The Educational Review, USA, 2025, 9(1), 117-132
https://www.hillpublisher.com/journals/er/
ISSN Online: 2575-7946
ISSN Print: 2575-7938

Factors Influence Readiness to Use Artificial Intelligence (AI) Applications in Teaching and Learning Among College Faculty Members of China: A Case Study of Guangdong Medical University

Linjun Xu

School of Foreign Languages, Guangdong Medical University, Dongguan 523808, Guangdong, China.

How to cite this paper: Linjun Xu. (2025). Factors Influence Readiness to Use Artificial Intelligence (AI) Applications in Teaching and Learning Among College Faculty Members of China: A Case Study of Guangdong Medical University. *The Educational Review, USA*, 9(1), 117-132.
DOI: 10.26855/er.2025.01.017

Received: December 27, 2024
Accepted: January 24, 2025
Published: February 21, 2025

Corresponding author: Linjun Xu, School of Foreign Languages, Guangdong Medical University, Dongguan 523808, Guangdong, China.

Abstract

This study examines the intention to use Artificial Intelligence (AI) among academicians at Guangdong Medical University in China, using the Technology Acceptance Model (TAM) as a theoretical framework. The research examines the association between the perceived benefits of AI in higher education and teaching and learning, attitudes towards AI, and the desire to employ AI in teaching and learning. A sample of 260 faculty members was collected via convenience sampling and analyzed using Pearson correlation and multiple regression. The results demonstrate a significant and positive relationship between the perceived advantages of artificial intelligence (AI) in higher education and teaching and the inclination to utilize AI. Nevertheless, an intricate and reciprocal correlation with sentiments towards AI is also noted. The study emphasizes the significance of perceived advantages in promoting the adoption of AI in an academic environment while also acknowledging the subtle influence of attitudes toward technology. This resource offers pragmatic insights for educational institutions to effectively promote the usage of artificial intelligence. Although the study's scope is limited to a specific school, which may restrict its applicability to other contexts, it provides valuable insights into the implementation of AI in higher education and proposes avenues for further investigation. These include conducting more comprehensive and long-term studies and considering additional elements that may influence the outcomes.

Keywords

Artificial Intelligence (AI); Technology Acceptance Model (TAM); Guangdong Medical University (GDMU); Attitudes Towards AI

1. Introduction

China is a nation that leads the global Artificial Intelligece (AI) innovation and application in education sectors. The massive investment and collaboration among policymakers, private sectors, and research institutions have been in evidence since the introduction of China's AI Vision 2030 (State Council Notice, 2017). According to Hao (2019), almost USD 1 billion in investment fueled the development of AI applications in the Chinese education system. China's government also approaches and actively seeks strategy partners, particularly in countries that leading China in AI such as the USA and the UK (He & Bowser, 2017).

As a result, the partnership particularly between Chinese AI research institutes and AI-driven international institutions like Standford University and Carnegie Melon boosts AI innovations (Barton et al., 2017). This initiative successfully integrated AI experts globally and the collaboration was done in more efficient and effective ways as redundancy of innovations can be avoided because of the pools of data and information sharing (Alsheibani, Cheung, & Pan, 2018; Ding, 2018). Mutual collaboration between forefront nations in AI-related industry would benefit all in terms of drafting international AI policy guidance, improving the AI ecosystem, and joint hand in countermeasure strategies against misuse of AI for cross-border crimes, cyberattacks, and terrorism(Ayanwale et al., 2022; Gunn & Mintrom, 2013; Jonathan Woetzel et al., 2023).

Apart from building international strategic partnerships, China took a major step in the development of AI-related industries by transforming the existing education system with a new AI-integrated education ecosystem. The transformation process of AI tools in education is still a work in progress yet shows some remarkable results. As updated in June 2023, there are 97 AI tools in teaching and learning that were innovated by local startup companies since 2010 and still operating to date (Tracxn Technologies Limited, 2023). Hence, it is deemed important to seek an understanding of the factors that can influence the attitude, and intention to use and adopt AI technology in teaching and learning. Understanding the intention to use AI will benefit the whole education ecosystem as the inputs from the investigation will improve not only the performance of AI applications but also the marketability aspect of it.

To understand the phenomenon of the study, this research proposes three research questions that guide the direction and purpose of the study's implementation. The three research questions are as follows.

(1) Does the perceived benefits of artificial intelligence (AI) in higher education positively influence the intention to use AI among Guangdong Medical University faculty members?
(2) Does the perceived benefits of artificial intelligence (AI) in teaching and learning positively influence the intention to use AI among Guangdong Medical University faculty members?
(3) Does attitude toward artificial intelligence (AI) positively influence the intention to use AI among Guangdong Medical University faculty members?

This study is conducted to answer the questions posed above to achieve the following objectives. (1) To determine the positive influence of perceived benefits of artificial intelligence (AI) in higher education towards intention to use AI among Guangdong Medical University faculty members. (2) To determine the positive influence of perceived benefits of artificial intelligence (AI) in teaching and learning towards intention to use AI among Guangdong Medical University faculty members. (3) To determine the positive influence of attitude towards artificial intelligence (AI) on the intention to use AI among Guangdong Medical University faculty members.

Basically, there are five (5) important concepts in this study, and to ensure readers are able to understand the discussion, this study proposes a definition to operationalize the concept. The operational definitions are as follows.

Artificial Intelligence in Teaching and Learning: Artificial intelligence (AI) in teaching and learning refers to the computing system that can perform human-like functions, which appears to be a promising alternative to traditional classroom instructions and sessions (Alnasib, 2023).

Perceived Benefits of Artificial Intelligence in Higher Education: Perceived benefits of AI in higher education refer to the faculty members' optimism that AI use would significantly improve the standards, standing, and worth of higher education institutions on the educational, social, and national levels (Alnasib, 2023).

Perceived Benefits of Artificial Intelligence in Teaching and Learning: Perceived benefits of AI in teaching and learning refer to the degree to which faculty members thought that using a new system would enable them to improve their job performance significantly (Alnasib, 2023).

Attitude towards Artificial Intelligence: Attitude towards AI refers to the degree to which faculty members view a specific behavior favorably or unfavorably (Alnasib, 2023).

Intention to Use Artificial Intelligence in Teaching and Learning: Intention to use AI in teaching and learning refers to the degree to which an individual feels confident about oneself in disseminating AI education (Alnasib, 2023).

2. Literature Review

2.1 Intention to Use Artificial Intelligence (AI)

Understanding the intention to use new technology, in general, can help businesses tailor the consumption cues to better produce and market the new products. Intention to use new technology like Artificial Intelligence (AI) refers to the likelihood of individuals using and adopting new technologies. It is also reflected in the psychological readiness of individuals to engage and embrace new technologies to accomplish their goals at home and work (Parasuraman, 2000).

Previous literature highlights the intention to use new technology determined by many factors. For instance, Davis (1989), through the Technology Acceptance Model (TAM) verifies perceived usefulness and ease of use as the main determinants for new technology. In other words, both types of perceived benefits significantly affect the intention to use new technology, which later leads to the adoption of the technology, according to Davis, Bagozzi, and Warshaw (1989).

