International Journal of Business and Technology Management
e-ISSN: 2682-7646 | Vol. 5, No. 2, 30-48, 2023
http://myjms.mohe.gov.my/index.php/ijbtm

Adoption of Artificial Intelligence in the Games and Amusements Board: A Stepwise Multiple Linear Regression Analysis

Mark Anthony D. Libunao[1*]

[1] College of Liberal Arts, Technological University of the Philippines Manila Campus, Philippines

*Corresponding Author: markanthony.libunao@tup.edu.ph

Received: 25 March 2023 | Accepted: 1 May 2023 | Published: 1 June 2023

DOI: https://doi.org/10.55057/ijbtm.2023.5.2.4

Abstract: *The Games and Amusements Board (GAB) of the Philippines was the subject of this study which aimed to determine the factors that have the most impact on the adoption of artificial intelligence (AI). In accordance with the combined constructs of the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), a survey questionnaire was administered to a sample of 99 GAB officials and employees. To analyze the data, stepwise multiple linear regression and related statistical tools were performed using the IBM Statistical Package for Social Sciences (SPSS) and Microsoft Excel. Correlation analysis revealed that the attitude toward using AI and the behavioral intention to use AI showed a very strong positive correlation with the adoption of AI in the GAB. Meanwhile, social influence, effort expectancy, and performance expectancy exhibited a strong positive correlation with the AI adoption. On the other hand, facilitating conditions showed a moderate positive correlation while the perceived risk is the lone variable which exhibited a weak negative correlation. The stepwise multiple linear regression analysis revealed that out of the seven independent variables, the attitude toward using AI and the effort expectancy are the strongest factors that influence the adoption of AI. Further, the model revealed that 63.6% of the variance of the dependent variable can be explained by the predictor variables. This means that the 36.4% unexplained variance can be explained by the variables that are not included in the conceptualization of this research study. This paper makes a contribution to the growing body of research on how government agencies are governing, accepting, and adopting AI.*

Keywords: artificial intelligence, TAM, UTAUT, professional sports, Philippines

---

1. Introduction

Even though various gaps still exist in terms of technology adoption in different parts of the world, particularly in the countries that are considered to have the least developed economies, the pace at which new technologies are being developed and implemented has been dramatically accelerating over the past few decades. As reported by the United Nations Conference on Trade and Development (UNCTAD, 2020), because of the rapid advancement of technology, every sector of the business, society, and culture is being impacted.

Technologies such as the Internet of Things, robotics, big data, 3D printing, machine learning, nanotechnology, biotechnology, drone technologies, satellite and the focus of this study – artificial intelligence (AI), are all a part of the rapid development in technology. They present a sizeable window of opportunity to accomplish the objectives of the 2030 Agenda on the Sustainable Development Goals (UNCTAD, 2020).

The application of AI is having a dramatic impact on economies all over the world because of its ability to boost productivity, increase the delivery of public services, and stimulate economic growth. Individuals, businesses, and governments have the potential to be significantly impacted by the rise of AI (Goralski & Tan, 2020). As a matter of fact, several governments around the world have already begun using AI into their strategies, policies and procedures (United Nations, 2020; Girasa, 2020; Valle-Cruz et al., 2019).

The Philippines Department of Trade and Industry (DTI) emphasized that cutting-edge technology like AI can assist the Philippine government in thriving in an environment that has been left in the wake of a COVID-19 pandemic (Santhika & Ocampo, 2023). According to DTI (2023), innovative technologies allow for better management of global difficulties; therefore, Philippines cannot fall behind in this area.

Every day, our lives are impacted in some way by AI, and the field of professional sports is not exempted (Dataconomy, 2022). Statistics and data analytics have been used in the sporting industry from the beginning of time. Because sports now quantify everything that can be quantified, this sector of the economy offers a fertile environment for the application of AI.

In relation thereto, the Philippine government, with the Games and Amusements Board (GAB) serving as the watchdog over all professional sports and games in the country, as well as professional athletes' performance in the game, must always "continue its efforts at providing world class services to its clientele and encourage the growth of professional sports in the country through effective regulation and the institution of best practices. This includes improving ease of doing business with GAB and upgrading of competencies not only on its own supervisors but all sports officials and licensees." (GAB, 2022).

It is in this context that this study is conducted in order to offer insights on the GAB officials' and employees' attitude and behavior toward AI which could affect the government's success of AI's implementation in the field of professional sports and across the country.

1.1 Research Objectives

The following are the research objectives of this paper:

i. To capture the perceptions of AI acceptance factors and AI adoption in the GAB;
ii. To identify the relationship between the AI acceptance factors and AI adoption in the GAB; and
iii. To investigate which factors most influence the adoption of AI in the GAB.

1.2 Research Questions

There are research questions that the respondents must answer based on the research objectives. This paper addresses the following research questions:

a) How do the officials and employees of the GAB perceive the use of AI for e-government initiatives?
b) Is there any significant relationship between the AI acceptance factors and the adoption of AI in the GAB?
c) What are the factors that most influence the adoption of AI in the GAB?

2. Literature Review

2.1 Artificial Intelligence (AI)

At the academic, government, and community levels, there is a problem with defining artificial intelligence. The definition of AI is highly debatable, and there has been very little progress made toward reaching a consensus across the many different domains in which the terminology is utilized (Kelly, 2022). Smart speakers, smart refrigerators, and smartphones, like autonomous automobiles, are called AI (Ghorayeb et al., 2021, Park et al., 2021). This is because these technologies all share certain characteristics. Due to the absence of an adequate definition, we are unable to determine whether people accept actual AI or their own conception of what constitutes AI (Kelly & Oviedo-Trespalacios, 2022).

AI, as explained by the Columbia University (2022), is *"the field of developing computers and robots that are capable of behaving in ways that both mimic and go beyond human capabilities. AI-enabled programs can analyze and contextualize data to provide information or automatically trigger actions without human interference."*

According to Dickson (2017), there are three distinct types of AI. To begin, there is AI that is only capable of performing a single task at a time, such as predicting the outcome of judicial procedures. Second, there is artificial general intelligence, which is considered to be a powerful form of AI due to its capacity to mimic some of the capabilities of the human brain, despite the fact that it is unable to perform more sophisticated tasks such as reasoning. And third, there is what is known as artificial super intelligence, which is considered to be a futuristic version of AI that is capable of doing everything that a human brain can accomplish and even beyond it in some cases.

