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An Analysis of the Factors Affecting Intention to Use Artificial Intelligence Technology in Learning: A Case Study of Hanoi Students

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Abstract
In light of several widely adopted factors impacting the adoption of new technology, this study aims to determine college students' intention to use artificial intelligence (AI) in their learning. The factors considered in this study include optimism, innovativeness, discomfort, perceived usefulness, and perceived ease of use. An online survey was conducted among students from eight universities in Hanoi, Vietnam, with a major in business who either are currently studying or recently graduated. A total of 192 questionnaires were validated and analyzed, applying a regression analysis. The results indicate that perceived ease of use and perceived usefulness significantly affect the usage intention of AI technology among college students. No difference was found based on the number of years of studies. The technology innovativeness dimension, however, failed to have a positive effect on college students' perception of the usefulness of AI technology. This finding is inconsistent with previous studies and highlights the idiosyncrasies of Vietnamese students regarding perceived AI usefulness.

Keywords: Artificial Intelligence, Usage Intention, Student Learning, TR, TAM, Vietnam.

1. Introduction

This study focuses on Artificial Intelligence (AI) in the context of higher education. Until recently, students and lecturers followed traditional learning and teaching methods. Students could only have access to knowledge through paper documents, hardcopy reference books, and the material provided by professors in the classroom. Typically, those who wanted to search for documents had to go to the library and manually looked up for the relevant information. Likewise, a professor who, for some particular reasons could not come to university to teach, had to reschedule his/her classes. In addition, if students had questions, they could only make an appointment with teachers or tutors at a specific time of the day for meeting and discussion. However, with the introduction of AI technology and recent breakthroughs in this field, all this has changed.

Students' learning experience is now increasingly supported by AI. This is the case for example with the search for material and self-learning. Today, when looking for materials, students have a variety of method, such as Google Scholar search engine or the search for e-books on online libraries using advanced filters to speed the task. To improve the mastery of the material covered in class, students can also choose to engage in self-learning with virtual tutors, which can provide answers and make suggestions instantly. Moreover, these virtual tutors not only provide support in problem solving for many students, they are also available for unlimited time around the clock (Tuomi, 2018). As to lecturers, those who were unable to be physically present on campus can now teach online, a trend which the current COVID-19 pandemic has accelerated as students have been forced to attend classes online. While the fact that teachers do not have to be in the classroom may only be temporary, online teaching offers new possibilities for students and lecturers alike that are bound to be more generalized in the future. AI technology also helps teachers arrange classes, class hours and grading (Marr, 2018). Many repetitive tasks that took up a lot of time in the past are now implemented synchronously and quickly by AI, creating time for more rewarding endeavors such as research.

The AI technology targeted in this study pertains to these various AI-induced changes in students' ways of learning. Obviously, to learn or to conduct research from home requires students to embrace this new technology, which raises among others the question of what factors affect students' intention to use AI technology. This study aims to address this query in the context of Vietnam. Specifically, it surveys college students enrolled at eight universities in Hanoi, Vietnam, as business majors (as mandated by the Ministry of Education there is a business school in every university, regardless of its core specialty). Understanding the technology usage motivations of this group of students is especially important as, unlike science or engineering students, they may be less inclined to endorse new technology and therefore less enthusiastic adopting AI technology in learning.

2. Literature Review and Hypothesis Development

- *Artificial Intelligence*

As a concept, AI has been around for centuries. Initially, as illustrated by Shelley's (1818) famous novel, Frankenstein, it was discussed solely as a fiction and a source of great fear; something threatening that would destroy humanity. Obviously, the perception of AI has drastically changed since. Today, rather than a danger, it is increasingly seen as a way of enhancing the human experience and assisting in daily chores as Industrial Revolution 4.0 is causing the fusion of digitalization with traditional industry processes. The main purpose of AI technology is to support people (Anderson & Rainie, 2018). AI assists people by performing repetitive tasks, which all used to be painstakingly done by human beings in the past, instantly and by delivering accurate results to users (Goh et al., 2019). AI technology has been embraced by researchers and the public at large as a form of progress and has been gradually infiltrating our lives. The development of AI technology has made major advances possible in almost every sector, including education (Kirkland, 2018). It now pertains to almost every aspect of our existence; a trend which the Covid-19 pandemic is accelerating.