Another key factor influencing an intention to use is attitude towards the new technology. Ajzen (1985) introduced this factor as part of the Theory of Reasoned Action (TRA), which later emerged as a fundamental theory in business studies. The theory posits that a positive attitude towards a new technology and its potential benefit will induce the intention to use it. Besides attitude, another predictor in TRA, subjective norm, can also influence intention to use. Subjective norm refers to the belief that an important person or group will approve and support a particular behaviour. In the context of AI usage, individuals might intend to use AI because they receive social pressure from peers, colleagues, or spouses to use AI technology.

Understanding the knowledge behind the factor intention to use will help researchers and practitioners design and implement new technologies that are more likely to be adopted and used effectively. For this study, the perceived benefits of AI formulated based on TAM will be utilized to investigate the intention to use AI in teaching and learning.

2.2 Perceived Benefits of Artificial Intelligence (AI) in Higher Education

Alnasib (2023) defined the perceived benefits of AI in higher education as faculty members' optimism that AI use would significantly improve the standards, standing, and worth of higher education on the educational, social, and national levels. Popenici & Kerr (2017) highlighted that AI tools significantly benefit higher education in terms of services and academic programs. With AI, higher education is able to expand its services beyond the traditional face-to-face method. For instance, higher education institutions successfully adopted AI tools such as the Blackboard platform to conduct online teaching delivery throughout the global health crisis during the COVID-19 pandemic period (Xu, 2020).

With the rapid growth of AI implementation in various sectors, demand for graduates with AI-related skills also increased. This situation benefits higher education as the institutions can further initiate new academic programs integrated with AI technology skill sets (Ayanwale et al., 2022). Besides, higher education may gain benefits from AI development because educators need to undergo training in AI-related skills as it is required for the teaching of AI-integrated subjects. Thus, higher education with AI-equipped staff and educators will also be considered as a perceived benefit (Damerji & Salimi, 2021).

2.3 Perceived Benefits of Artificial Intelligence (AI) in Teaching and Learning

This study will borrow the definition of the perceived benefits of artificial intelligence in teaching and learning (Venkatesh et al., 2003). The study described the perceived benefit of AI in teaching and learning as the degree to which faculty members thought that using a new system would enable them to significantly improve their job performance. In other words, this factor is considered performance expectancy.

Previous findings recorded significant effects of the perceived benefit of AI to teaching and learning. Among the benefits AI can offer in teaching and learning is a personalized learning experience. For instance, Baker, Lindsey, Malone, and Gowda (2015) explained AI tools can personalize online learning based on student needs and pace. The study explained that AI can personalize the learning experience and schedule the content appropriate for student's performance and mastery level. In addition, AI technology significantly enhances engagement and motivation to learn for instance virtual reality simulation can help students to understand complex concepts with fun learning (Wu et al., 2019). Another AI benefit is the ability to enhance accessibility and learning support systems. According to Paez, Chen, and Lee (2014), AI automatic text-to-speech and speech-to-text tools can assist students with writing and reading difficulties even if they are located in remote learning.

2.4 Attitude Towards Artificial Intelligence (AI)

Attitudes towards Artificial Intelligence (AI) in general are very complex and multifaceted. As the study is set in higher education institutions, we utilized the definition from Ayanwale et al. (2022) where the conducted study attitude towards AI is defined as the degree to which faculty members view a specific behaviour favorably or unfavorably. Previous studies highlight both favorable and unfavorable attitudes towards technology which lead to adoption and rejection of technology. Chouthai, Belkhir, and Ricard (2022) and Popenici and Kerr (2017) revealed that people generally perceived AI as having the potential to improve efficiency, productivity, and problem-solving in various domains like healthcare, education, and business. In contrast, studies by Lancelot Miltgen, Van der Ploeg, and De Reuver (2013) and Lusk, Roosen, and Bieberstein (2014) to name a few found that individuals have negative attitudes toward new technology because of bias, transparency in AI raise ethical concerns, leading to distrust and fear of potential misuse.

2.5 Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) is a prominent framework utilized in research related to information technology. TAM was developed by Fred Davis in 1989 and was initially used to understand why individuals choose to accept or reject the new technology. According to Davis, (1989) there are TWO main factors that influence a user's attitude towards using new technology which are perceived usefulness (PU) and perceived ease of use (PEOU). An influence in user's attitudes will then lead to the influence on their intention to use the new technology.

The model also proved that both PU and PEOU have a direct positive impact on user's attitudes toward using new technology, and consequently, the attitude has a direct positive impact on user's intention to use new products. This model has been tested in numerous research settings especially relating to the adoption of new technology. For example, the intention to use consumer-generated media in travel (Ayeh et al., 2013), the intention to use mobile commerce (Ghazali et al., 2018), and the intention to use smart in-store technology (Kim et al., 2017) to name a few. As the main topic in this research paper concerning intention to use AI technology, TAM was chosen as the underpinning theory.

2.6 Development of Research Framework and Hypothesis

Within the literature review discussed previously in this chapter, the research framework has been developed to answer the research questions presented in Chapter 1 as presented in Figure 1.

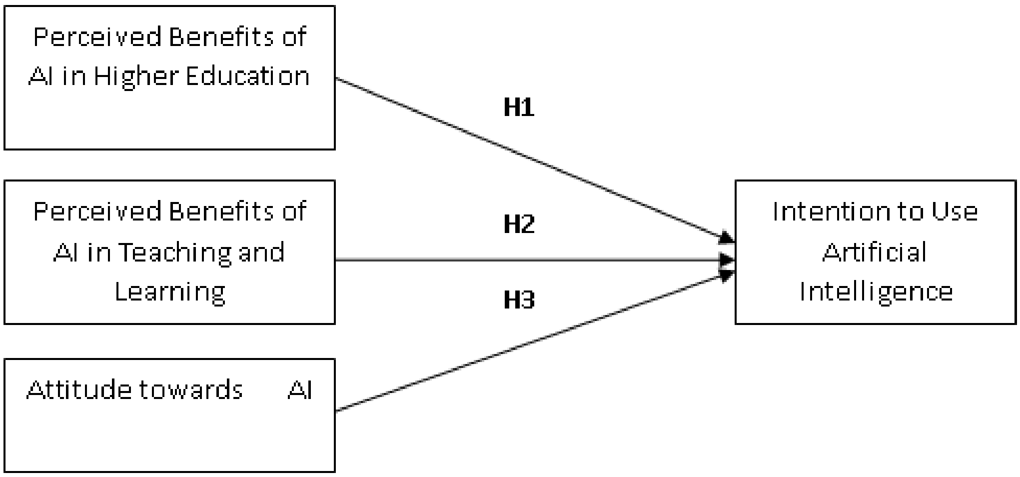

Figure 1. Research Framework.