2.2 The Acceptance of AI by Users

Users have to be willing to adopt AI in order to fully embrace and benefit from the technology's potential applications. A lack of acceptability might lead to a reduction in user adoption of AI, which would lead to a waste of resources, an abundance of AI gadgets, and possibly a slowdown in technical innovation, all of which would be to the harm of consumers (Kirlidog & Kaynak, 2013; Lee & See, 2004). Acceptance is a predictive indicator that captures a human decision, such as the informed purchase of AI technology (Kelly, 2022). Acceptance is a measure that can be used to anticipate the future. To put it another way, purchasing a piece of technology with the awareness that it incorporates some kind of artificial intelligence. Alternately, acceptance can be an action that is carried out without the participant's knowledge, such as when utilizing AI chatbots that can pose as non-AI agents. For example, an AI chatbot for online banking may appear as a customer service agent, giving customers the impression they are talking to a real person. Because of this, there are many different agency levels engaged in the process of user acceptability. Stakeholders must analyze user acceptability to determine how to maximize technology adoption in various circumstances. Some of the models that have been used to analyze the user adoption of AI include the Technology Adoption Model (TAM; Davis, 1985, Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al., 2003).

2.3 Technology Acceptance Model (TAM)

Davis (1989) proposed that a person's behavioral purpose is the primary factor in determining whether or not they will accept new technology. There are two primary factors that contribute to a person's behavioral intention. To begin, he defined utility as the amount to which the user sees the technology as advantageous in terms of improving one's performance. Research on AI conducted in a variety of sectors, including medicine, has lent credence to the idea that an individual's perception of a behavior's usefulness bears a substantial relationship both with that individual's attitude toward the action and their intention to put it into practice (Alhashmi et al., 2019). On the other hand, Davis meant to speak to the amount of effort that the user puts into utilizing the technology when he talked about the "perceived ease of use."

2.4 Unified Theory of Acceptance and Use of Technology (UTAUT)

Venkatesh and his colleagues (2003), who are in favor of the UTAUT, align their arguments with those of Davis (1989). However, as the key determinants of behavioral intention to use new technologies, they use the words "performance expectancy" and "effort expectancy." They gave their full backing to the concept (Davis, 1989; Davis et al., 1989) that established a connection between usefulness and comparative advantage as well as an external incentive.

The researchers also identified social influence as an important component, which they described as the extent to which the user's environment and social circle effect the user's utilization of technology. In Venkatesh's most recent article (2022), he argues that UTAUT is more relevant than ever in this day and age of artificial intelligence. The infrastructure that underpins the technology is frequently referred to as "facilitating conditions" by those who advocate for the UTAUT. However, in addition to the infrastructure, which often refers to the software and hardware, studies have shown that conducive conditions connected to the culture and practices of an organization, such as information transmission, may affect how quickly a technology is adopted (Gruzd et al., 2012).

Self-efficacy, as defined by UTAUT, refers to the user's confidence in his or her ability to make effective use of the technology. Venkatesh (2021) went on to clarify that individual traits such as self-efficacy are particularly significant toward technology adoption, and that people who are more "risk-seeking, tolerant of uncertainty, and with a desire to learn" have a higher probability of embracing and adopting the technology. Self-efficacy refers to “a person's belief in their own ability to perform a task successfully” (Pattinson, 2018). Anxiety, on the other hand, was characterized by Venkatesh and colleagues (2003) as the user's concerns regarding the technology. Gruzd et al. (2012) conducted a study that demonstrated how various forms of anxiety, such as time restrictions and information overload, prevent academicians from using social media. This is despite the fact that some studies consider this element to be insignificant when it comes to the acceptance and adoption of new technologies. The third part of UTAUT is called the behavioral goal, and it explains why the user intends to employ the technology in the first place.

2.5 The National AI Strategy Roadmap for the Philippines

The National AI Strategy Roadmap was developed by the DTI to serve as a guide for government and private sector stakeholders in the application of AI technologies and the development of AI economies (DTI, 2021). This was formulated while keeping in mind the potential consequences and impacts that algorithms may have on business models and processes. The application of AI to better the lives of ordinary Filipinos, boost the efficiency of Philippine businesses, and make the country's economy more competitive is the primary focus of the roadmap.

Figure 1: Roadmap of AI

2.6 The Present Stand of AI Applications and the Digital Government

Since it started its AI conceptualization in 2017, the Philippines is considered a beginner to AI technology. Several of its worldwide enterprises in business analytics, manufacturing and automation, energy, agriculture, metrological infrastructure, and customer experience already use AI (Kupper et al. 2018; Elahi et al., 2019). In spite of this, and despite the difficulties created by Covid-19 as well as a shrinking budget for research and development, in terms of the use of AI, the Philippines is making progress for it ranked 54 out of 181 countries in the Government AI Readiness Index 2022. With a score of 55.42 out of 100, it was higher than the worldwide average of 44.61. Also, the Philippines ranked 9th out of 17 comparable nations in East Asia (Oxford Insights, 2022). However, the Philippines rated 89th on the UN E-government Development Index (EGDI) in 2022, twelve steps worse than in 2020 (UN, 2020 & 2022).

In the published paper of OpenGov Asia (2021), it is anticipated that the processing of AI would become a new and developing sector in the Philippines. The DTI (2021) noted in their report to the President and the Nation that the government and private sector are collaborating in order to increase the availability of artificial intelligence technologies across the country. The DTI was sure that the Philippines had the potential to become a hub for the processing of big data, and they predicted that AI would be the next center for excellence after BPO which is what the Philippines is known for (Santhika & Ocampo, 2023).

However, governments around the world, including the Philippines, face a number of obstacles that could prevent them from adopting AI and capturing the value that AI offers. These obstacles include a lack of specialized talent (Johnson et al., 2021), limited investments in AI research and innovation (Yigitcanlar et al., 2021) and rules that aren't always clear to make sure AI is used in a way that is responsible, safe, clear, and focused on people (Gasser & Almeida, 2017; Perry & Uuk, 2019). As a matter of fact, when it comes to the development and deployment of AI, it is of the utmost importance for governments to actively evaluate and manage the continuously changing privacy situation (Taeihagh, 2021), as well as the potential ethical and safety hazards posed by the technologies of AI that they may be exposed to (Yu & Carroll, 2022).