In the field of education, AI technology benefits students and teachers alike. For instance, it supports research, helps to store information, and provides search suggestions (George, 2020). Moreover, with the ability to convert images and voices into digital signals, the concepts of "voice recognition", "face recognition", and "fingerprint recognition" are shifting industries into a new era and opening new doors for education. With regard to higher education, AI can help students better understand the material taught via enhancing the quality of lectures with additional documents (Li, 2020). AI technologies also facilitates teamwork and gives students more flexibility regarding the space and time of meetings as online meetings and conferences enable them to discuss projects with smart support through virtual tutors. This ensures assignment completion on time. In addition, AI facilitates the future orientation of students as it can suggest suitable learning paths and identify the appropriate subjects and activities in line with their future goals (Ayoub, 2020).

With the COVID-19 epidemic raging everywhere and the world struggling to control it, online arrangements and selection of classes, teamwork and learning process, which allow students to work from home, are more critical than ever. All that said, using AI technology improperly or overusing it can lead to unavoidable failures along one's educational path (Kharkovyna, 2018).

- *Intention to Use Technology*

The concept of 'intention' was first introduced by Fishbein and Ajzen in 1975 as part of their study of one's behavior towards one's intention to use technology and as part of the development of the Theory of Reasoned Action (TRA). According to this theory, intention to use technology increases the likelihood that one will implement one's actions, i.e., use technology. Thirty-five years later, Fishbein and Ajzen (2010) updated the TRA to further emphasize that the intention use factor is the best single factor that can be used to predict an object's behavior. Intention is a mental state that shows the certainty that a future behavior will be implemented (Bratman, 1987). The mental activities involved include planning and forethoughts of the intended behavior. In 1989, Davis developed a technology acceptance model (TAM model) based on Fishbein and Ajzen's (1975) conceptual grounding and introduced the concepts of perceived usefulness and perceived ease of use (Davis, 1989). As stated in the model, one's attitude towards usage intention is impacted by both perceptions. Davis and Venkatesh (1996) updated the model and removed the 'attitude' factor due to its weak impact as a mediator, focusing instead on the direct impact of usage intention on perceived usefulness. The TAM model has since become the most widely used model to predict acceptance of a technology target group (Legris, Ingham, & Collerette, 2003). A number of studies have borrowed Davis' theory and applied the TAM model to different subjects (e.g. Aypay, Celik, & Sever, 2012; Shroff, Deneen, & Ng, 2011; Park, 2009). These studies show statistically significant impact results.

- *Technology Readiness*

A Technology Readiness (TR) model was introduced by Parasuraman in 2000. Using an index, it measures a person's adaptability when he/she comes into contact with new technology (Parasuraman, 2000). The index comes as additional support to the TAM model. However, it only assesses the readiness of a subject for technology in general. The TR model includes four factors: optimism, innovativeness, discomfort and insecurity. The first two factors are identified as contributor factors and the other two as inhibitor factors. The validity of this model has been tested in a number of regions and in regard to various technologies (Jaafar et al, 2007; Mishra, Maheswarappa, & Colby 2018; Vaittinen & Martinsuo, 2019). Lee and Jun (2007) suggested that in using the TR model it is necessary to study other external factors that may affect both perceived factors (usefulness and ease of use) and therefore affect intention to use a particular technology. Consequently, subsequent research combined factors from the TR model and the TAM model into the Technology Readiness and Acceptance Model (TRAM model) (Damerji, 2019; Buyle et al., 2018). Although some of the factors differ, this model aims to determine the impact of intention to use on actual technology usage.

Since there is ample evidence of the weak effect of the 'attitude' factor, this study will ignore the attitude dimension as well. Consequently, based on the TAM and TR models and Lee and Jun's (2007) modified TR model, five of the factors affecting one's intention to use technology will be used in this research study to determine students' intention to use AI technology. They include three factors from the TR and TRAM models – optimism, innovativeness, and discomfort, which will be used as independent variables, and two factors from the TAM model – perceived ease of use (PEOU) and perceived usefulness (PU), to be used as dependent variables. Each of these independent variables will now be briefly discussed, starting with perceived ease of use.