2.6.1 Perceived Benefits of AI in Higher Education

Previous findings reported that the perceived benefits of Artificial Intelligence (AI) in Higher Education significantly influenced the technology readiness, AI adoption, and behaviour intention to use AI (Alnasib, 2023; Damerji & Salimi, 2021; Sudaryanto et al., 2023). These studies research in the context of accounting department faculty members' intention to use and adopt AI technology. Based on the above argument, the study posits that:

H1: There is a significant influence of Perceived Benefits of AI in Higher Education on the intention to use AI in Teaching and Learning.

2.6.2 Perceived Benefits of AI in Teaching and Learning

Previous studies reported that the perceived benefits of AI in Teaching and Learning significantly influenced the intention to use AI for teaching and learning (Baker et al., 2015; Paez et al., 2014; Wu et al., 2019; Xiong et al., 2020). These studies were conducted in different levels of educational institutions, from high school to college, and university. In the university setting, the participants' study areas are also distinct from one another, some studies focused on science-related faculty while others were conducted in business study programs. In this regard, this paper intends to investigate further perceived benefits that influence to intention to use AI. The following hypothesis is derived:

H2: There is a significant influence of Perceived Benefits of AI in Teaching and Learning on intention to use AI in Teaching and Learning.

2.6.3 Attitude Towards AI

Unlike two other independent variables, the previous finding on attitude towards technology in general and towards AI specifically results in inconsistent findings. Some recorded positive attitudes towards AI while others reported negative attitudes toward AI. These studies were conducted in different study settings where Ayanwale et al. (2022) and Chouthai et al. (2022) recorded positive attitudes towards AI in education while Goh, Suki, and Fam (2014) find that consumer has positive attitudes toward online banking applications.

In contrast, Kelly, Mulvaney, and Bardone (2023), Shiohira (2021), and Bowers (2019) to name a few recorded negative attitudes toward new technology. The reasons behind negative attitudes vary across studies. Perceived risk, perceived trust, worry about job replacement by AI, transparency and lack of knowledge are among the reasons that lead to negative attitudes towards new technology. Based on the above discussion, the following hypothesis was developed.

H3: There is a significant influence of Attitude towards AI on intention to use AI in Teaching and Learning.

3. Research Methodology

3.1 Research Design

Research design is a strategic framework for conducting scientific studies aimed at obtaining accurate and reliable results (Creswell, 2009; Zikmund et al., 2010). It outlines the methods and procedures used to collect and analyze data, addressing the research questions effectively (Bhatti & Sundram, 2015). In this study, a quantitative research approach was employed to answer the research questions. This approach involves the collection of numerical data, which is then statistically analyzed to draw conclusions (Hair et al., 2007). Furthermore, his approach is highly structured, often involving statistical techniques to analyze data collected through surveys, experiments, or secondary data sources (Sekaran & Bougie, 2010).

By using quantitative methods, the study benefits from the ability to measure and quantify variables, allowing for a more objective and generalizable understanding of the factors influencing the intention to use AI among faculty members at Guangdong Medical University. This design enables the researchers to statistically assess the relationships and effects among different variables related to the Technology Acceptance Model (TAM), providing a clear and concise understanding of the academic members' intentions and attitudes toward AI adoption in teaching and learning.

In this study, the quantitative research approach, utilizing a cross-sectional design and a correlational type of investigation, focuses on exploring the relationship between several predictor variables and the dependent variable. A cross-sectional design involves collecting data at a single point in time rather than longitudinally over an extended period (Sekaran & Bougie, 2010). This method is efficient for gathering a snapshot of the current state of intention to use AI among faculty members at Guangdong Medical University. It provides a timely and relevant picture of their attitudes and intentions regarding AI technologies.

The predictor variables include perceived benefits of AI in higher education, perceived benefits of AI in teaching and learning, and attitude towards AI. These factors are crucial in understanding the faculty's perception and acceptance of AI technology. The dependent variable is the intention to use AI in teaching and learning. This structure allows the study to examine how perceptions and attitudes toward AI influence the willingness of faculty members at Guangdong Medical University to integrate AI into their teaching practices. By employing a cross-sectional design, the study captures a snapshot of these variables at a single point in time, providing a clear picture of current attitudes and intentions. The correlational investigation then identifies the strength and nature of the relationships between the perceived benefits and attitudes towards AI and the actual intention to use AI.

3.2 Sample and Population

The population for this study encompasses academicians in China, representing a broad and diverse group of professionals engaged in higher education and research. Within this broad population, the sample selected for this study is specifically drawn from Guangdong Medical University, a distinguished institution ranked in the top 1% in clinical medical disciplines. The choice of Guangdong Medical University as the sample for this study is strategic, as it provides insights from a leading institution known for its excellence in a specialized field, thus offering valuable perspectives on the adoption of AI in a high-caliber academic environment.

The sampling technique employed in this study is convenience sampling. This method involves selecting participants in a non-random manner, primarily based on their availability and willingness to participate. In this case, the study involves all academic members of Guangdong Medical University who are available and willing to participate. This approach, while not random, allows for a comprehensive inclusion of various viewpoints within the university, ensuring that the study captures a wide range of experiences and attitudes towards AI in teaching and learning. By focusing on a specific, well-regarded institution and using convenience sampling, the study aims to provide detailed insights into the perceptions and intentions of academicians regarding AI adoption in a top-tier academic setting.

In the context of this study, the total number of employees at Guangdong Medical University is 1,900, out of which 1,384 are academicians. Based on these numbers, Krejcie and Morgan's (1970) table suggests that a sample size of 297 is suitable. This size is large enough to be statistically representative of the academician population at the university, thereby ensuring that the study's findings are reliable and can be generalized to the entire population of academicians.

The sampling method used to reach this number was convenience sampling. This approach involves selecting participants who are readily available and willing to participate, rather than using random sampling methods. The sample was thus conveniently selected from the pool of academicians until the desired number of 297 was reached. While convenience sampling is less random than other methods, it is often used in practical research settings where time and resources are limited, and it can still provide valuable insights, especially when the sample size is calculated to be representative of established guidelines like those of Krejcie and Morgan (1970).