International Journal of Business and Technology Management
e-ISSN: 2682-7646 | Vol. 5, No. 2, 30-48, 2023
http://myjms.mohe.gov.my/index.php/ijbtm

2.7 Conceptual Framework

This study will be conducted under the direction of the TAM and the UTAUT in order to capture the perceptions of AI adoption in the GAB and to investigate which factors influence the adoption of AI in the GAB. There are 6 aspects that will be taken for consideration regarding the AI adoption, namely: performance expectancy, effort expectancy, social influence, facilitating condition, perceived risk, attitude toward using AI and behavioral intention to use AI (Figure 2).

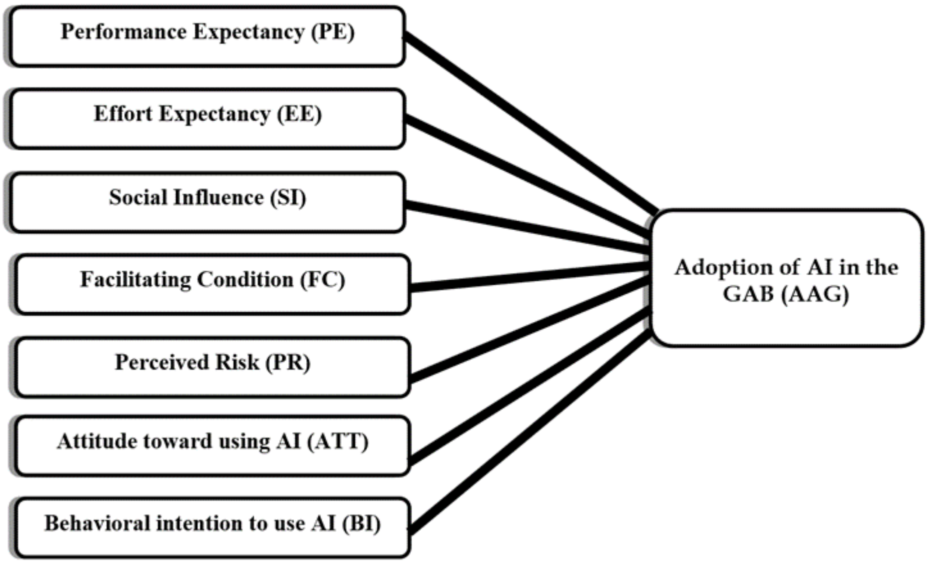

Figure 2: Conceptual Framework Integrating TAM and UTAUT

2.8 Research Hypotheses

The hypothesis statements are as follows:

Performance Expectancy (PE) is the *"perceived usefulness of adopting a system and the belief that the use of the adopted system will aid them in their job performance"* (Venkatesh et al., 2003). Within the context of this research, PE will be explored in relation to AAG.
H1: There is a statistically significant relationship between PE and AAG.

Effort Expectancy (EE) is defined by Venkatesh et al. (2003) as *"the level of ease in adopting the use of a system."* Within the context of this research, EE will be explored in relation to AAG.
H2: There is a statistically significant relationship between EE and AAG.

Social Influence (SI) is described by Venkatesh et al. (2003) as *"how an individual perceives the degree that 'important others' think that they should adopt the use of a new system."* Within the context of this research, SI will be explored in relation to AAG.
H3: There is a statistically significant relationship between SI and AAG.

Facilitating Condition (FC) is defined as *"the extent concerning to which an individual believes that the conducive technical and allied infrastructure are effectively available to support the usage of the new system"* (Venkatesh et al. 2003). Within the context of this research, FC will be explored in relation to AAG.
H4: There is a statistically significant relationship between FC and AAG.

Perceived Risk (PR) refers to the user's belief that there is a possibility that he or she may incur financial loss as a result of pursuing a particular goal (Warkentin et al., 2002). It refers to the combination of "environmental insecurity" and "behavioral insecurity." The inhospitable character of the functions of the internet is a major contributor to behavioral insecurity, and the capricious character of the internet is to blame for environmental insecurity (Zhang & Maruping, 2008). Within the context of this research, PR will be explored in relation to AAG.
H5: There is a statistically significant relationship between PR and AAG.

Attitude toward using AI (ATT) is defined by Andrews et al. (2021) as *"the preferences, including positive feelings, negative ones, or apprehension regarding intentions to adopt AI."* Within the context of this research, ATT will be explored in relation to AAG.
H6: There is a statistically significant relationship between ATT and AAG.

Behavioral Intention to use AI (BI) refers to the process of evaluating an individual's level of commitment to carrying out a certain action as a function of the circumstances in which they find themselves (Fishbein and Ajzen, 1975). The performance of the actual activities in which that intention is manifested can be effectively predicted using this BI (Zhang & Gutierrez, 2007). BI functions as a mediating variable in this situation, successfully influencing behavior in favor of an activity to which one's purpose is conveyed (Nasrallah, 2014). Within the context of this research, BI will be explored in relation to AAG.
H7: There is a statistically significant relationship between BI and AAG.

Both the models that were conceptually built and the hypotheses that were conceptually formulated will need to be tested, and the model will need to be verified using the appropriate methodology.

3. Methodology

This study utilized a questionnaire to investigate the factors that influence AI adoption in the GAB. The study used descriptive, correlation, and regression analysis to answer the research objectives, with data collected via Google Form and were analyzed using the IBM SPSS and Microsoft Excel.

3.1 Research Design

The quantitative research design was used in this research study. This paper employed the descriptive correlational research design which aside from describing distribution patterns, also compared groups and correlate study variables. The main purpose of the study is to capture the perceptions of AI adoption in the GAB and to investigate which factors influence the adoption of AI in the GAB.

To come up with this, the researchers utilized a survey questionnaire. The first section of this survey consists of GAB officials' and employees' demographic information such as sex, age, education attainment, division/section, length of service in current position, and length of service in GAB. The second section, which consists of 30 questions, is about the GAB's performance expectancy, effort expectancy, social influence, facilitating conditions, perceived risk, attitude toward using AI, behavioral intention to use AI, and adoption of AI. The Likert Scale is used in this questionnaire, and it has five scales: strongly disagree (1), disagree (2), neutral (3), agree (4), and strongly agree (5).

The independent variables of this study are performance expectancy, effort expectancy, social influence, facilitating conditions, perceived risk, attitude toward using AI, and behavioral intention to use AI. On the other hand, the adoption of AI in the GAB is the dependent variable.

3.2 Research Location

This research study was conducted at the Makati Central Office of the Games and Amusements Board (GAB). The GAB is a national government agency under the Office of the President of the Philippines which is mandated by law to regulate and supervise professional sports and allied activities in order to combat and prevent the existence and proliferation of illegal bookies and other forms of organized illegal gambling associated with all pay-for-play sports and amusement games.