- *Perceived Ease of Use*

Perceived ease of use is the perception that one can easily use technology without investing too much in-depth research time (Davis, 1986; Davis, 1989). According to Davis (1989), one's ability to accept technology will be higher if the subject perceives that technology is easy to use. The impact of perceived ease of use on intention was confirmed by Wu et al. (2008) and Smit, Roberts-Lombard, and Mpinganjira (2018). It was also validated by Damerji's (2019) research. In addition, after evaluating the correlation between perceived ease of use and perceived usefulness and target groups' intention to use technology, Davis (1989) found that perceived ease of use had a strong influence on perceived usefulness. Specifically, he determined that the effect of ease of use on usage intention has decreased by 91 percent after controlling perceived usefulness.

Various studies have found that perceived ease of use has a strong impact on intention to use AI technology (e.g. Lule, Omwansa, & Waema, 2012; Aypay et al., 2012; Park, 2009). Moreover, in their research study on the acceptance of a clinical information system by 604 medical staff members at 14 hospitals in Greece, Melas et al. (2011) found that the impact of perceived ease of use on technology adoption was stronger than the impact of perceived usefulness on one's intent to use technology. Shroff et al. (2011) confirmed this finding. Focusing on accounting students in the US, a recent study by Damerji (2019) concluded that perceived ease of use had a positive effect on these students' intention to use technology. However, research by Park (2009) showed a different outcome. The survey of Korean bachelor students revealed no direct impact between easy-to-use awareness and the intention to use online learning technology. Another study conducted by Lee, Hsieh, and Hsu (2011) in Taiwan also indicated that for employees of companies using online training systems, perceived ease of use had no impact on usage intention. Thus, based on the above literature, the following hypothesis can be proposed:

> **H1**: *Perceived ease of use of AI technology has a positive effect on college students' intention to use this technology*

- *Perceived Usefulness*

Perceived usefulness can be defined as one's perception that one will work more effectively if one uses technology (Davis, 1986; Davis, 1989). According to Davis (1989), the higher the level of usefulness perceived by the subject, the higher the likelihood of technology adoption. Later research confirmed this finding (e.g. Bagozzi, Davis, & Warshaw, 1992; Adams, Nelson, & Todd, 1992; Larasati, Widyawan, & Santosa, 2017; Nugroho & Fajar, 2017). This effect was also significant in Damerji's (2019) applied research as was also the case in Smit et al's (2018) study.

In their study on the effect of perceived usefulness and perceived ease of use on the acceptance of a word processing program, WriteOne, among MBA students at the University of Michigan, Davis, Bagozzi, and Warshaw (1989) determined that perceived usefulness had a strong impact on one's intention to use technology. This determination was also made in subsequent studies (e.g. Park, 2009; Lee et al., 2011; Lule et al., 2012). Focusing on the impact of these two perception factors on NFC mobile payment acceptance among South Korean college students, Shin and Lee (2014) concluded that perceived usefulness positively affected their intention to use technology. Their perception that the payment program was easy to use, however, had little impact on their usage intention. Moreover, in their study of bachelor students in Hong Kong, Shroff et al. (2011) found that perceived usefulness did not affect students' intention to use technology, here, e-portfolio learning system. Accordingly, the following hypothesis has been developed:

> **H2:** *Perceived usefulness of AI technology has a positive effect on college students' intention to use this technology*

- *Technology Optimism*

As one of the elements of the TR model discussed above, technology optimism is used by many researchers to analyze the impact on the intention to use technology (e.g. Panday & Rachmat, 2019; Buyle et al., 2018; Nugroho & Fajar, 2017). Technology optimism can be defined as the positive perception of technology. In the case of AI technology, it indicates that technology can support people to work more autonomously, effectively and flexibly (Parasuraman, 2000). According to Parasuraman and Colby (2001), perceived optimism promotes the feeling that technology is good and human-friendly. This in turn has an impact on perceived ease of use and perceived usefulness. Larasati et al. (2017) and Damerji (2019) have determined that optimism influences students' intention to use AI technology in relation to learning. The technology optimism rhetoric usually refers to its positive aspects, which are often related to its usefulness, performance (contiguous with high accuracy) and whether it can be easily managed with only a small number of employees. It can also pertain to the contribution of AI technology in improving the quality of life, living standards and work performance (Parasuraman & Colby, 2001).