3.3 Research Instrument

Table 1. Research Instrument

Construct	Instrument	No. of Item
Perceived Benefits of Artificial Intelligence in Higher Education	*Using AI in higher education is beneficial to society.* *Using AI in higher education will make education more interactive.* *Using AI in higher education will be cost-effective.* *Using AI in higher education will make teaching and learning activities more interesting.* *Using AI is essential to meet the future needs of higher education.* *AI provides smart private tutoring platforms to be used in distance education.* *Using AI applications will help identify skills needed for the labor market.*	7
Perceived Benefits of Artificial Intelligence in Teaching and Learning	I can use AI technology to get things done more quickly. *Using AI technology increases my effectiveness and professional and research productivity.* *AI technology is useful for teaching and learning activities.* *AI technology can be used to meet students' differences.* *AI technology can be used to enhance student self-learning.* *AI technology can be used to answer students' queries.* *AI technology can be used to evaluate students and provide them with feedback.* *AI provides automatic correction of certain types of coursework that frees up the teacher's time for other tasks.* *I can present the most complex topics by employing AI in course teaching.* *AI technology benefits students and me because it relates to our lifestyle.* *AI technology introduces new ways to interact with information, such as using Google to adjust search results according to the learner's geographic location.* *AI technology increases interaction between students and course content, for example, adding a chatbot service for content that can recognize the learners' language and have a real conversation with them.* *AI technology achieves student inclusion and better classroom management through a virtual experience such as Classcraft.* *AI technology expands opportunities for learners to communicate and collaborate.*	14

Table 1 Continued

Attitude to Artificial Intelligence	*I think it is fun to use AI technology.* *I enjoy using AI technology.* *When I think about the capabilities of AI, I think about how difficult my future will be.** *I have a feeling of discomfort when I think of AI.** *AI technology is not easy to learn.** *I need to put much effort into learning AI technology.** *I think AI-powered educational content is not always right.**	6
Intention to Use Artificial Intelligence	*I can learn AI technology quickly.* *I will continue to try to know AI better.* *I will keep myself up to date with the latest emerging AI applications.* *I plan to spend some time studying AI technology in the future.* *I intend to use AI technology to help my teaching in the coming years.*	5

The research instruments for this study were adapted from those developed by Alnasib (2023). A total of 32 items were used to measure various aspects related to the adoption and perception of AI in higher education. These items were measured using a 5-point Likert scale, ranging from 1 - strongly disagree to 5 - strongly agree, allowing participants to express their level of agreement or disagreement with each statement. This scale provides a nuanced and comprehensive way to gauge the attitudes, perceptions, and intentions of academicians regarding AI.

Detailed in Table 1, these instruments cover a broad range of factors and are designed to capture the multifaceted nature of AI adoption in an academic setting. The reliability of these instruments is a critical aspect of the study's methodology. In this context, reliability refers to the consistency and dependability of the instruments in measuring what they are intended to measure. To ensure reliability, the Cronbach alpha value is used as a standard measure. In this study, all instruments are considered reliable and suitable for use if the Cronbach alpha value is more than 0.70 for each construct.

3.4 Data Collection Method

The data collection method for this study involves the use of an online survey, a choice that brings several distinct advantages. This method involves distributing questionnaires to faculty members at Guangdong Medical University through WeChat. The first advantage of this approach is its convenience and accessibility (Bhatti & Sundram, 2015). WeChat is a widely used communication platform in China, making it easy for participants to access the survey. The ability for faculty members to respond at their convenience potentially increases the response rate, as they can participate at times that suit them best.

The online distribution of questionnaires allows for rapid dissemination and collection of responses (Bhatti & Sundram, 2015). This study's successful collection of a sufficient number of samples within a three-week timeframe underscores the time efficiency of online surveys. This quick turnaround is especially valuable in time-sensitive research contexts, where gathering data promptly is crucial.

Compared to traditional survey methods, such as paper-based surveys or face-to-face interviews, online surveys significantly reduce costs associated with printing, distribution, and data entry. This cost reduction is particularly beneficial when dealing with a large sample size, as it makes the research more economical while still maintaining a broad reach (Sekaran & Bougie, 2010).

The anonymity provided by such surveys can lead to more honest responses, as participants may feel more comfortable being candid without the presence of an interviewer. Additionally, the digital nature of the responses allows for straightforward data management and analysis. Responses collected online can be directly imported into data analysis software like IBM SPSS, which simplifies and streamlines the subsequent stages of data analysis. Despite some limitations, such as potential self-selection bias and excluding non-WeChat users, the online survey method remains an efficient, effective, and practical approach for this study.

3.5 Data Analysis Techniques

The data analysis phase of this research will be methodically conducted through a four-step process, ensuring the integrity and accuracy of the results. The first step involves data validation, a critical phase where data cleaning is performed. Here, any incomplete, inaccurate, or irrelevant data are identified and either corrected or removed from the dataset. This step is crucial for maintaining the quality of the data.

Following validation, the second step is the data editing process. This stage further refines the dataset, ensuring that the data is consistently formatted and error-free. The meticulous attention to detail in this phase enhances the reliability of the data. The third step is data coding, where responses are systematically categorized for ease of analysis. This step transforms raw data into a structured format that can be efficiently analyzed, facilitating a more streamlined analysis process.

Finally, the fourth stage is the actual analysis of the data. The cleaned and structured dataset will be analyzed using the IBM SPSS 27 statistical package. This analysis involves two primary types of statistics. First, descriptive statistics such as mean, median, mode, frequency, and range will be calculated to provide a basic understanding of the data's distribution and central tendencies. Second, inferential statistics, specifically correlation analysis, will be conducted to examine the relationships among the observed variables.

3.6 Summary

In conclusion, this study about factors influencing the intention to use artificial intelligence (AI) among academic members of Guangdong Medical University is a quantitative study. This study utilizes the convenience sampling method in collecting samples for the study. The number of samples was based on the recommendation of Krejcie and Morgan (1970), where the suggested sample size for N=1300 is n=297. This study used inferential statistical analysis to measure three (3) constructs and one dependent variable, intention to use AI.

4. Results and Discussion

4.1 Data Screening

In the data screening phase of this study, an initial total of 287 questionnaires were collected through WeChat. However, before proceeding to data analysis, a thorough screening process was conducted to ensure the quality and reliability of the data. This process involved identifying and addressing issues such as missing data and lenient responses, which are common challenges in survey-based research. As a result of this rigorous screening, the number of questionnaires deemed suitable for analysis was reduced to 260. This step was crucial to maintain the integrity of the research findings.

Additionally, the study conducted a reliability analysis to assess the internal consistency of the survey instruments. For this purpose, Cronbach's alpha was used as the primary statistical measure. The rule of thumb for acceptable reliability in social science research is a Cronbach's alpha value of 0.70 or above. This threshold ensures that the survey items consistently measure the intended constructs, thereby contributing to the overall validity of the study. By adhering to this standard, the research upholds the necessary rigor in its methodological approach, enhancing the credibility and trustworthiness of the results.

Table 2. Reliability Analysis

Variable	No. of Item	Cronbach's Alpha
Perceived Benefits of AI in Higher Education	7	0.946
Perceived Benefits of AI in Teaching and Learning	14	0.959
Attitude to Artificial Intelligence*	5	0.637
Intention to Use Artificial Intelligence	5	0.875

Notes" *contains 4 negative items and ATAI2 was deleted due to poor α value.

The reliability of the survey instruments is presented in Table 2. For the construct perceived benefits of AI in higher education, assessed through 7 items, the Cronbach's Alpha value is very good $\alpha=0.946$, indicating a very high level of reliability. Similarly, the perceived benefits of AI in teaching and learning, encompassing 14 items, demonstrate excellent internal consistency with a Cronbach's Alpha of 0.959.