3.3 Sampling

Respondents were selected based on the following criteria: 1) they are officials and employees of the GAB; and 2) they are willing to give consent. As of January 31, 2023, GAB has 130 filled-out plantilla positions and 1 job order or a total of 131 employees. Using Slovin's formula, the researchers enlisted the help of 99 respondents from a combination of management and rank-and-file GAB employees. The researchers used a technique called purposive sampling, in which the respondents were selected on the basis that they are the individuals who are in the best position to supply the required information on account of their knowledge and experience (Landreneau & Creek, 2009).

3.4 Research Instrument

The survey questionnaire was adopted from the following: 1) TAM Model (Davis, 1989); 2) UTAUT Model (Venkatesh et al., 2003); and 3) the research instruments designed and modified by Chatterjee and Kumar (2020), Andrews et al. (2021) and Distor et al. (2021). For the purpose of this study, the researchers utilized a modified version of the survey questionnaire (Appendix I) with 30 perception statements, using a 5-point Likert scale, which made it simpler for respondents to finish filling out the questionnaire. The main sources of measures for all the constructs and their items are listed in Table 1 below.

Table 1: Sources of Constructs and Items of Survey Questionnaire

	Constructs/ Factors	Scales	Sources	No. of Questions
Independent Variables				
1	Performance Expectancy (PE)	Strongly Disagree–Strongly Agree	Davis (1989); Venkatesh et al. (2003); Chatterjee & Kumar (2020); Andrews et al. (2021); Distor et al. (2021)	4
2	Effort Expectancy (EE)			4
3	Social Influence (SI)			4
4	Facilitating Conditions (FC)			4
5	Perceived Risk (PR)		Davis (1989); Venkatesh et al. (2003); Chatterjee & Kumar (2020); Distor et al. (2021)	4
6	Attitude Toward Using AI (ATT)			4
7	Behavioral Intention to Use AI (BI)			4
Dependent Variable				
8	Adoption of AI in the GAB	Strongly Disagree–Strongly Agree	Chatterjee & Kumar (2020); Andrews et al. (2021)	2

3.5 Data Analysis

The quantitative data that were collected in this study were encoded and analyzed using the IBM SPSS and Microsoft Excel. The statistical tools that were used are the following:

i. **Factor Analysis** was carried out to assess the validity of the questionnaire by examining whether the items are measuring the same construct or dimension (Floyd & Widaman, 1995, Guadagnoli & Velicer, 1988, DeVellis, 2017).
ii. **Cronbach's Alpha (α)** was used to measure and evaluate the degree to which a set of scale items or test items has internal consistency or reliability (Nunnally & Bernstein, 1994).
iii. **Frequency counting and percentage** was employed to find the demographic profile of the respondents (Babbie, 2016).
iv. **Weighted mean** was utilized to assess the dependent and independent variables. Within the prescribed limit, a qualitative description of the weighted mean for all variables were provided (Huck, 2012).
v. **Pearson correlation coefficient** was used to compute the correlation of all variables. Cohen (1988) suggested the following rule of thumb to figure out what the value of ρ is: $|r| \leq 0.1$ means very weak correlation, $0.1 < |r| \leq 0.3$ means weak correlation, $0.3 < |r| \leq 0.5$ means moderate correlation, $0.5 < |r| \leq 0.7$ means strong correlation, $0.7 < |r| \leq 0.9$ means very strong correlation, and $|r| > 0.9$ means extremely strong correlation.
vi. **Stepwise Multiple Linear Regression Analysis** was performed to determine the factors that most influence the adoption of AI in the GAB. The concept of "regression" originates in the study of statistics, where it refers to the models that are used to the problem of establishing how various variables are connected to one another (Bangdiwala, 2018). By employing a regression analysis, one can gain an evaluation of the extent to which two or more variables are related to one another in terms of their causes and results. This evaluation can be used to draw conclusions about the nature of the relationship between the variables (Uyanik and Güler, 2013). The primary purpose of regression analysis is to construct an equation that can be applied to all members of a population in order to make accurate projections regarding the values of the dependent variable (Meyers et al., 2016).

4. Results and Discussion

4.1 Demographic Profile of Respondents

Table 2 is a breakdown of basic characteristics of the respondents. Most of the respondents are female which is 57.6% (n=57) compared to male which is 42.4% (n=42). A large percentage (49.5%) reported their marital status as married (n=49) while the others (47.5%) are single (n=47). The vast majority of the respondents (63.6%) hold a Bachelor's degree (n=63). Of the 99 respondents, 45.5% has 1 to 5 years length of service in current position (n=45) and 44.4% has 6 to 10 years length of service in the GAB (n=44).

Table 2: Profile of the Respondents by Selected Variables

Variables	Category	Frequency	Percentage
Sex	Male	42	42.4
	Female	57	57.6
	Total	**99**	**100.0**
Age	25 to 34 years old	37	37.4
	35 to 44 years old	17	17.2
	45 to 54 years old	20	20.2
	55 to 65 years old	25	25.3
	Total	**99**	**100.0**
Marital Status	Single	47	47.5
	Married	49	49.5

	Separated	3	3.0
	Total	**99**	**100.0**
Educational Attainment	Associate Degree	3	3.0
	Bachelor's Degree	63	63.6
	Master's Degree	27	27.3
	Doctorate Degree	6	6.1
	Total	**99**	**100.0**
Length of service in current position	1 to 5 years	45	45.5
	6 to 10 years	38	38.4
	11 to 15 years	4	4.0
	16 to 20 years	3	3.0
	21 to 25 years	6	6.1
	26 years and above	3	3.0
	Total	**99**	**100.0**
Length of service in GAB	1 to 5 years	11	11.1
	6 to 10 years	44	44.4
	11 to 15 years	12	12.1
	16 to 20 years	10	10.1
	21 to 25 years	12	12.1
	26 years and above	10	10.1
	Total	**99**	**100.0**

4.2 Convergent Validity and Consistency Reliability Test

The measurement model was assessed to verify the reliability and validity, including item loadings, Cronbach's Alpha, Construct Reliability (CR) and Average Variance Extracted (AVE). The results are shown in Table 3.