One of the first studies to use this factor looked at it in the context of employees' technology adoption at a Belgian multi-site financial service provider (Walczuch, Lemmink, & Streukens, 2007). Participants were asked to select the software application they used most and then to fill out a questionnaire about their feelings on that application. The results showed that technology optimism has a positive effect on both perceived ease of use and perceived usefulness of that technology. Erdoğmuş and Esen (2011) surveyed HR managers at private companies in Turkey and determined that these two perceptions had a positive impact of optimism. However, targeting a more general audience of small and medium enterprises in Indonesia, Larasati et al. (2017) came up with different results. Optimism about technology only affected perceived ease of use. Buyle et al. (2018) studied private and public company employees in Belgium and concluded that optimism about technology does not have a statistically significant effect on the perception that technology is easy to use and useful. Based on these various findings, the following hypotheses have been developed:

H3*: Optimism about AI technology has a positive effect on college students' perception of the ease of use of this technology.*

H4*: Optimism about AI technology has a positive effect on college students' perception of the usefulness of this technology.*

- Innovativeness

Another element of the TR model used in this study is innovativeness. It has been defined as the perception that an organization with state-of-the-art technology will be considered a leader in that particular technological field (Parasuraman, 2000). Innovativeness accounts for the perception of an organization as a technology pioneer or a thought leader. It acts as a motivation factor and enhances a person's readiness for technology (Parasuraman & Colby, 2001). The impact of the innovativeness of technology on perceived usefulness and ease of use has been extensively researched. In a recent study by Buyle et al. (2018), innovativeness was shown to have a considerable impact on both perception factors. Earlier, Erdoğmuş and Esen (2011) had reached a similar conclusion. Shin and Lee (2014) studied Korean students' intention to use AI technology (NFC mobile payment) and confirmed the positive effect of innovativeness on perceived ease of use. In 2019, Panday and Rachmat conducted a study on employee technology readiness and acceptance at a company located in Indonesia and also found that innovativeness had a positive effect on perceived ease of use. Larasati et al. (2017) studied small and medium-sized companies in Indonesia and concluded that innovativeness had a positive impact on perceived ease of use and perceived usefulness. Based on the above, the following hypotheses will be used:

H5: *AI technology innovativeness has a positive effect on college students' perception of the ease of use of this technology.*

H6: *AI technology innovativeness has a positive effect on college students' perception of the usefulness of this technology.*

- Discomfort

As explained earlier, discomfort is the third element of the TR model used in this study. It represents a sense of uncertainty and difficulty controlling the technology used. One may even feel overwhelmed by the technology (Parasuraman, 2000). According to Parasuraman and Colby (2001), this factor will give one a sense that the new technology does not seem suitable for a 'normal' person with a medium level of knowledge in technology. That person may end up feeling that technology is too complicated for him or her. Therefore, a higher level of technological knowledge is required to understand new technology and be able to use it. Technology discomfort has been shown by many scholars to have an impact on perceived ease of use and perceived usefulness (e.g. Buyle et al., 2018; Purba, 2015; Godoe & Johansen, 2012). This finding was verified in a recent study by Panday and Rachmat (2019), who conducted research on employees of an Indonesian company. Based on the above, the following hypotheses can thus be proposed:

H7: *Discomfort with AI technology has a negative effect on college students' perception of the ease of use of this technology.*

H8: *Discomfort with AI technology has a negative effect on college students' perception of the usefulness of this technology.*

3. Methodology

This study uses a quantitative approach to analyze and test the eight hypotheses articulated for this research based on the three independent variables and two dependent variables discussed above. The scale for measuring the questionnaires is adopted from previous studies, most notably Damerji's (2019). Data is collected using an online survey questionnaire. The data collected and the hypotheses are then tested with the SPSS 22.0 and AMOS 22.0 software. Data was collected from college students from the following universities in Hanoi: National Economics University, Foreign Trade University, Banking Academy, Academy of Finance, Vietnam University of Commerce, Thang Long University, Hanoi University of Mining and Geology, and Vietnam National University of Agriculture (as mentioned earlier, in Vietnam, there is a business school in almost every university, regardless of the name and core specialty of the university).