However, the attitude to artificial intelligence construct initially posed a reliability challenge, with a Cronbach's Alpha of only 0.578. To increase the reliability, an item (ATAI2 – *I enjoy using AI technology*) was removed, which effectively increased the alpha value to 0.637. This adjustment, aligning with Sekaran & Bougie's (2010) guideline that a value above 0.60 is acceptable for social science research, ensured the construct's reliability.

Lastly, the intention to use an artificial intelligence construct, consisting of 5 items, also exhibited strong internal consistency, as reflected by its Cronbach's Alpha of 0.875. Overall, the reliability table in the thesis comprehensively demonstrates the high degree of reliability of the survey instruments, with the exception of the initial lower value for ATAI, which was successfully rectified.

4.2 Demographic of Respondent

In discussing the demographic profile of the respondents for this study, it's important to note that the total number of respondents was 260. This demographic profile provides essential insights into the characteristics of the participant group, such as gender, age, academic rank, college type, educational background, and teaching experience.

Figure 2 in the study provides a detailed breakdown of the gender distribution among the 260 respondents. Out of these, 139 are male academic members, while the remaining 121 are female. This gender distribution is an important demographic detail as it offers insights into the balance and representation of genders in the sample.

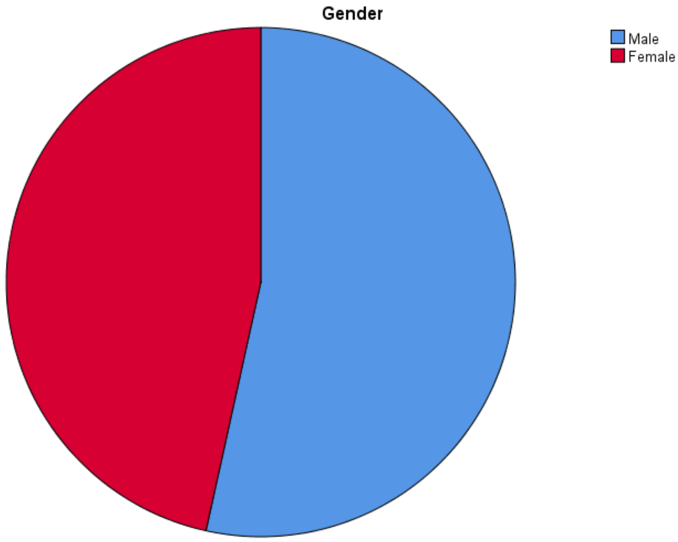

Figure 2. Gender Profile.

The age distribution of the respondents in this study is a key demographic aspect, providing valuable insights into the diversity of the participant group. The youngest age group, consisting of those aged 20-30 years, includes 67 respondents, representing a significant portion of the sample. This group is likely to include early-career academics and those recently introduced to the profession.

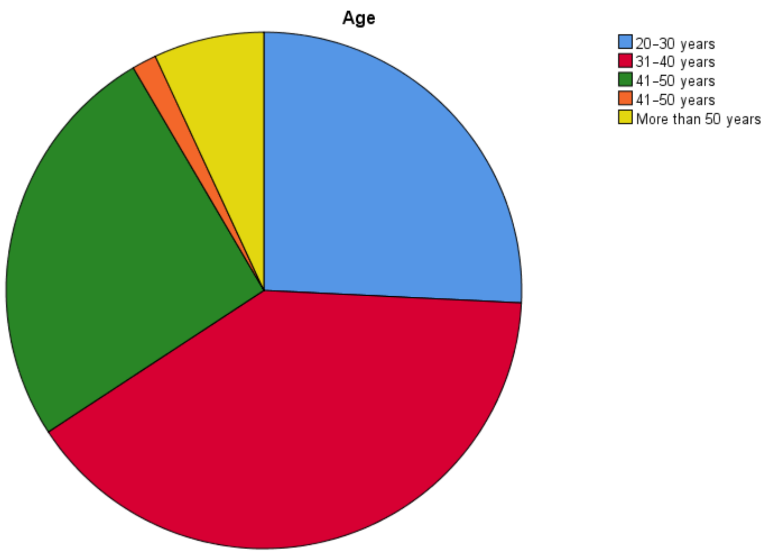

Figure 3. Age of Respondents.

The next age bracket, 31-40 years, comprises the largest segment of the sample, with 104 respondents, indicating a strong representation of mid-career professionals who are potentially at a pivotal stage in their academic careers. The 41-50 years age group, mirroring the 20-30 years category, also consists of 67 respondents. This similarity in numbers suggests a balanced representation of both emerging and established academicians. Finally, the age group of over 50 years includes 18 respondents, providing insights from the most experienced segment of the academic community. Figure 3.

Figure 4 in the study presents a breakdown of the respondents according to their academic ranks, offering a glimpse into the professional composition of the sample. The majority of respondents are teaching assistants, with 122 individuals falling into this category, indicating a strong presence of early-career academics or those in the initial stages of their academic journey. The next significant group is lecturers, comprising 88 respondents. This group likely represents individuals with some experience in academia, potentially engaged in both teaching and research activities. Associate professors, with a count of 37, form the next category, reflecting a more advanced stage of academic careers where individuals have established a substantial presence in their respective fields. Finally, the category with the least representation is professors, consisting of 13 respondents.

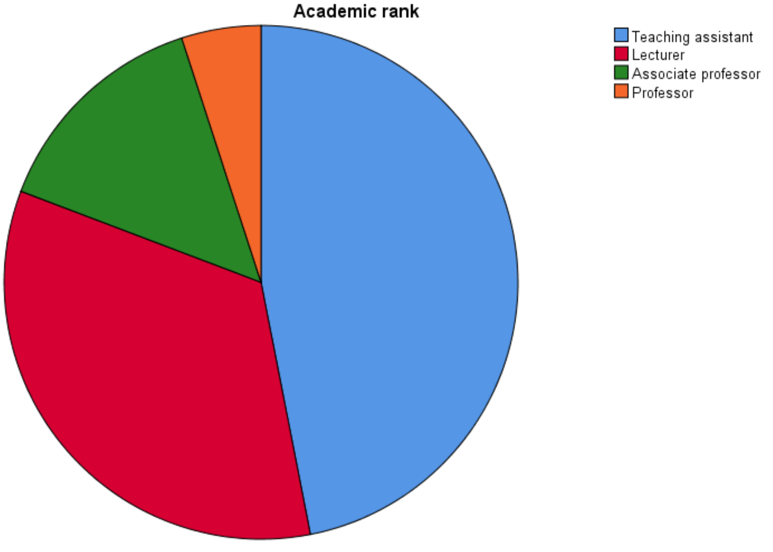

Figure 4. Academic Rank.

