ISLA 2022 Proceedings
Latin America (ISLA)

8-8-2022

An Artificial Intelligence Adoption Intention Model (AI2M) inspired by UTAUT

Alexandre Nascimento

Fernando S. Meirelles

An Artificial Intelligence Adoption Intention Model (AI2M) inspired by UTAUT

Completed Research Paper

Alexandre M. Nascimento
Stanford University
alexandremoreiranascimento@alum.mit.edu

Fernando de Souza Meirelles
EAESP-FGV
fernando.meirelles@fgv.br

Abstract

Artificial Intelligence (AI) adoption and benefits are not well understood yet in businesses, leading to a low rate of adoption success by companies. The well-known Unified Theory of Acceptance and Use of Technology (UTAUT) and its extensions do not account for AI and specific business size specificities. In this context, this study's primary goal is to propose a new model inspired by UTAUT to account for AI-based IS and distinct business sizes' specificities. The proposed Artificial Intelligence Adoption Intention Model (AI2M) was tested using a sample of 363 participants, confirming the significance of UTAUT's influencing factors: Perceived Performance, Social Influence, and Expected Effort. Furthermore, distinctly to the context, UTAUT was proposed, Facilitating Condition was found to influence Behavior Intention. In addition, mediation tests revealed that Self-efficacy and Social Influence mediate the effect of the other three factors on the adoption intention. Finally, a moderation relationship was found between the company's size on the effect of self-efficacy and social influence on the adoption intention. AI2M explains 48% of the variance of the adoption intention, reaching generalization for different business sizes. Therefore, the present study helps reduce the gap in studies related to technology adoption and the adoption of AI-based technologies in companies of distinct sizes, supporting future academics' investigations and managers' decisions.

Keywords

Artificial Intelligence, Machine Learning, Technology Adoption, Adoption Model, User Acceptance, UTAUT, Large Business, Medium Business, Small Business.

Introduction

Artificial Intelligence (AI) seeks the development of information systems (IS) to imitate and complement human intelligence (Simon, 1995). AI's recent progress is creating potential opportunities for businesses (Gu et al., 2019), such as a positive impact on productivity (Alexopoulos & Cohen, 2019; Mayer, Strich, & Fiedler, 2020). Those opportunities and promises are driving companies to seek to adopt AI IS (Nascimento & Bellini, 2018).

However, AI's many techniques (Nascimento, Cunha, Meirelles, Scornavacca, & Melo, 2018) make AI IS different from conventional IS. For example, Machine Learning (ML) (Russell & Norvig, 2016) is one of the currently most promising AI subfields, which encompasses computing techniques that allow computers to learn directly from data rather than demand human specialists to analyze data, draw conclusions about the rules governing their behavior, and program the computer with those rules. Other techniques, such as Reinforcement Learning (RL), allow computers to learn by themselves by relying upon positive reward mechanisms. For example, RL allows computers to learn to play videogame (Mnih et al., 2013) and other board games (Silver et al., 2016) by themselves, without needing any previous games' rules and strategies to be previously programmed.

Those characteristics and differences from conventional IS make AI IS adoption poorly understood (Venkatesh, 2022). The classical IS adoption models, such as the Technology Acceptance Model (TAM) (Davis, 1986) and Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh, Morris, Davis, & Davis, 2003), were not designed considering those distinct characteristics (Venkatesh, 2022). Moreover, they do not consider those characteristics' effect on the different business sizes, particularly small and medium businesses (SMB) (Okafor, Nico, and Azman, 2016).

Because those factors seem to play an important role in AI IS adoption (Venkatesh, 2022), since most AI IS adoption initiatives in business are currently failing (Staff, 2019), Venkatesh (2022) suggested the research community seek for UTAUT's extensions to take them into account. Seeking to contribute to the understanding of AI-based IS adoption in businesses, the present research's primary goal is to propose an Artificial Intelligence Adoption Intention Model (AI2M) extending UTAUT towards AI IS and emcompassing also SMB.

Theoretical Background

In 2003 UTAUT (Figure 1) (Venkatesh et al., 2003) was proposed to unify the many distinct factors influencing IS adoption from eight well-known user adoption models. Using data from four companies, they found Performance Expectancy (PE), Effort Expectancy (EE), and Social Influence (SI) affect the Behavior Intention (BI) of adopting an IS. They also found Facilitating Conditions (FC), and BI affect the Use Behavior (BU). UTAUT exceeded each reference model individually (Venkatesh et al., 2003). Figure 1 illustrates UTAUT.

