOS: \( \chi^2/df = 1.285 \), RMSEA = 0.052, GFI = 0.872, and AGFI = 0.860. These results show that the research model had a good fit to the collected data. The indexes for Incremental Fit Measures include the Normed Fit Index (NFI), Non-Normed Fit Index (NNFI), Incremental Fit Index (IFI), Comparative Fit Index (CFI), and Relative Fit Index (RFI). NFI, NNFI, IFI, CFI, and RFI values greater than the 0.90 cutoff value are considered a good fit (Hair et al., 2019). Additionally, the Parsimonious Adjusted Measures include the Parsimony Comparative Fit Index (PCFI), the Parsimonious Normed Fit Index (PNFI), and the Parsimonious Goodness of Fit Index (PGFI). Table 4 shows that the Parsimonious Fit Measures indices of this study were as follows: PNFI = 0.873 and PGFI = 0.794; as they both exceeded 0.50, the model is considered to have a good fit. Based on Hair et al., (2019), these results suggest that the proposed model was effective.

| Index | Threshold | Results | Model fit judgment |
|-------|-----------|---------|--------------------|
| N     | >200      | 380     | Supported          |
| \( \chi^2 \) | <.05      | 123 (p<.000) | Supported          |
| \( \chi^2/df \) | 1 ~ 5     | 1.285   | Supported          |
| PNFI  | >0.50     | 0.873   | Supported          |
| PGFI  | >0.50     | 0.794   | Supported          |
| GFI   | >0.8      | 0.872   | Supported          |
| AGFI  | >0.8      | 0.860   | Supported          |
| NFI   | >0.9      | 0.918   | Supported          |
| NNFI  | >0.9      | 0.980   | Supported          |
| IFI   | >0.9      | 0.981   | Supported          |
| CFI   | >0.9      | 0.981   | Supported          |
| RFI   | >0.9      | 0.914   | Supported          |
| SRMR  | <0.08     | 0.052   | Supported          |
| RMSEA | <0.08     | 0.027   | Supported          |

### 6.4 Path analysis

According to the significance test of model structural parameters (Hair et al., 2019), Fig. 3 shows that the influence path coefficient of DBVW on perceived value is \( \beta = -0.320 (p<0.001) \), and that of technological innovativeness is \( \beta = 0.447 (p<0.001) \). This means that the higher the DBVW is, the lower the perceived value is; on the contrary, the higher the technological innovativeness, the higher the perceived value. Moreover, the influence path coefficient of perceived value on intention to use was \( \beta = 0.406 (p<.001) \), indicating that the higher the persistent value, the higher the CIU (see Fig. 3).

The explanatory power (R²) is the interpretable variation or total variation to judge the explanatory degree of the model. In this study, the R² of each facet is 0.383, and the R² of intention to use is 0.165. The R² of each facet is not equal to 0, which shows...
that the variables of each facet have explanatory power of the model, as they are above the threshold (Cohen, 1988). In this study, the overall effect size in each path was calculated with $f^2 = \frac{R^2}{1-R^2}$ (Cohen, 1988) based on the effect quantity of Cohen’s $f^2$. The reference value of Cohen’s $f^2$ is 0.35, 0.15, and 0.02, which respectively indicate a high, moderate, and low effect (Lamb & Kwok, 2019). In this study, the Cohen’s $f^2$ value of each construct is 0.621, indicating a high effect. The Cohen’s $f^2$ value of CIU is 0.198, indicating a moderate effect.

### 6.5 Indirect effect analysis

In this study, the bootstrap method was used to analyze the indirect effects. The path coefficient is the direct effect between the facets, and the criterion is whether the confidence interval contains 0. If the value does not include 0, it means that indirect effects exist; if the value includes 0, there is no indirect effect (Guo et al., 2018). As shown in Table 5, the indirect effect is 0.002, indicating that DBVW and technological innovativeness have a significant effect on the continuous intention to use face recognition systems through perceived value; both indirect effect coefficients are 0.002. Accordingly, H4 was supported.

| Table 5 Indirect Effect Analysis |
|----------------------------------|
| Constructs | DBVW | Technological innovativeness |
|            | β    | 95% CI        | β    | 95% CI        |
| DBVW       | 0.002** | [-0.169,-0.083] | 0.002** | [0.123,0.248] |