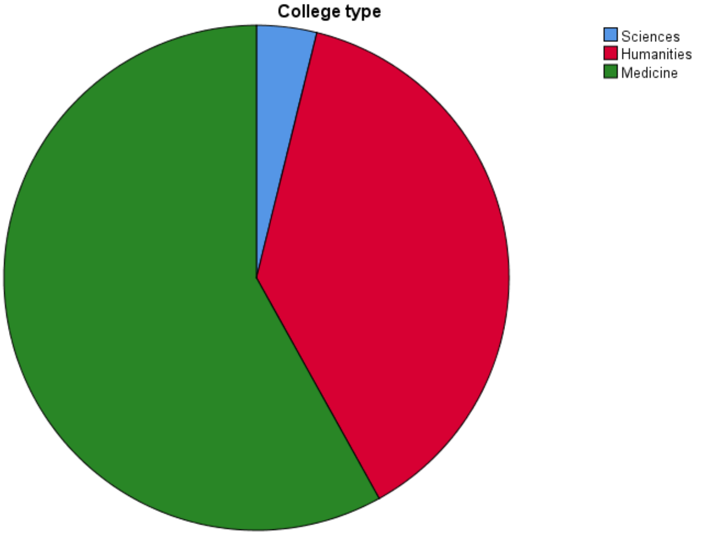

Figure 5. College Type.

Figure 5 in the study illustrates the distribution of respondents based on their college affiliations, highlighting the diversity of academic disciplines involved in the survey. The data shows that 10 respondents are from the Sciences College, indicating a representation from fields likely focused on natural and physical sciences. This group, while smaller in number, provides insights from disciplines that are often at the forefront of technological integration in research and teaching.

A significantly larger group of 99 respondents belongs to the Humanities College. This substantial representation suggests a keen interest or engagement with AI technologies among those in disciplines traditionally less associated with technological advancements. Their perspectives are particularly valuable in understanding how AI is perceived and potentially integrated into diverse academic areas beyond the sciences. The largest group of respondents, numbering 151, comes from the Medicine College. This dominance in the sample is notable, reflecting the significant interest and potential impact of AI in medical education and research.

Figure 6 in the study provides an overview of the teaching experience of the respondents, which is a crucial factor in understanding their perspectives on AI adoption in education. The distribution of teaching experience among the participants is varied, offering insights across a range of career stages.

The largest group, consisting of 122 respondents, has 1 to 5 years of teaching experience. This group likely includes many early-career educators who are relatively new to teaching. Their perspectives are particularly important as they represent a generation of educators who may be more familiar with and open to integrating new technologies like AI in their teaching practices.

The next category, with 74 respondents, comprises those who have 6 to 10 years of teaching experience. This group represents mid-career educators who have substantial experience but are still in the relatively early stages of their careers. Their views might provide a balance between traditional teaching methods and the adoption of innovative technologies.

Educators with 11 to 15 years of teaching experience form a smaller group of 32 respondents. This cohort is likely to have witnessed significant changes in educational technologies over their careers and might offer insights into the evolution and acceptance of such technologies in the academic setting.

Finally, the group with more than 15 years of teaching experience includes 42 respondents. This group represents the most seasoned educators, who bring a wealth of experience and potentially a different perspective on the integration of AI in teaching, shaped by their long-term observation of trends and changes in educational methodologies.

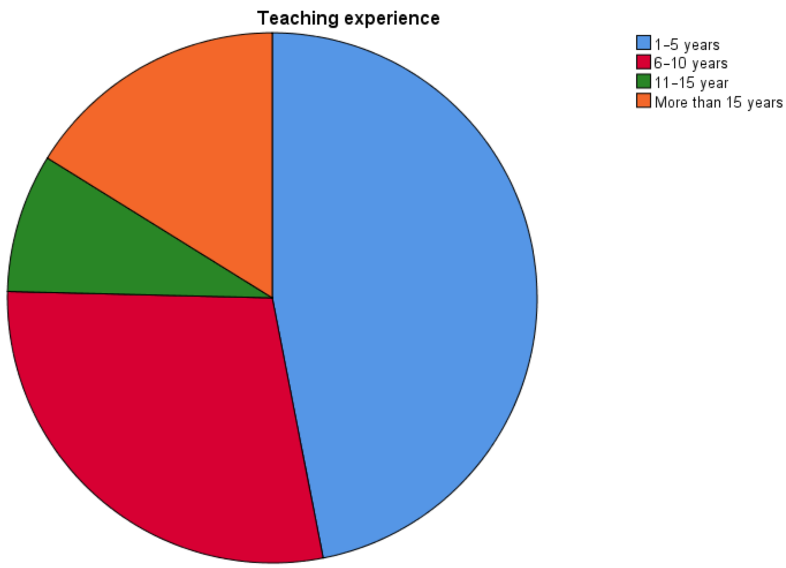

Figure 6. Teaching Experience.

4.3 Hypothesis Testing

In this chapter, the study uses two statistical methods, Pearson correlation, and multiple regression, to test the hypotheses and explore what influences decision-making behaviors. First, Pearson correlation is applied to identify how the different variables are related to each other. This step is important to make sure that the variables are appropriate for further analysis. Then, multiple regression analysis is conducted. This method helps to understand how four key predictor variables, when considered together, impact the dependent variable. This approach provides a clearer picture of the combined effect of these predictors on decision-making behaviors.

Table 3. Pearson Correlation

	PBHE	PBTL	Attitude	Intention
PBHE	1			
PBTL	.852**	1		
Attitude	-0.084	-0.073	1	
Intention	.724**	.669**	-.188**	1

Notes: **Significant at the level p<0.001
PBHE – Perceived Benefits of AI in Higher Education; PBTL – Perceived Benefits of AI in Teaching and Learning; Attitude – Attitude to AI; Intention – Intention to Use AI.

Table 3 in the study reveals interesting correlations among four key variables: Perceived Benefits of AI in Higher Education (PBHE), Perceived Benefits of AI in Teaching and Learning (PBTL), Attitude towards AI, and Intention to Use AI. There is a very strong positive correlation (r^2=.852) between PBHE and PBTL, indicating that those who see AI as beneficial in higher education also perceive it as beneficial in teaching and learning. However, the correlations between PBHE and Attitude (r^2=-0.084), and PBTL and Attitude (r^2=-0.073), are both very weak and negative, suggesting that perceiving AI as beneficial does not significantly influence attitudes towards AI.

On the other hand, the intention to use AI is strongly positively correlated with both PBHE (r^2=.724) and PBTL (r^2=.669), implying that seeing AI as beneficial in either higher education or teaching and learning is associated with a greater intention to use it. Interestingly, there is a moderate negative correlation (r^2=-.188) between attitude and intention to use AI, suggesting that more negative attitudes towards AI are linked to a lower intention to use it. These findings highlight the strong influence of perceived benefits on the intention to use AI, while attitudes towards AI have a lesser, though still significant, impact.

Next, the multiple regression results are presented in Table 4 and Table 5. The model's R-value is 0.742, indicating a strong positive correlation and suggesting a substantial relationship between the combined predictors and the outcome. The R^2 value, which stands at 0.591, reveals that about 59.1% of the variance in the dependent variable is explained by the predictors, indicating good explanatory power of the model.