This study focuses on students with business major, who form a fairly large and coherent group in every of these universities. To generalize the result across the population, the sample size was determined based on the following formula: n = 5 * m, where m is the number of observed variables (Comrey & Lee, 2013; Worthington & Whittaker, 2006). In this study, the number of observed items is 23. Therefore, the minimum sample size must be 115. However, since participants were selected by using the convenient sampling method, the number of questionnaires collected was less than expected as some students failed to fully and truthfully respond to the questionnaire. As a result, the sample size of this study was 230 students. This meets the minimum sample size requirement. Participants were asked to give their opinions on questions related to their feeling about AI technology in the field of education by filling out an online survey questionnaire. The first ten participants who completed the survey were contacted via mobile phone audio calls to give them feedback on the questionnaire, which was recorded and then analyzed to improve the survey instrument.

A total of 204 fully answered online questionnaires were collected. After checking for inappropriate answers, 12 invalid questionnaires were removed, bringing the total number of valid questionnaires down to 192. The data shows that most of the respondents are currently in the third year of their bachelor's degree (64.6%). Only 2.1% of them had already graduated. One of the reasons for this low figure is that since after they graduate students often change their contact numbers, few could be contacted. Among the universities surveyed, students from National Economics University and Banking Academy account for 88.6% of the respondents. Part of the reasons is the larger number of students enrolled in those universities. Another is that the author being at NEU, it was easier to ensure that students would fill out the questionnaires. All the items in the questionnaire (except for the questions about demographics) were measured using a 5-point Likert scale, ranging from 1, "Extremely disagree", to 5, "Extremely agree". The scales in the research model were adopted from previous studies (Parasuraman & Colby, 2001; Panday & Rachmat, 2019; Damerji, 2019).

4. Research Findings and Discussion

- *Reliability Tests*

Since this study uses a Structural Equation Model (SEM) to analyze the impact of the factors described above, an Exploratory Factor Analysis (EFA) was conducted to test the data reliability, using the Promax rotation method. After conducting the EFA test three times, three items were removed and one item moved from perceived usefulness to intention. Another index used in this study is the Kaiser-Meyer-Olkin (KMO) index. At 0.863 and Sig. < 0.001, it confirms the goodness of the EFA results. Both are considered good data set as determined by Hair et al. (2013). As indicated in Table 1, the data explains 59.436 percent of the real effects in real life.

Table 1: Data Reliability Test Result: EFA Approach

	1st Test	2nd Test	3rd Test
KMO	0.882	0.861	0.863
Sig.	0.000	0.000	0.000
Total variance explained	58.256	58.71	59.436
Number of factors	6	6	**6**
Number of original items	23	21	20
Number of remaining items	21	20	**20**

Source: Data analysis compiled by authors

The Cronbach's Alpha test for reliability shows that all the items and data are reliable since all Cronbach's alpha index are above 0.7 as per the criteria suggested by Peterson (1994). In addition, the average level of agreement with regard to perceived usefulness and intention to use AI technology in learning is more than 4 on the 5-point scale. This indicates that students in Hanoi (at least those tested, all of them business majors) feel that AI technology is very useful and are willing to apply it to their learning process. The technology optimism factor also received a high average answer, which shows that students have positive thoughts about AI technology.

Table 2: Descriptive Statistic of Variables

Variables	Mean	Cronbach's Alpha	Standard Deviation
Technology optimism	4.031	0.802	0.642
Innovativeness	3.216	0.734	0.881
Discomfort	2.944	0.706	0.651
Perceived ease of use	3.570	0.885	0.886
Perceived usefulness	4.090	0.822	0.592
Intention to use AI technology in learning	4.094	0.834	0.602

Source: Data analysis compiled by authors

- ***Impact on Intention Analysis***

According to Hair et al. (2013), in the presence of the three types of variables, namely, independent, moderate, and dependent variables, the Structural Equation Model (SEM) should be used. Since the PEOU and PU are both moderate and dependent variables, this study therefore applied the SEM model to the theoretical model to analyze impact. The model used is shown below.