Notes: *$p<.05$, **$p<.01$, ***$p<.001$
7 Discussion

Although implicit and explicit attitudes are different, they can both affect behaviors, and individuals’ attitude can promote the value perception before performing a behavior (Kaiser et al., 2021). In line with this, the present study explored parents’ DBVW and technological innovativeness in the value perception of the use of face-recognition systems, and continuous intention to use such systems as a research framework. The results presented in Table 1 indicate that the average score of parents’ DBVW is 3.865, which is higher than the average level (3.000), indicating that the parents were worried about the disclosure of students’ personal privacy, and generally had a cautious attitude towards new technologies (Perry & Sibley, 2010). The average score of parents’ technological innovativeness is 3.796, which is higher than the average level (3.000), indicating that the parent respondents tended to accept new technology (Wang & Lee, 2020). The average score of parents’ perceived value is 3.919, which is much higher than the neutral level (3.000), indicating that the parents generally recognize the value of face recognition systems (Kim et al., 2007). The average score of CIU is 3.776, which is higher than the neutral level (3.000), indicating that the respondents generally preferred to continue using the face recognition system at the campus entrance. On the whole, although the parent respondents thought that the face recognition system had certain risks, they were willing to try technological innovation and they thought the system was valuable, so they intended to continue using it.

According to the VAM model, this study designed the conceptual framework to explore the correlates between dangerous belief in the virtual world and perceived value, technological innovativeness and perceived value, and perceived value and continuance use intention. SEM was used to verify the hypotheses. The results of the hypotheses were tested as follows.

According to the results of the path analysis coefficient test, the DBVW was negatively correlated with perceived value, supporting H1, which is consistent with previous studies (Dhaggara et al., 2020). The results of this study indicate that there was a significant negative correlation between users’ anxiety about face recognition technology and their perceived usefulness. When users could trust that they had information security on the Internet, they would have lower information leakage anxiety and higher use intention (Singh & Sinha, 2020). Therefore, this study suggests that the higher the parents’ DBVW, the lower the value they perceived.

The results of the path analysis coefficient test revealed that technological innovativeness has a positive correlation with perceived value, supporting H2. The results are consistent with previous studies (Albertsen et al., 2020; Lee, 2013), which proved that personal innovation had a positive relationship with perceived usefulness which accounts for the relationship between parents’ technological innovativeness and perceived value in this research. This study found that the higher the technological innovativeness, the higher the perceived value.

The results of the path analysis coefficient test revealed that perceived value has a positive correlation with continuance use intention, supporting H3. The result is consistent with previous studies (Singh & Sinha, 2020; Wang et al., 2020) in which their results showed that accounting for higher perceived usefulness, there was a positive association between perceived usefulness and CIU (Singh & Sinha, 2020; Wang et
al., 2020). Therefore, this study found that the higher the parents’ perceived value, the higher their CIU.

Drawing on the attitude-value-behavior model, implicit and explicit attitudes differ, but they can both affect behaviors through value perception (Serenko & Turel, 2019). To examine the indirect prediction of CIU by parents’ DBVW and technological innovativeness, the results showed that DBVW can negatively predict CIU, but technological innovativeness can positively predict CIU, and both are mediated by value perception. As Kaiser & Lange (2021) suggested, explicit attitude influences behavior by triggering behavioral responses, while implicit attitude operates through the habituation of behaviors (Serenko & Turel, 2019). On the other hand, those people with strong explicit attitudes have a greater tendency to perform behavior as value increases (Kaiser et al., 2021). Thus, H4 was verified to understand how parents’ DBVW and technological innovativeness significantly related to CIU mediated by value perception.

8 Conclusions

To explore parents’ CIU antecedents, this study investigated the correlates between DBVW and technological innovativeness and perceived value of using face recognition as a campus access control approach. Moreover, this study designed a conceptual framework based on VAM, and verified the hypotheses with SEM. The results of this study revealed that while DBVW is negatively related to perceived value, the other two paths are positively related.

8.1 Implications

8.1.1 Theoretical implication

In theoretical value, this study developed the Value-based Adoption Model by applying dangerous belief and technological innovativeness to explore the formation of continuous intention mediated by value perception. This provided an effective new theoretical model for studying people’s continuous use of new technologies. In addition, this study filled a research gap on parents’ attitudes towards the use of artificial intelligence in campuses, which provided a reference for follow-up research.

8.1.2 Practical implication

In practical value, the results of this study implied that when parents think that a system is useful and valuable, they will be more willing to use it. Therefore, if school administrators want to promote parents’ support for face recognition systems by enhancing the level of technological innovativeness first, and promoting them to perceive the value of the system, it may encourage other parents to have more confidence in using face recognition systems. Parents usually care about the protection of their children’s privacy, so schools should integrate some Internet protection measures into face recognition systems. For example, schools can suggest that the firms
which produce face recognition systems demonstrate their high-quality service with Internet security protection, such as firewall erection, an Internet intrusion system, and Internet access control. With this consideration, parents’ BDVW can be reduced, which will then favor their continued use of the system.