The adjusted R square, at 0.546, is slightly lower but still robust, considering the number of predictors and the sample size. This suggests that the model remains a good fit after adjustment. The standard error of the estimate is 0.491, implying that the observed values are, on average, close to the regression line, denoting a good fit of the model.

Crucially, the p-value of 0.0001 is highly significant, confirming the statistical significance of the model and the low likelihood of the results occurring by chance. Overall, these results point to a strong and significant relationship between the predictors and the dependent variable, underscoring the robustness of the model.

Table 4. Model Summary

Model	R	R^2	Adjusted R Square	Std. Error of the Estimate	p-value
1	0.742	0.591	0.546	0.491	0.0001

The table presents the results from a regression model, showcasing the influence of various predictor variables on a dependent variable, as indicated by their respective beta (β) coefficients, t-values, and p-values. Firstly, the constant has a β of 1.112 with a t-value of 3.620, and is highly significant (p = 0.000), indicating that the model has a significant intercept. Among the predictors, 'Perceived Benefits of AI in Higher Education' (PBHE) has the highest β coefficient at 0.618, with a t-value of 6.908 and a p-value of 0.000, signifying a strong positive impact on the dependent variable and high statistical significance. This suggests that PBHE is a major contributor to the model.

'Perceived Benefits of AI in Teaching and Learning' (PBRL) has a β of 0.216, a t-value of 2.366, and a p-value of 0.019, indicating a positive but comparatively smaller influence on the dependent variable than PBHE, yet it is still statistically significant. 'Attitude' has a β of -0.140, a t-value of -3.031, and a p-value of 0.003, showing a negative influence on the dependent variable, which is also statistically significant.

Comparing the β coefficients, PBHE emerges as the most influential predictor, having the greatest impact on the dependent variable, followed by PBRL and then 'Attitude'. The negative β of 'Attitude' suggests an inverse relationship with the dependent variable, indicating that more positive attitudes may lead to a decrease in the value of the dependent variable. The significant p-values for all predictors confirm that their contributions to the model are not by chance. This analysis provides a clear understanding of how each variable uniquely influences the outcome, with PBHE being the most dominant factor.

Table 5. Coefficient

Model	Variable	β	t	p-value
1	Constant	1.112	3.620	0.000
	PBHE	0.618	6.908	0.000
	PBRL	0.216	2.366	0.019
	ATTITUDE	-0.140	-3.031	0.003

4.4 Summary of Results

The following table summarizes the results of this study. In short, all three hypotheses are statistically supported, with 59.1% of the variance in the intention to use AI being explained by the three predictors, and the remaining variance might be explained by other factors which not included in this study.

Table 6. Summary of Results

	Hypothesis	Results
H1	There is a significant influence of perceived benefits of AI in Higher Education on the intention to use AI.	Supported
H2	There is a significant influence of perceived benefits of AI in Teaching and Learning on the intention to use AI.	Supported
H3	There is a significant influence of attitude toward AI on the intention to use AI.	Supported

5. Conclusion

The study's results begin with an analysis of the respondent profile, providing vital demographic insights. Out of 260 participants, the majority were male (139), with females accounting for the remainder. In terms of age, the respondents were distributed across various groups, with 67 in the 20-30 age bracket, 104 between 31-40, another 67 between 41-50, and 18 over 50 years old. The academic ranks of respondents varied, including 122 teaching assistants, 88 lecturers, 37 associate professors, and 13 professors, reflecting a wide range of experience levels. Additionally, the respondents came from diverse academic backgrounds: 10 from the Sciences College, 99 from Humanities, and 151 from the Medicine College. This varied demographic makeup provides a comprehensive view of different perspectives across the academic spectrum.

The study then employed Pearson correlation and multiple regression analyses to explore relationships between variables. The Pearson correlation showed a strong positive correlation between perceptions of AI's benefits in higher education and in teaching and learning. However, attitudes towards AI were weakly and negatively correlated with these perceptions. In the multiple regression analysis, the model exhibited strong positive correlations among the predictors and the dependent variable, with an R-value of 0.742. About 59.1% of the variance in the dependent variable was explained by the predictors ($R^2 = 0.591$), indicating a good model fit. The regression coefficients revealed that 'Perceived Benefits of AI in Higher Education' had the most substantial positive impact on the dependent variable, followed by 'Perceived Benefits of AI in Teaching and Learning', while 'Attitude' showed a negative impact. Collectively, these findings provide a nuanced understanding of the factors influencing AI adoption in higher education, highlighting the significant role of perceived benefits and the complex relationship with attitudes toward AI.

Next, results for H1 which posited a positive correlation between the perceived benefits of AI in higher education and the intention to use AI, aligns well with previous studies. Similar findings were reported by Alnasib (2023), Damerji and Salimi (2021), and Sudaryanto et al. (2023), who also found a significant positive correlation between the perceived benefits of AI in higher education and its intended use.

This consistency underscores the robustness of the perceived benefits as a predictor of technology adoption in academic settings. It suggests that when academicians perceive the clear benefits of AI in their professional context, they are more likely to embrace these technologies in their work. This insight is crucial for educational institutions aiming to foster AI adoption among faculty members, as it highlights the importance of demonstrating the tangible benefits of AI in higher education.

The results for H2, which examined the relationship between the perceived benefits of AI in teaching and learning and the intention to use AI, are consistent with findings from Wu et al. (2019), Liu and Lu (2020), and Paez et al. (2014). These studies similarly found a positive correlation between the perceived benefits of AI in specific applications, such as teaching and learning, and the willingness to use AI.

This agreement with prior research reinforces the idea that perceptions of utility in specific applications are crucial in influencing technology adoption decisions. It suggests that when academicians see how AI can concretely enhance teaching and learning processes, their inclination to use AI increases. This finding has practical implications for the development and presentation of AI tools in educational settings, as it indicates the importance of aligning AI applications with the specific needs and challenges of teaching and learning.

For H3, which explored the relationship between attitudes toward AI and the intention to use AI, the findings were consistent with those reported by Bowers (2019), Kelly et al. (2023), and Shiohira (2021). These authors also identified a negative influence of attitudes on the intention to use AI, indicating that less favorable attitudes toward AI could hinder its adoption. This finding is particularly insightful as it highlights a potential barrier to AI adoption in higher education. While positive perceptions of benefits drive adoption, negative attitudes could counteract this effect. This suggests that for the successful implementation of AI, educational institutions must not only showcase the benefits but also address and mitigate any negative attitudes or misconceptions about AI among academicians.

The findings of this study have significant implications, both theoretically and practically, in the context of AI adoption in higher education. From a theoretical standpoint, the strong correlation between the perceived benefits of AI in higher education and in teaching and learning reinforces and expands upon existing theories in technology acceptance, particularly the Technology Acceptance Model (TAM).

Funding

Higher Education and Teaching Research Projects of Guangdong Medical University (2024). A Research on the Practice Model of Undergraduate Tutorial System Based on AI (2JY24005).