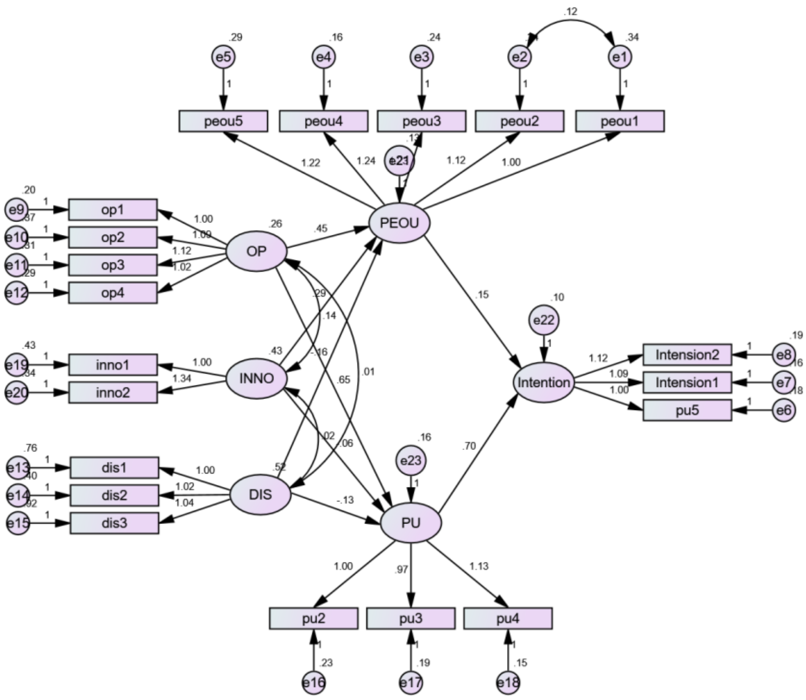

Figure 1: Theoretical Model Analysis: SEM Approach
Source: Data analysis results compiled by authors

Based on the criteria developed by Hair et al. (2013), the results of the Theoretical Model Analysis show that the model of this study is suitable for analysis. With a CMIN/df = 1,584 < 2, the Chi-square test index is acceptable. The GFI index is 0.882> 0.8, which is also acceptable. This is also the case of the CFI index, which equals 0.945> 0.9. The RMSEA index = 0.055 <0.8 therefore qualifies.

- ***Hypotheses Testing***

As the results of the SEM analysis in Table 3 indicate, both perceived usefulness and perceived ease of use have a statistically significant positive impact on students' intention to use AI technology in learning as both p-values are below 0.05. Hence hypothesis H1 and H2 are accepted. These findings are in-keeping with those determined by Damerji (2019) and Nugroho and Fajar (2017) on the same sample of university students. However, with a coefficient β = 0.696 (Se = 0.096; p <0.05), compared to β = 0.146 (Se = 0.071; p <0.05) for perceived ease of use, the impact of perceived usefulness on usage intention is significantly stronger. This proves that in deciding to adopt a new AI technology in learning, students (at least those majoring in business) are more concerned with its usefulness than whether or not it is easy to use.

Table 3: Hypothesis Test Result and Coefficients of Impacts

	β	Standard Error	P	Hypotheses
PEOU □ Intention	0.146	0.071	0.040	H1: Accepted
PU □ Intention	0.696	0.096	***	H2: Accepted
OP □ PEOU	0.448	0.095	***	H3: Accepted
OP □ PU	0.652	0.110	***	H4: Accepted
INNO □ PEOU	0.293	0.704	***	H5: Accepted
INNO □ PU	- 0.055	0.072	0.443	H6: Rejected
DIS □ PEOU	- 0.159	0.057	0.005	H7: Accepted
DIS □ PU	- 0.128	0.059	0.030	H8: Accepted

Source: Compiled by author

With p-values below 0,001 in both cases, technology optimism has a positive impact on the two moderate independent variables, perceived ease of use and perceived usefulness, thus confirming hypothesis H3 and H4. The level of optimism of student about AI technology in education is high (the average is superior to 4 on a 5-point scale) and is similar regardless of the years of study. There is, however, a slight difference among universities. The level of optimism among students from Foreign Trade University and Academy of Finance is lower than that of other universities. This could be due to the different level of application of AI technology to university activities. This could also be a result of the dissemination by other universities of positive information about AI technology, which would contribute to an optimistic feeling toward it.