8.2 Limitations and Future Study

Some limitations exist in this study. Regarding the use of face recognition systems, this study did not examine the usage timing, such as the time after returning to physical classrooms, returning after class, or evening self-study, which might influence the parents’ use intention. Similarly, the study did not focus on the usage scope, such as school gates or dormitories, which might also influence the parents’ use intention. These limitations could be addressed in future research.

Through using face recognition systems, researchers can compare students’ classroom behaviors such as attention and emotion change in the classroom with their academic performance. Nie & Li (2020) suggested that face recognition systems can also match teachers’ teaching situations with students’ classroom behaviors, and use students’ classroom performance data as feedback on teachers’ instruction. Thus, future studies may focus on how face recognition systems can be applied in classroom management and to improve teaching performance.

To examine attitude, this study re-designed DBVW and technological innovative-ness to measure participants’ implicit and explicit attitudes; however, there are some other scales from different perspectives to examine attitude. For example, the General Internet Attitude Scale (GIAS) was designed to examine the underlying components of individuals’ attitudes towards the Internet, and to measure three attitude components (affect, behavior, and cognition) (Joyce & Kirakowski, 2015). Another example, the Media and Technology Usage and Attitudes Scale, designed by Rosen et al., (2013), is a possible method for measuring media and technology involvement across different types of research studies including studies on the use of smartphones. Future studies may apply different scales to explore parents’ attitude toward using face recognition.

Different statistical approaches result different research findings. The current study applied SEM to verified the research model, while Analytic Hierarchy Process (AHP) could be used to determine the components of parental attitudes in future study (Arora et al., 2020; Goyal et al., 2021). In addition, we explored parental attenu-tudes towards facial recognition systems for campus access, but did not analyze the groups differences limited to the sample in our study. In the future, researchers can conduct AHP to analyze groups’ differences and compare the attitudes of parents, students, and teachers.

In construct the questionnaire, Gupta et al., (2021) suggested to use exploratory factor analysis (EFA) to test and purify the initial items, and to use CFA to verify the scale. However, the present study adapted questionnaire items from previous studies and ensure the content and face validity of each item, then conducted first-order CFA to examine the validity of items. Future study may implement EFA before CFA to obtain the purification of questionnaire items.
## 9 Appendix 1

### Items Retained in Each Construct.

| constructs                          | items                                                                 |
|-------------------------------------|----------------------------------------------------------------------|
| Dangerous Belief in the Virtual World | I think the current information system may leak personal data        |
|                                     | I think the current information system will expose personal information to the public when it is transmitted online |
|                                     | I think the current information system will be inappropriately used  |
|                                     | I think the current information system still has some bugs           |
|                                     | I think the current information system is easy to be tampered with   |
|                                     | I think the security of any information systems is doubtful         |
| Technological Innovativeness        | If I find the announcement of a new technological product, I will try to use it |
|                                     | I always read some new magazines to keep my technology knowledge up to date |
|                                     | My acceptance of new technology products is faster than that of my friends |
|                                     | I am always the first one to buy a new technological product         |
|                                     | Even if I hear that there is negative news about new technology products, I will still try to use them |
| Perceived Value                     | I think the face recognition system can be applied in school campus management |
|                                     | I think the face recognition system can improve the efficiency of students getting in and out of school |
|                                     | I think the face recognition system can enhance the campus security by stopping strangers from getting into the campus |
|                                     | I think the face recognition system can effectively manage the attendance of students in real time |
|                                     | I think the face recognition system can make it easier to identify the absence of students |
|                                     | I can trust the face recognition system to control the campus security |
| Continuous Intention to Use         | I would like to accept the face recognition system in any school activity |
|                                     | I think that in the future, when my child goes to high school, I will suggest that the school use the face recognition system as the access control method |
|                                     | I would like to encourage other parents to accept the face recognition system |
|                                     | In addition to the school gate, for faster classroom access, it is better to use the face recognition system |
|                                     | I would like to suggest that educational administrations apply more use of the face recognition system to enhance the effectiveness of school management |
|                                     | I prefer schools to continue to use the face recognition system      |
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Declarations

Ethics in publishing All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. This article does not contain any studies with animals performed by any of the authors.

Informed consent Informed consent was obtained from all individual participants included in the study.

Conflict of interest The authors declared that they have no conflicts of interest to this work. We declare that we do not have any commercial or associative interest that represents a conflict of interest in connection with the work submitted.

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