References

Alnasib, B. N. M. (2023). Factors affecting faculty members' readiness to integrate artificial intelligence into their teaching practices: A study from the Saudi higher education context. *International Journal of Learning, Teaching and Educational Research*, *22*(8), 465-491.

Alsheibani, S., Cheung, Y., & Pan, S. L. (2018). Artificial Intelligence Adoption: AI-readiness at Firm-Level. *Proceedings of the Pacific Asia Conference on Information Systems (PACIS)*, 251.

Ayanwale, M. A., Sanusi, I. T., Adelana, O. P., & Aruleba, K. . (2022). Teachers' readiness and intention to teach artificial intelligence in schools. *Computer & Education*, *3*.

Ayeh, J. K., Au, N., & Law, R. (2013). Predicting the intention to use consumer-generated media for travel planning. *Tourism Management*, *35*, 132-143. https://doi.org/10.1016/j.tourman.2012.06.010.

Baker, R. S., Lindsey, S. E., Malone, K. M., & Gowda, M. (2015). Predictive analytics in education: Learning and the learning analytics cycle. *American Behavioral Scientist*, *59*(10).

Barton, D., Woetzel, J., Seong, J., & Tian, Q. (2017). Artificial intelligence: implications for China. In *China Development Forum* (Vol. 2, Issue 3).

Bhatti, M. A., & Sundram, V. P. K. (2015). Business Research: Quantitative and qualitative methods. Pearson.

Bowers, K. (2019). What is smart technology and what its benefits? Rezaid. https://rezaid.co.uk/smart-technology-and-its-benefits/.

Chouthai, M., Belkhir, L., & Ricard, L. (2022). Understanding public expectations towards artificial intelligence: Toward a human-centered design framework. *Technology in Society*, *51*(1).

Creswell, J. (2009). Research Design (3rd ed.). SAGE Publications.

Damerji, H., & Salimi, A. (2021). Mediating effect of use perceptions on technology readiness and adoption of artificial intelligence in accounting. *Accounting Education*, *30*(2), 107-130.

Davis, F D, Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science*, *35*(8), 982-1003.

Davis, Fred D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319-340.

Ding, J. (2018). Deciphering China's AI Dream: The context, components, capabilities and consequences of China's strategy to lead the world in AI (Issue March).

Ghazali, E. M., Mutum, D. S., Chong, J. H., & Nguyen, B. (2018). Do consumers want mobile commerce? A closer look at M-shopping and technology adoption in Malaysia. *Asia Pacific Journal of Marketing and Logistics*, *30*(4), 1064-1086.

Goh, T. T., Suki, N. M., & Fam, K. (2014). Exploring a consumption value model for Islamic mobile banking adoption. *Journal of Islamic Marketing*, *5*(3), 344-365.

Gunn, A., & Mintrom, M. (2013). Global university alliances and the creation of collaborative advantage. *Journal of Higher Education Policy and Management*, *35*(2), 179-192.

Hair, J., Money, A., Page, M., & Samouel, P. (2007). Research Methods for Business. John Wiley and Sons.

Hao, K. (2019). China has started a grand experiment in AI education. It could reshape how the world learns. *MIT Technology Review*. https://www.technologyreview.com/2019/08/02/131198/china-squirrel-has-started-a-grand-experiment-in-ai-education-it-could-reshape-how-the/.

He, Y., & Bowser, A. (2017). How China is preparing for an AI-powered Future.

Jonathan Woetzel, A., Joe Ngai, S., Kong Jeongmin Seong, H., Kweilin Ellingrud, S., Nick Leung, M., Kong Franck Le Deu, H., Kong Sven Smit, H., Peixi Wang, A., & Editor Benjamin Plotinsky, S. (2023). The China imperative for multinational companies Reconfiguring for opportunity and risk (Issue January).

Kelly, J. R., Mulvaney, M., & Bardone, E. (2023). AI and the future of work: Understanding worker perspectives on automation and skills. *Technology, Innovation, Management & Policy*, *18*(1), 3-18.

Kim, H. Y., Lee, J. Y., Mun, J. M., & Johnson, K. K. P. (2017). Consumer adoption of smart in-store technology: assessing the predictive value of attitude versus beliefs in the technology acceptance model. *International Journal of Fashion Design, Technology and Education*, *10*(1), 26-36.

Knox, J. (2020). Artificial intelligence and education in China. *Learning, Media and Technology*, *45*(3), 298-311.

Krejcie, R. V, & Morgan, D. W. (1970). Determining sample size for research activities. *Educational and Psychological Measurement*, *30*, 607-610.

Lancelot Miltgen, K., Van der Ploeg, R., & De Reuver, M. (2013). Social and ethical implications of artificial intelligence: A philosophical exploration. *Ethics and Information Technology*, *15*(3), 183-196.

Lusk, J. L., Roosen, J., & Bieberstein, A. (2014). Consumer acceptance of new food technologies: Causes and roots of controversies. *Annual Reviews Resources Economy*, *6*, 381-405.

Paez, A., Chen, P. S., & Lee, J. J. (2014). A study of the impact of automatic speech recognition technology on the writing performance of students with learning disabilities. *Computers & Education*, *74*.

Parasuraman, A. (2000). Technology Readiness Index (TRI): A Multiple Scale Item to measure readiness to embrace new technologies. *Journal of Services Research*, *2*(4), 307-320.

Popenici, S. A. ., & Kerr, S. (2017). Exploring the impact of artificial intelligence on teaching and learning in higher education. *Reseach and Practice in Technology Enhanced Learning*, *12*(1), 1-13.

Sekaran, U., & Bougie, R. (2010). Research methods for business: A skill building approach (5th ed.). John Wiley & Sons.

Shiohira, K. (2021). Understanding the impact of artificial intelligence on skills development. In *United Nations Educational, Scientific and Cultural Organization*.

State Council Notice. (2017). A Next Generation Artificial Intelligence Development Plan.

Sudaryanto, M. R., Hendrawan, M. A., & Andrian, T. (2023). The effect of technology readiness, digital competence, perceived usefulness, and ease of use on accounting students artificial intelligence technology adoption. *E3S Web of Conferences*, *388*.

Tracxn Technologies Limited. (2023). AI in Education Startups in China. Tracxn Technologies Limited.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly: Management Information Systems*, *27*(3). https://doi.org/10.2307/30036540.

Wu, W.-C., Lin, T.-F., & Cheng, M. (2019). Enhancing learning quality: Virtual reality game based on scaffolding pedagogy. *International Journal of Information and Learning Technologies*, *35*(2), 196-214.

Xiong, P., Liu, M., & Lu, Y. (2020). Machine translation in education: Opportunities and challenges. *Asian Journal of Applied Linguistics*, *10*(2), 319-333.

Xu, L. (2020). The dilemma and countermeasures of AI in education application. *4th International Conference on Computer Science and Artificial Intelligence Proceeding*, 11-13.

Zikmund, W. G., Babin, B. R., Carr, J. C., & Griffin, M. (2010). Business Research Methods (Cencage Learning (ed.); 8th ed.).