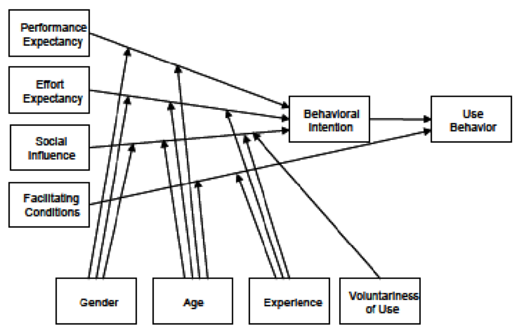

Figure 1. UTAUT

Compeau, Higgins, & Huff, (1999) and Compeau & Higgins (1995a, 1995b) proposed one of those eight models. It applied and extended the Social Cognitive Theory (SCT) to the context of computer utilization. One of its independent constructs was self-efficacy (SE). SE concept was created by Bandura (1977) under the SCT. Bandura (1986) defined self-efficacy as people's judgment on their ability to organize and execute courses of action needed to achieve designated types of performances. Because self-efficacy is related to personal beliefs about success in a specific task, subject, or environment (Bandura, 1986), Compeau and Higgins (1995a, 1995b, 1999) hypothesized that self-efficacy plays an essential role in technology adoption.

Self-efficacy theory states that efficacy expectations are distinguished from outcome expectancies. The efficacy expectation is the people's belief about their own ability to perform the behavior required to achieve the outcomes, and the outcome expectancy is the individual evaluation that a particular behavior will produce a specific outcome. Therefore, according to Bandura (1977), outcome and efficacy expectations are differentiated because even when people believe a behavior can produce a specific outcome, it will not influence their own activities unless they believe they can perform the required behavior.

Also, Bandura (1977) pointed out in most studies that expectations are mainly concerned with people's hopes for favorable outcomes rather than with their sense of personal mastery. The author explained that those measures in clinical psychological studies reflect a mixture of hope, wishful thinking, belief in the power of the procedures, and faith in the therapist, which have little relation to the magnitude of behavioral change.

When proposing the UTAUT, Venkatesh et al. (2003) found that self-efficacy did not significantly influence behavior intention and removed it from the UTAUT. The authors found that EE captured self-efficacy's effect, which resulted in a non-significant effect. They have not been revisited in the newer versions of the UTAUT: UTAUT2 (Venkatesh, Thong, & Xu, 2012) and UTAUT3(Farooq et al., 2017).

Proposed Model

Hypothesis H1 is formulated as **H1: FC has an influence in BI towards the adoption of AI-based tools**. FC has been reported to influence adoption (Farooq et al., 2017; Venkatesh et al., 2003, 2012). However, Venkatesh et al. (2003) found the FC effect on the BI non-significant because EE captures its effect in UTAUT. Years later, Venkatesh et al. (2013) found the FC effect to be significant on the BI in UTAUT2, confirmed in UTAUT3 by Farooq et al. (2017). PE, EE, and SI as factors influencing BI have been extensively discussed and accepted in the technology adoption literature. They are already factors influencing the BI in UTAUT (Venkatesh et al., 2003), UTAUT2 (Venkatesh et al., 2012), and UTAUT3 (Farooq et al., 2017). Therefore, the hypotheses H2, H3, and H4 were formulated as **H2: PE has an influence in BI towards the adoption of AI-based tools; H3: EE has an influence in BI towards the adoption of AI-based tools; H4: SI has an influence in BI towards the adoption of AI-based tools.**

Compeau and Higgins (1995)'s model was tested in 1995, and SE was found to influence BI. UTAUT was tested in 2003, and SE's influence was discarded. Therefore those models were tested in distinct moments of computers and IS diffusion. Indeed, between those years, the number of households with computers doubled while the number of households with internet tripled[1]. User experience was enhanced by graphical user interfaces (GUIs) replacing old-school text interfaces on newer operating systems, web browsers, and IS versions. Those changes probably reduced people's fear and improved their self-efficacy on average as they were exposed to more user-friendly IS. This effect may have weakened the self-efficacy effect on BI over the diffusion time.