Generally, factor loadings above 0.4 or 0.5 are considered acceptable, while those above 0.7 are considered strong (Costello and Osborne, 2005, Hair et al., 2010). Overall, the factor loadings in Table 3 suggest that the items in the questionnaire are strong, providing support for the construct validity of the questionnaire. To determine whether or not variables are genuine, the AVE for each variable was examined. AVE represents the amount of variance in a set of items that is explained by the construct they are intended to measure. Typically, an AVE value of 0.5 or higher is considered to indicate good convergent validity (Fornell & Larcker, 1981, Wong, 2013). As shown in Table 3, every AVE value is greater than 0.5. In this case, each AVE indicates that the variance in the items is explained by the construct they are intended to measure. This suggests that the questionnaire has strong convergent validity and that the items are highly related to one another.

Furthermore, a CR value of 0.7 or higher is considered to indicate good internal consistency and reliability (Raykov, 2009). In this case, all values of CR in Table 3 indicate that the questionnaire has good internal consistency and reliability. This suggests that the items are highly related to one another and that they are measuring the same construct in a consistent manner.

Table 3: Results of Convergent Validity and Consistency Reliability Test

Model Construct	Items	Loading Factors	Cronbach's Alpha	CR	AVE
Performance Expectancy	PE1	0.951	0.928	0.95	0.83
	PE2	0.916			
	PE3	0.927			
	PE4	0.837			
Effort Expectancy	EE1	0.629	0.867	0.916	0.74

	EE2	0.902			
	EE3	0.947			
	EE4	0.917			
Social Influence	SI1	0.930	0.932	0.953	0.83
	SI2	0.938			
	SI3	0.898			
	SI4	0.887			
Facilitating Conditions	FC1	0.707	0.764	0.855	0.60
	FC2	0.837			
	FC3	0.868			
	FC4	0.664			
Perceived Risk	PR1	0.856	0.909	0.936	0.79
	PR2	0.904			
	PR3	0.931			
	PR4	0.854			
Attitude Toward Using AI	ATT1	0.826	0.887	0.933	0.78
	ATT2	0.922			
	ATT3	0.883			
	ATT4	0.890			
Behavioral Intention to Use AI	BI1	0.540	0.851	0.905	0.71
	BI2	0.914			
	BI3	0.925			
	BI4	0.931			
Adoption of AI in the GAB	AAG1	0.969	0.936	0.969	0.94
	AAG2	0.969			

Finally, Cronbach's Alpha was applied in this study in order to determine its level of internal consistency. George and Mallery (2003) proposed the following rule of thumb: ≥ 0.9 means Excellent, ≥ 0.8 means Good, ≥ 0.7 means Acceptable, ≥ 0.6 means Questionable, ≥ 0.5 means Poor, and ≤ 0.5 means Unacceptable. As can be seen in Table 3, each of the variables achieved either excellent or good level of reliability.

Thus, the results show that the measurement model has construct reliability and validity. This test allowed this study to make further analysis and discussion.

4.3 Descriptive Statistics

Table 4 shows the overall mean scores of each group variable among the surveyed officials and employees in the GAB. The respondents most agreed with the statements describing six variables with the highest means, namely: adoption of AI in the GAB (3.81), attitude toward using AI (3.79), performance expectancy (3.76), social influence (3.7), effort expectancy (3.68), and behavioral intention to use AI (3.61). Meanwhile, facilitating conditions (3.33) and perceived risk (3.16) received a neutral overall mean score.

Table 4: Overall mean scores of each group variable

Variables	N	Mean	Standard Deviation	Interpretation	Rank
Performance Expectancy	99	3.76	0.94	Agree	3
Effort Expectancy	99	3.68	0.71	Agree	5
Social Influence	99	3.70	0.89	Agree	4
Facilitating Conditions	99	3.33	0.74	Neutral	7
Perceived Risk	99	3.16	0.68	Neutral	8
Attitude Toward Using AI	99	3.79	0.66	Agree	2
Behavioral Intention to Use AI	99	3.61	0.72	Agree	6
Adoption of AI in the GAB	99	3.81	0.97	Agree	1

4.4 Correlation Analysis

Based on Table 5, most of the independent variables have moderate to very strong positive relationship with the adoption of AI in the GAB. The attitude toward using AI ($r = 0.758$, $\rho < 0.05$) and the behavioral intention to use AI ($r = 0.756$, $\rho < 0.05$) showed a very strong positive correlation with the AI adoption. Meanwhile, social influence ($r = 0.692$, $\rho < 0.05$), effort expectancy ($r = 0.624$, $\rho < 0.05$), and performance expectancy ($r = 0.602$, $\rho < 0.05$) exhibited a strong positive correlation with the adoption of AI. On the other hand, facilitating conditions ($r = 0.503$, $\rho < 0.05$) exhibited a moderate positive correlation.

Table 5: Correlation of AI acceptance factors on the adoption of AI in the GAB

Independent Variables	Adoption of AI in the GAB			Interpretation
AI Acceptance Factors	Total N	Pearson Correlation (r)	Sig.	
Performance Expectancy	99	0.602*	0.000	Strong positive correlation
Effort Expectancy	99	0.624*	0.000	Strong positive correlation
Social Influence	99	0.692*	0.000	Strong positive correlation
Facilitating Conditions	99	0.503*	0.000	Moderate positive correlation
Perceived Risk	99	-0.278*	0.005	Weak negative correlation
Attitude Toward Using AI	99	0.758*	0.000	Very strong positive correlation
Behavioral Intention to Use AI	99	0.756*	0.000	Very strong positive correlation
*. Correlation is significant at the 0.05 level (2-tailed).				

Perceived risk ($r = -0.278$, $\rho < 0.05$) is the lone variable which exhibited a weak negative correlation. This means that as the perceived risk of AI increases, the adoption of AI in the GAB decreases.

Some of the related studies confirm the result of this study wherein perceived risk has a negative relationship with the adoption of AI in the government. The study of Bostrom & Heinen (2019) found that perceived risk is negatively associated with government AI adoption in China. They suggested that increasing public trust in AI and addressing ethical concerns can help mitigate perceived risks and promote government AI adoption. Zhang et al. (2020) agreed that increasing public trust in AI and addressing ethical concerns can help mitigate perceived risks and promote government AI adoption. To support this claim, Heo et al. (2021) also found that perceived risk is negatively associated with the adoption of AI in the government in both the US and South Korea. The authors suggested that addressing perceived risks, such as concerns about privacy and security, is essential for successful government AI adoption. Hence, perceived risk can be generally considered a barrier to AI adoption, as it can lead to concerns about safety, privacy, and job displacement.

4.4 Stepwise Multiple Linear Regression Analysis

A stepwise multiple regression analysis was performed to evaluate whether performance expectancy, effort expectancy, social influence, facilitating condition, perceived risk, attitude toward using AI and behavioral intention to use AI predict the adoption of AI in the GAB. It is observed in Table 6 that both attitude toward using AI and effort expectancy are significant predictors of the adoption of AI.