Innovativeness positively affects students' perceived ease of use. With p-value lower than 0.001, Hypothesis H5 is accepted. However, while it is positive, its impact on perceived usefulness is not statistically significant (p-value = 0.443 > 0.05), which means that hypotheses H6 is rejected. Regarding the various universities involved in this study, students across the board feel innovative about AI technology at the same level, just more than 3 in 5-point Likert scale (medium level). This result disaffirms the conclusions of previous studies by Buyle et al. (2018) and Erdoğmuş and Esen (2011). Whereas the feeling of innovativeness about AI technology impacts students' perception of ease of use of new technology, it does not change students' perceived usefulness.

By contrast, the discomfort factor has a statistically significant negative impact on the two perception variables. Therefore, hypotheses H7 and H8 are accepted. This finding is inconsistent with several previous studies that focus on different research subjects and circumstances as explained in the literature review section (Damerji, 2019; Erdoğmuşa & Esen, 2011; Walczuch et al., 2007). This could be due to cultural differences. Vietnamese students' cautiousness comes from the fact that generally they tend to prioritize efficiency in learning and if they feel that using AI technology may be uncomfortable, it will affect their performance. Thus, any hard-to-use AI technology in learning will not be deemed useful in learning.

5. Conclusion and Recommendations

This research aimed to assess AI technology usage intention in learning among college students majoring in business at various universities in Hanoi. Based on the results discussed above, the following conclusions can be drawn.

Firstly, at 4.094 on 5-point scale, students' intention to use AI technology in learning is relatively high, which means that a majority of students are eager to embrace existing AI intelligence technology – and most likely any new future developments – and integrate it as part of their learning tools. For example, if, and when, new virtual teaching assistants are introduced, students with a business major (i.e., those surveyed in this research study) are likely to accept it and readily use it. Customer acceptance though is always an issue when product or service innovation makes its way into markets, especially technology-pushed innovation, which, as opposed to market-led technology, does not respond to a demand but does create a need. A case in point is driverless cars. Market research indicates that the public is not ready yet to hop in a car and read a book or take a nap while being driven around. Car manufacturers are aware of this and are dealing with this obstacle by integrating ever more AI technology into new cars so as to get consumers accustomed to it. As this study shows, however, AI technology in learning is widely accepted by students, regardless of the year of study. This augurs well for the AI industry focusing on this sector and for future innovation. A rejection of radical innovation can never be fully discarded though.

The results indicate that there are slight differences in the level of application of AI technology from one institution of higher learning to another. A closer look at the universities surveyed reveals that the Academy of Finance has less changes in terms of learning software and websites compared to the other universities considered in this research. This may be due to differences in university policies regarding the promotion of the use of AI technology in learning. This may also be due to budgetary constraints or to a diverging philosophy regarding new AI technology, but without any further investigation this is difficult to ascertain.

Secondly, the technology optimism dimension shows that when students feel optimistic about new AI technology, they are more likely to use it. Students' positive perception of technology is essentially linked to its ease of use and – to a lesser degree – to its usefulness. It is also inversely proportional to the discomfort dimension. The more students develop a sense of uncertainty and difficulty controlling AI technology in learning, the higher their level of discomfort with AI technology is likely to be and the lower their level of technology optimism and therefore the lower their intention to adopt AI technology. When students feel that that technology is less efficient and more difficult to use, a reduction in their tendency to apply it to learning occurs. This shows that innovativeness may not just be achieved at the expense of ease of use as the lack thereof tends to generate a sense of discomfort and adversely impacts the optimism dimension. The findings in this study are at odds with previous research studies. While they found that technological discomfort affected technological ease of use, many of them concluded that it was not statistically significant and thus rejecting the impact of discomfort on perceived ease of use (Panday & Rachmat, 2019; Buyle et al, 2018; Purba, 2015; Godoe & Johansen, 2012).