However, AI is at a different diffusion moment. Although the field is old, machine learning techniques, which are responsible for most businesses' demands, are still beginning to be adopted by most companies. Therefore, it is reasonable to assume that perhaps the moment is analogous to Compeau and Higgins's study. Therefore self-efficacy may play a significant role in the intention of adoption. Thus, it may be an essential factor to be considered in the context of AI. Because of it, the following hypothesis is formulated for SE: **H5: SE influences BI towards adopting AI-based tools.** Therefore, the proposed model was initially based on five initial hypotheses: H1, H2, H3, H4, and H5.

Methodology

Most acceptance studies rely on quantitative methods to assess an IS acceptance or usage intention, such as the study performed by Dellinger and Leech (2007) or the one executed by Alia (2017). Here, a quantitative approach was used as well. The protocol used to achieve the following goals is illustrated in figure 2: (1) test the initial hypothesis; (2) investigate the influence of SE and its interplay with EE; (3) evaluate the influence of the business size as other control variables; (4) understand how much of the variance of the behavioral intention is explained by the factors; (5) produce as an outcome a model to explain adoption intention to support future research.

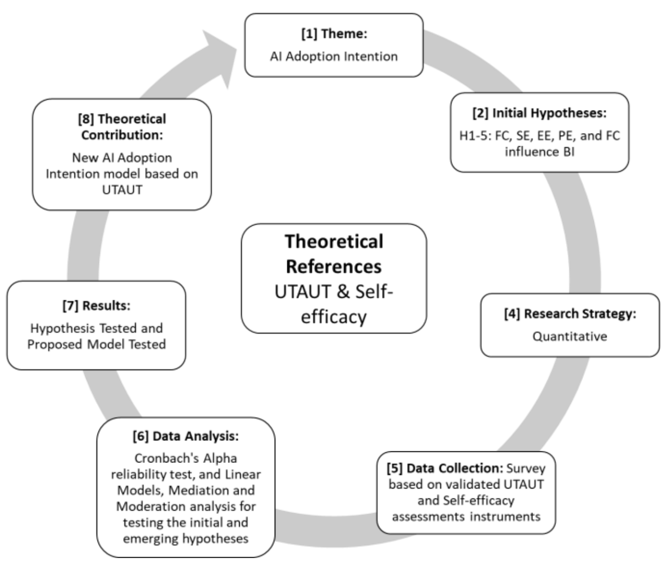

Figure 2. Research Protocol. Adapted from Neuman (2007)

An early definition of validity for quantitative research was done by Garrett (1937) as "the extent to which it measures what it purports to measure". Many statistical techniques have been used to help to ensure validity. The following steps and techniques were executed in order to ensure the validity of the present study: (1) research instrument development based on validated assessment instruments; (2) sample identification and sizing; (3) survey sampling;

[1] https://www.infoplease.com/math-science/computers-internet/us-households-with-computers-and-internet-use-1984-2014

(4) data collection; (5) Cronbach's Alpha reliability test; (6) hypotheses test at a 5% significance level; (6) combined hypotheses test at a 5% significance level; (7) mediation analysis; (8) moderation analysis; (9) investigation of demographic variables' influence.

Research instrument

Aiming to measure the six constructs (EE, PE, SI, SE, FC, BI), a questionnaire (see Appendix) was formulated based on validated scales. The questions for the constructs EE, PE, SI, FC, and BI, were adapted from the UTAUT assessment instrument (Venkatesh et al., 2003). The questions for the construct SE were based on the validated instrument created by Tuan, Chin, and Shieh (2005). Also, nine demographic questions have been added to capture the firm size, the company outreach, the company industry, the company economic sector, the company type of business, and some data about the participants, such as their position (hierarchical level) and their experience. The final instrument based on 87 questions was inputted into Google Forms. Three attention check questions have been added to the instrument.

The attention check questions asked the respondent the select a specific answer. They were assigned randomly. Those questions were inserted to check if the respondents were paying enough attention when reading the questions and answering. All the answers from participants who failed at least one attention check question were discarded.

A link to the Google Forms questionnaire was sent by e-mail to the participants (from small, medium, and large companies) on October 20th, 2020. The e-mails were sent to a mailing list available. The data was collected until October 30th, 2020. Therefore, convenience was the criteria used to select the participants.