Table 6: Regressors of the Adoption of AI in the GAB (n=99)

Model	Unstandardized Coefficients		Standardized Coefficients Beta	*t*-value	Sig.
	B	Std. Error			
(Constant)	-0.953	0.374		-2.546	0.012
Attitude Toward Using AI	0.865	0.107	0.595	8.059	0.000
Effort Expectancy	0.404	0.101	0.296	4.015	0.000
a. Dependent Variable: Adoption of AI in the GAB					

Given the information in Table 6, it appears that the attitude toward using AI is the strongest significant predictor of the AI adoption. The unstandardized coefficient of 0.865 indicates that for each unit increase in the attitude toward using AI, the adoption of AI in the GAB increases by 0.865 units, holding all other variables constant. The standardized coefficient of 0.595 and the t-value of 8.059 indicate that the relationship between attitude toward using AI and adoption of AI in the GAB is statistically significant at the 0.000 level. This means that it is highly unlikely that this relationship is due to chance.

This result is consistent with the findings of the study of Chang et al. (2020) when they investigated the elements that influence the intention of government officials to use AI. They discovered that a government's stance toward AI has a considerable and positive effect on the likelihood that the government will accept AI. Moon (2019), in the results of a study of the general public's opinions toward AI and its prospective application in government, argued that public support for AI in government is influenced by perceptions of the technology's potential advantages and risks. In addition, when Vasileiou et al. (2020) investigated the influence of trust and attitude on the intention of personnel in the public sector to use AI, they found that both trust and attitude have significant positive effects on the intention to use AI in the public sector.

Hence, attitudes regarding AI have a significant impact in the acceptance and deployment of AI in government. To put it another way, having a positive attitude can result in increased adoption and support, whereas having a negative attitude can result in delayed adoption or opposition.

Furthermore, it appears that the effort expectancy is the next significant predictor of the adoption of AI adoption. The standardized coefficient of 0.296 and the t-value of 4.015 indicate that the relationship between effort expectancy and adoption of AI in the GAB is statistically significant at the 0.000 level. This means that it is highly unlikely that this relationship is due to chance. The positive beta value of 0.296 suggests that as effort expectancy increases by one unit, the AI adoption increases by 0.296 units, holding all other variables constant. This shows that effort expectancy is a positive predictor of the adoption of AI in the GAB.

This reveals that the perspective of the GAB employees on how easy it is to use AI intervention and how they see AI's usefulness in their Division's/Section's functions were strongly related with the higher intention to adopt AI tools. In other words, when GAB employees notice that AI tools have an easy interface and are simple to use, they are more likely to have a higher perception that the AI tool can make their Division's or Section's responsibilities more effective.

Previous researches have similarly reached the conclusion that effort expectancy has a substantial bearing on the degree to which AI is implemented in the public sector. Siau et al.

(2020) investigated the factors that determine whether or not a government organization will embrace AI, one of which was the effort expectancy. The authors came to the conclusion that an individual's perception of the amount of work that will be required to use AI in government has a large and favorable effect. When Wang et al. (2020) and Alalwan et al. (2021) researched the factors that influence government officials' desire to embrace AI, one of the things they looked at was effort expectancy. Both sets of researchers came to the same conclusion. In general, the findings of their investigations imply that the anticipated level of effort is a critical component in the implementation of AI in government. It is possible that perceptions of user friendliness will play a role in determining whether or not government officials would adopt AI, which in turn may contribute to the successful adoption of AI in government services.

In general, the findings of the stepwise multiple linear regression analysis reveal that a favorable attitude toward the application of AI and the perceived effort expectancy are the strongest factors that determine the adoption of AI in the GAB.

Table 7: ANOVAa

Model		Sum of Squares	df	Mean Square	F	Sig.
2	Regression	58.063	2	29.031	83.870	.000[b]
	Residual	33.230	96	0.346		
	Total	91.293	98			
a. Dependent Variable: Adoption of AI in the GAB Predictors: (Constant), Attitude Toward Using AI, Effort Expectancy						

The ANOVA in Table 7 indicates that the regression model as a whole is statistically significant. The F-value of 83.870 and the associated p-value of 0.000 indicate that the regression model is a good fit and the independent variables are useful in explaining the variance of the dependent variable.

Table 8: Model Summaryc

Model	R	R Square	Adjusted R Square
2	0.797[a]	0.636	0.628
a. Predictors: (Constant), Attitude Toward Using AI, Effort Expectancy b. Dependent Variable: Adoption of AI in the GAB			

As can be gleaned from Table 8, the multiple correlation coefficient (R) of 0.797 indicates that there is a strong positive relationship between the predictor variables included in the model and the dependent variable. This means that the predictor variables are able to explain a significant proportion of the variance in the dependent variable. The R2 value of 0.636 means that approximately 63.6% of the variance in the dependent variable can be explained by the predictor variables included in the model. This means that the 36.4% unexplained variance can be explained by the variables that are not included in the conceptualization of this research study. The adjusted R2 value of 0.628 takes into account the number of predictor variables included in the model, and adjusts the R2 value accordingly. This indicates that even after adjusting for the number of predictor variables included, the model is still a good fit for the data.

Overall, these results suggest that the predictor variables included in the model are good predictors of the dependent variable, and that the model is a good fit for the data

5. Conclusion and Recommendation

Using the case of the GAB, this research provides some insights into how employees of the public sector in the Philippines think about the application of AI for e-government efforts. The findings of this study add to the expanding body of literature on the acceptance and adoption of AI, particularly in the context of government, where such research is still in developmental stages. Based on the findings of this study, the researchers were able to conclude the results as follows:

	Hypotheses	Accepted/Rejected
H1:	There is a statistically significant relationship between performance expectancy and the adoption of AI in the GAB.	Accepted
H2:	There is a statistically significant relationship between effort expectancy and the adoption of AI in the GAB.	Accepted
H3:	There is a statistically significant relationship between social influence and the adoption of AI in the GAB.	Accepted
H4:	There is a statistically significant relationship between facilitating conditions and the adoption of AI in the GAB.	Accepted
H5:	There is a statistically significant relationship between perceived risk and the adoption of AI in the GAB.	Accepted
H6:	There is a statistically significant relationship between attitude toward using AI and the adoption of AI in the GAB.	Accepted
H7:	There is a statistically significant relationship between behavioral intention to use AI and the adoption of AI in the GAB.	Accepted

Most of the independent variables showed a significant positive relationship with the adoption of AI in the GAB. On the other hand, the perceived risk is the lone variable which exhibited a weak negative correlation. This implies that the adoption of AI in the GAB decreases as the perceived risk of AI rises. Of all the independent variables, the stepwise multiple linear regression analysis revealed that the strongest factors that influence the adoption of AI in the GAB are the officials' and employees' attitude toward using AI and the effort expectancy. In conclusion, a positive attitude can lead to increased adoption and support, whereas a negative attitude might lead to delayed adoption or opposition. On the other hand, the GAB employees' perceptions of how simple it is to utilize AI intervention might lead to a desire of embracing AI tools.