Since these studies were conducted in countries other than Vietnam, their findings are not necessarily applicable to Vietnamese students. This research study simply demonstrates that Hanoi, students' sense of comfort towards technology has a stronger impact on perceived ease of use compared to users in other regions. This may be due to less emphasis on technology at Vietnamese universities and the relatively lower access to IT compared to those the countries in these studies, which are all at higher level of economic development. Technological discomfort was also determined in previous studies to have no impact on perceived usefulness (e.g. Nugroho & Fajar, 2017; Larasati et al., 2017; Kuo, Liu, & Ma, 2013). Yet, it has a negative impact in this study. Again, Hanoi students' views about discomfort in technology differ from those of Koreans, Indonesians and Taiwanese much for the same reasons mentioned above. Another key factor in the case of usefulness is Vietnamese students' concern about the fact that they could easily end up misusing AI technology in learning and jeopardizing their studies by getting into activities, which, while attractive and playful, may not necessarily be useful or relevant to their studies. This is also related to the amount of outside information that students receive each day. It is well-known that news with negative content attracts Vietnamese, especially with regard to technology (e.g. cybercrimes), and contributes to instilling a pessimistic mindset about new technology. Students should assess the pros and cons of technology optimistically and objectively and leave aside any preconceived ideas.

Thirdly, in line with the above remarks, while students believe that innovativeness make their use of AI technology easier, they do not necessarily see it as enhancing its usefulness. This finding debunks the commonplace idea that the more features AI technology brings to markets, including to students, the more useful it appears to be. In the eyes of Vietnamese students, innovativeness does not necessarily equate with usefulness, let alone the fact that it may compromise ease of use.

- *Recommendations to Students*

While student should take advantage of AI technology to enhance their learning experience, they should also make sure that they do not become dependent on AI technology. Therefore, they should always actively combine its use with traditional learning methods. Second, it is important for students to develop a positive attitude towards technology and continue to explore new technologies in learning with an open and constructively critical mind. The leading power of mastering new AI technology that enhances their learning experience cannot be discarded as it can provide students with a sustainable competitive advantage not only while learning at university but also in their future careers as it is quite probable, that given the fast pace of innovation, they will have to learn, adopt, and adapt to various new technologies, including radical innovation, in the course of their professional lives. They should thus remain more open-minded and confident to learn from others, including those who might be younger but nonetheless well-versed in AI technology.

- *Recommendations to Universities*

Given that students are ready to embrace AI technology in learning, universities should offer them support and encourage those still hesitant to adopt it. They should help them further develop their knowledge of AI and promote the formation of support groups on social networks, which could significantly contribute to enhance their confidence using this technology in learning. In addition, they should keep updating information about innovations and upgrade the level of mastery of AI technology of lecturers. Since innovativeness can substantially impact student intention, universities could organize activities to make students see the benefits of being pioneers in using AI technology. This could be done in collaboration with and under the sponsorship of key players in the industry. Lecturers should encourage students to use AI technology as part of their assignments and recognize those resorting to unique applications. In order to reduce pressure, drills requiring the use of AI technology could become part of the curricula and be scored as basic assessments of how students fare. Finally, ethical issues involved in the use of AI technology should be discussed and publicized.

- Limitations and Future Research Directions

Due to the Covid-19 pandemic, this study only used a quantitative approach (a survey) to collecting data from a number of universities located in Hanoi. Yet, the author' initial intention was to complement the online survey questionnaires with some deep face-to-face semi-structured interviews with some of the participants so as to obtain more feedback from them; something which obviously was not possible because of the lockdown imposed by Hanoi as a preventive measure. Since semi-structured interviews by definition involve a high level of spontaneity and improvisation as well as observation of the interviewees, it would not have been realistic to conduct them online. Next studies on this topic should therefore use a mixed methodology.

Also due to the coronavirus pandemic, the author had no option but to conduct the survey completely online. Since students generally postpone completing surveys – and in many cases never get to them as a result, the author intended to distribute the questionnaires and collect them in person so as to increase the sample size. If the distribution could have been done face-to-face, a bigger sample could have been obtained, something which would have increased its validity. Further research should therefore include a broader sample; one that also better balances the number of first-year, second-year, third-year, and fourth-year students as well as the proportion of students among the universities targeted. Finally, this study solely explored the impact of various factors on the intention to use AI technology. Future studies could develop a model that would explore use intention and the actual use of AI technology and its direct and indirect effects on future use intention.

In addition, this study solely focused on students majoring in business in Hanoi. The results might have been different in other areas and with students with different majors. In future studies, researchers could therefore choose to have a more general sample of respondents to increase the validity of the findings. They could also aim for a research focus on survey respondents with different physical and psychological backgrounds.

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