Results

The total number of respondents was 581. They were downloaded from Google forms as a comma-separated values (CSV) file. The file was imported to R Studio, the statistical tool used to support the quantitative data analysis. 238 (37.5%) responses were discarded by failure on attention check questions. Therefore, 363 (62.5%) respondents were considered. According to the power analysis realized using software G* power, this sample size achieves an explanation power of 99.99% for five predictors (EE, PE, SI, SE, FC).

Cronbach's alpha tests were performed to check the internal consistency of questions used to measure each theoretical driven construct. This test is essential to validate how closely related the questions are as a group, indicating the construct reliability. The function *alpha* from R Studio package *psych* was used to perform Cronbach's alpha tests. All alpha values were equal or higher than 0.7 (PE: 0.9, EE: 0.9, SI: 0.8, FC: 0.7, SE: 0.8, BI: 0.8), which indicated good reliability. The results from Cronbach's alpha tests support each construct to be measured per participant as the average of the values attributed to all the related questions. After the factor means had been computed, the correlations were computed.

Then, a linear model was used to test the effect of the five constructs together in BI. The model $BI = \beta 0 + \beta 1' * FC + \beta 2' * PE + \beta 3' * EE + \beta 4' * SI + \beta 5' * SE + Error$ was tested. Supplementary Table 1 shows the results for the βs and p-values. The multiple R^2 and adjusted R^2 were 0.369 and 0.359, respectively. The F-statistic was 38.3 on 5 and 328 DF. The p-value was < 2e-16. The residual error was 0.791 on 328 degrees of freedom. Except for EE, the p-value of the other constructs was significant at the 5% level. It is noteworthy in this complete model that the significance of EE and SE were considerably affected. EE lost its significance, which indicates a potential mediation effect (MacKinnon, Fairchild, & Fritz, 2007). This finding was similar to what Venkatesh et al. (2003) reported. Venkatesh et al. (2003) hypothesized that SE would not have a significant influence on the BI and found SE "did not have any direct effect on intention" (Venkatesh et al., 2003).

Because Venkatesh et al. (2003) described SE to be "non-significant due to the effect captured by effort expectancy" (Venkatesh et al., 2003) when proposing the UTAUT, another linear model without SE ($BI = \beta 0 + \beta 1'' * FC + \beta 2'' * PE + \beta 3'' * EE + \beta 4'' * SI$) was tested. The multiple R^2 and adjusted R^2 were 0.356 and 0.348, respectively. The F-statistic was 45.4 on 4 and 329 DF. The p-value was < 2e-16. The residual error was 0.798 on 329 degrees of freedom. Supplementary Table 2 shows the results for the βs and p-values. At this time, all the construct's p-values were significant at a 5% level. Because EE is significant (at a 5% level) in the model without SE, it indicates SE captures EE significance. This finding confirms the interplay between those two constructs found by Venkatesh et al. (2003). However, Venkatesh et al. (2003) found that SE captures EE significance rather than the opposite. Moreover, while Venkatesh found that SE did not directly affect BI, SE effect on BI was found (H5). Notably, the interplay between SE and EE was the opposite of what Ventakesh et al. (2003) reported. Venkatesh et al. (2003) reported SE effect was not significant because EE captured it. However, here the effect of EE became non-significant when SE was added, demonstrating SE was capturing the effect of EE.

Moreover, when comparing each construct's effect sizes (β) and p-values between the model with and without SE, SE seemed to capture the significance of PE and FC, although FC kept the significance level below 5% even when SE was added. However, SE does not seem to capture the effect of SI. Because this effect can indicate a potential mediation effect (MacKinnon, Fairchild, & Fritz, 2007), the following hypothesis was formulated: **H6: EE effect on BI is mediated by SE; H7: FC effect on BI is mediated by SE; H8: PE effect on BI is mediated by SE; H9: SI effect on BI is not mediated by SE.**

Mediation Analysis

The mediation tests were performed using the function *mediate* from the R Studio package *psych*. The first test was performed to evaluate hypothesis H6. Supplementary Table 3 shows the results of the direct and indirect effects of the meditation validity test for H6. As the lower and upper limits of the confidence interval ([0.25; 0.53]) did not include zero, mediation was found at a 1% significance level (p-value < 1.34e-23), accepting hypothesis H6. Therefore, when considering an AI tool, the effect of EE on BI is mediated by SE. Supplementary Figure 1 (see Appendix) shows a diagram illustrating the mediation and the values involved in the effect, where c' and c represent the direct effect and total effect estimates on BI.