For the GAB, it is recommended to foster an organizational culture that recognizes the potential of AI to improve the delivery of public service. This can involve building awareness and understanding of AI technologies among employees, as well as ensuring that AI systems are designed to support and augment human decision-making rather than replacing it. Furthermore, the GAB may develop a comprehensive AI strategy that outlines the goals, scope, and implementation plan for AI in the organization. This strategy should include ethical considerations, guidelines for data management, and clear guidelines for implementation and evaluation. The GAB may also invest in AI education and train its officials and employees to build technical skills and increase familiarity with AI technology. This will enable employees to better understand the potential uses and limitations of AI, as well as the ethical considerations that must be taken into account.

To obtain a more comprehensive understanding on the adoption of AI in the public sector, future researchers may employ mixed-methods study instead of relying solely on quantitative analysis. To expand the constructs of TAM and UTAUT, future studies may integrate sub-themes and thematic analysis and may delve deeper into the concepts of performance improvement, convenience, transparency and accountability. To provide more robust empirical evidence on how government agencies govern, accept, and adopt AI, future researchers could also consider including other actors in government, such as citizen-clients and/or stakeholders as respondents of their study.

References

Artificial Intelligence (AI) vs. Machine Learning. 2023 Columbia University, The Fu Foundation School of Engineering and Applied Science, Columbia Video Network. (2022, March 3). Retrieved April 1, 2023, from https://ai.engineering.columbia.edu/ai-vs-machine-learning/

Artificial Intelligence in Sports Market Statistics: Forecast - 2030. Allied Market Research. (n.d.). Retrieved April 2, 2023, from https://www.alliedmarketresearch.com/artificial-intelligence-in-sports-market-A12905

Alalwan, A. A., Dwivedi, Y. K., & Rana, N. P. (2021). Artificial intelligence adoption in government services: A qualitative study of perceived benefits and barriers. Government Information Quarterly, 38(1), 101502.

Alhashmi, S. F., Salloum, S. A., & Abdallah, S. (2019, October). Critical success factors for implementing artificial intelligence (AI) projects in Dubai Government United Arab Emirates (UAE) health sector: applying the extended technology acceptance model (TAM). In *Proceedings of the International Conference on Advanced Intelligent Systems and Informatics 2019* (pp. 393-405). Cham: Springer International Publishing.

Andrews, J. E., Ward, H., & Yoon, J. (2021). UTAUT as a model for understanding intention to adopt AI and related technologies among librarians. *The Journal of Academic Librarianship*, *47*(6), 102437.

Babbie, E. R. (2016). The basics of social research (7th ed.). Boston, MA: Cengage Learning.

Bangdiwala, S. I. (2018). Regression: binary logistic. *International journal of injury control and safety promotion*, *25*(3), 336-338.

Bostrom, R. P., & Heinen, J. S. (2019). Artificial intelligence governance in public administration: An exploratory study of challenges and opportunities. Public Administration Review, 79(6), 799-809.

Chang, H.-C., Chou, C.-H., & Kuo, F.-Y. (2020). The effects of attitude, subjective norm, and perceived behavioral control on intention to adopt AI in government: An empirical study. International Journal of Public Administration, 43(1), 44-54.

Costello, A. B., & Osborne, J. W. (2005). Best practices in exploratory factor analysis: Four recommendations for getting the most from your analysis. Practical Assessment, Research & Evaluation, 10(7), 1-9.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly*, 319-340.

Davis, F. D. (1985). *A technology acceptance model for empirically testing new end-user information systems: Theory and results* (Doctoral dissertation, Massachusetts Institute of Technology).

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.

DeVellis, R. F. (2017). Scale development: Theory and applications (4th ed.). Los Angeles, CA: Sage Publications.

Dickson, B. (2017, May 12). What is narrow, general and super artificial intelligence. TechTalks. https://bdtechtalks.com/2017/05/12/ what-is-narrow-general-and-super-artificial-intelligence/

Does AI spoil the naturalness of sports? Dataconomy. (2022, November 3). Retrieved April 2, 2023, from https://dataconomy.com/2022/11/artificial-intelligence-in-sports-examples/

Dutta, S., Lanvin, B., León, L. R., & Wunsch-Vincent, S. (Eds.). (2021). *Global innovation index 2021: tracking innovation through the covid-19 crisis*. WIPO.

Elahi, E., Weijun, C., Zhang, H., & Nazeer, M. (2019). Agricultural intensification and damages to human health in relation to agrochemicals: Application of artificial intelligence. *Land use policy*, *83*, 461-474.

Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intention and behaviour: An introduction to theory and research*. Addison-Wesley.

Floyd, F. J., & Widaman, K. F. (1995). Factor analysis in the development and refinement of clinical assessment instruments. Psychological Assessment, 7(3), 286-299.

Gasser, U., & Almeida, V. A. (2017). A layered model for AI governance. *IEEE Internet Computing*, *21*(6), 58-62.

Ghorayeb, A., Comber, R., & Gooberman-Hill, R. (2021). Older adults' perspectives of smart home technology: Are we developing the technology that older people want? *International journal of human-computer studies*, *147*, 102571.

Girasa, R. (2020). Applications of AI and projections of AI impact. In Artificial intelligence as a disruptive technology (pp. 23–67). Palgrave Macmillan.

Goralski, M. A., & Tan, T. K. (2020). Artificial intelligence and sustainable development. *The International Journal of Management Education*, *18*(1), 100330.

Government AI readiness index 2022. Oxford Insights. (n.d.). Retrieved April 1, 2023, from https://www.oxfordinsights.com/government-ai-readiness-index-2022

Gruzd, A., Staves, K., & Wilk, A. (2012). Connected scholars: Examining the role of social media in research practices of faculty using the UTAUT model. *Computers in Human Behavior*, *28*(6), 2340-2350.

Guadagnoli, E., & Velicer, W. F. (1988). Relation of sample size to the stability of component patterns. Psychological Bulletin, 103(2), 265-275.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). Multivariate data analysis (7th ed.). Upper Saddle River, NJ: Prentice Hall.

Heo, J., Lee, S. M., & Park, Y. J. (2021). Factors influencing government AI adoption: A comparative study of the US and South Korea. Government Information Quarterly, 38(1), 101506.

Hinkle, D. E., Wiersma, W., & Jurs, S. G. (2003). *Applied statistics for the behavioral sciences* (Vol. 663). Houghton Mifflin college division.

Huck, S. W. (2012). Reading statistics and research (6th ed.). Boston, MA: Pearson.

Johnson, M., Jain, R., Brennan-Tonetta, P., Swartz, E., Silver, D., Paolini, J., ... & Hill, C. (2021). Impact of big data and artificial intelligence on industry: developing a workforce roadmap for a data driven economy. *Global Journal of Flexible Systems Management*, *22*(3), 197-217.

Kelly, S., Kaye, S. A., & Oviedo-Trespalacios, O. (2022). What Factors Contribute to Acceptance of Artificial Intelligence? A Systematic Review. *Telematics and Informatics*, 101925.

Kirlidog, M., Kaynak, A. (2013). Technology acceptance model and determinants of technology rejection. In *Information Systems and Modern Society: Social Change and Global Development* (pp. 226-238). IGI Global. https://doi.org/10.4018/jissc.2011100101.

Kupper, D., Lorenz, M., Kuhlman, K., Bouffault, O., Lim, Y., Van Wyck, J., & Schlageter, J. (2018). AI in the factory of the future: The ghost in the machine. *Boston Consulting Group*.

Lee, J. D., & See, K. A. (2004). Trust in automation: Designing for appropriate reliance. *Human factors*, *46*(1), 50-80.

Meyers, L. S., Gamst, G., & Guarino, A. J. (2016). *Applied multivariate research: Design and interpretation*. Sage publications.

Moon, M. J. (2019). Public attitudes toward artificial intelligence and the future of government. Public Administration Review, 79(6), 841-844.

Nasrallah, R. (2014). Learning outcomes' role in higher education teaching. *Education, Business and Society: Contemporary Middle Eastern Issues*, *7*(4), 257-276.

Nunnally, J. C., & Bernstein, I. H. (1994). Psychometric theory (3rd ed.). New York, NY: McGraw-Hill.

Raykov, T. (2009). Evaluation of scale reliability for unidimensional measures using latent variable modeling. Measurement and Evaluation in Counseling and Development, 42(3), 223-232.

United Nations. (2020). E-government survey 2020: Digital government in the decade of action for sustainable development. United Nations Digital Library. https://digitallibrary.un.org/record/3884686?ln=en

Park, J., Hong, E., & Le, H. T. (2021). Adopting autonomous vehicles: The moderating effects of demographic variables. *Journal of Retailing and Consumer Services*, *63*, 102687.

Pattinson, E. (2018). *An Investigation into the Relationship Between Diving, Self-Efficacy and Performance in Competitive Diving* (Doctoral dissertation, University of Winchester).

Perry, B., & Uuk, R. (2019). AI governance and the policymaking process: key considerations for reducing AI risk. *Big data and cognitive computing*, *3*(2), 26.

Santhika, E., & Ocampo, Y. (2023, January 13). *The Philippines collaborating to enhance AI and Cloud - OpenGov asia*. OpenGov Asia -. Retrieved April 1, 2023, from https://opengovasia.com/the-philippines-collaborating-to-enhance-ai-and-cloud/

Siau, K., Wang, W., & Chua, A. (2020). Exploring the determinants of artificial intelligence adoption in government: A case study of Singapore. Journal of Organizational Computing and Electronic Commerce, 30(1), 72-90.

Taeihagh, A. (2021). Governance of artificial intelligence. *Policy and society*, *40*(2), 137-157.

The impact of rapid technological change on sustainable development. UNCTAD. (2020, February 17). Retrieved April 1, 2023, from https://unctad.org/publication/impact-rapid-technological-change-sustainable-development

Uyanik, G. K., & Güler, N. (2013). A study on multiple linear regression analysis. *Procedia-Social and Behavioral Sciences*, *106*, 234-240.

Valle-Cruz, D., Alejandro Ruvalcaba-Gomez, E., Sandoval-Almazan, R., & Ignacio Criado, J. (2019, June). A review of artificial intelligence in government and its potential from a public policy perspective. In *Proceedings of the 20th Annual International Conference on Digital Government Research* (pp. 91-99).

Wang, H., Xie, Y., & Song, R. (2020). An empirical study of factors influencing government intention to adopt artificial intelligence. Government Information Quarterly, 37(3), 101428.

Warkentin, M., Gefen, D., Pavlou, P. A., & Rose, G. M. (2002). Encouraging citizen adoption of e-government by building trust. *Electronic markets*, *12*(3), 157-162.

Yigitcanlar, T., Corchado, J. M., Mehmood, R., Li, R. Y. M., Mossberger, K., & Desouza, K. (2021). Responsible urban innovation with local government artificial intelligence (AI): A conceptual framework and research agenda. *Journal of Open Innovation: Technology, Market, and Complexity*, *7*(1), 71.

Yu, S., & Carroll, F. (2022). Implications of AI in National Security: Understanding the Security issues and Ethical challenges. In *Artificial Intelligence in Cyber Security:*

Impact and Implications: Security Challenges, Technical and Ethical Issues, Forensic Investigative Challenges (pp. 157-175). Cham: Springer International Publishing.

Vasileiou, K., Sachini, E., & Stergioulas, L. K. (2020). The impact of trust and attitude on the intention to use AI in the public sector. Government Information Quarterly, 37(3), 101453.

Venkatesh, V. (2022). Adoption and use of AI tools: a research agenda grounded in UTAUT. *Annals of Operations Research*, 1-12

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS quarterly*, 425-478.

Zhang, J., Liu, Y., & Xue, L. (2020). Exploring the factors influencing government adoption of artificial intelligence in China. Government Information Quarterly, 37(1), 101395.

Zhang, W., & Gutierrez, O. (2007). Information technology acceptance in the social services sector context: An exploration. *Social Work*, *52*(3), 221-231.

Zhang, X., & Maruping, L. M. (2008). Household technology adoption in a global marketplace: Incorporating the role of espoused cultural values. *Information systems frontiers*, *10*, 403-413.