The second test was performed to evaluate hypothesis H7. Supplementary Table 4 shows the results of the direct and indirect effects of the meditation validity test for H7. As the lower and upper limits of the confidence interval did not include zero, mediation was found at a 1% significance level (p-value < 4.98e-27), accepting the hypothesis H7. Therefore, when considering an AI tool, the effect of FC on BI is mediated by SE. Supplementary Figure 2 (see Appendix) shows a diagram illustrating the mediation and the values involved in the effect, where c' and c represent the direct effect and total effect estimates on BI.

The third test was performed to evaluate hypothesis H8. Supplementary Table 5 shows the results of the direct and indirect effects of the meditation validity test for H8. As the lower and upper limits of the confidence interval [0.17; 0.38] did not include zero, mediation was found at a 1% significance level (p-value < 2.05e-26), accepting the hypothesis H8. Therefore, when considering an AI tool, the effect of PE on BI is mediated by SE. Supplementary Figure 3 (see Appendix) shows a diagram illustrating the mediation and the values involved in the effect, where c' and c represent the direct effect and total effect estimates of PE on BI, where c' and c represent the direct effect and total effect estimates on BI.

The fourth test was performed to evaluate hypothesis H9. Supplementary Table 6 shows the results of the direct and indirect effects of the meditation validity test for H9. As the lower and upper limits of the confidence interval did not include zero, mediation was found at a 1% significance level (p-value < 1.51e-29), rejecting the hypothesis H9. Therefore, when considering an AI tool, the effect of SI on BI is not mediated by SE. Supplementary Figure 4 (see Appendix) shows a diagram illustrating the results of the mediation test, where c' and c represent the direct effect and total effect estimates on BI.

A test was performed to check the complete model encompassing all mediations. Supplementary Figure 5 (see Appendix) shows the resulting model. Supplementary Table 7 shows the results of the direct and indirect effects of the meditation validity test on the effect between BI and independent variables (EE, PE, FC, and SI) mediated by SE. Mediation was found because the lower and upper limits of the confidence interval did not include zero for EE and PE. There is a borderline mediation for FC. However, the lower and upper limits of the confidence interval included zero for SI. Therefore no mediation was found for this construct. The model's adjusted R^2 was 0.36, which is acceptable, and its p-value equals 6.32e-33 is considerably good. The F value was 40.46 on 5 and 357 DF.

As previously described, the mediation between SI and BI was confirmed when tested alone but was not confirmed when tested together with the other constructs in the complete model. Also, a considerable interaction between PE and SI, FC and SI, and EE and SI could be observed. Because of those findings, it was hypothesized that the SI could mediate the relationship between BI and the independent variables PE, EE, and FC. Therefore, a new hypothesis was proposed encompassing both SE and SI as mediators: **H10: PE, EE, and FC effects on BI are mediated by SI and SE.**

The *mediate* function from the R package *psych* was used again. Supplementary Figure 6 (see Appendix) shows the final model. Supplementary Table 8 shows the results of the direct and indirect effects of the meditation validity test on the effect between BI and the independent variables (EE, PE, and FC), mediated by SE and SI. Considering SE as a mediator, the mediation effect was found for EE and PE since the lower and upper limits of the confidence interval did not include zero. The same borderline mediation effect of SE was found between FC and BI. Considering SI as a mediator, the mediation effect was found for EE, PE, and FC since the lower and upper limits of the confidence interval did not include zero. Therefore, hypothesis H10 could be accepted despite the borderline mediation found for FC. The model's adjusted R^2 was 0.36, which is acceptable, and its p-value equals 6.32e-33 is considerably good. The F value was 40.46 on 5 and 357 DF.

Demographic Variables' Analysis

The next step was a set of analyses to understand the effects of the control variables (demographics) in the proposed model. The variables considered were the business size (BS) (small, medium, or large), the company reach (CR) (local, region, national, international), the company industry (CI), the region where the company is located (RE) (north, south, southeast, northeast, or center-west), the company economic sector (ES) (primary, secondary, tertiary), the company type of business (BT) (commerce, industry, or service), and some data about the participants, such as their age (AG), position in the company (HL) (hierarchical level) and their experience (EX) (years). The questions related to the company industry and executive position (in the company) were open questions. Therefore, systematic work was performed to standardize those answers and replace them with codes.

For guiding the effort to understand how the control variables influence the behavior intention of adopting AI-based tools, the following hypothesis was formulated: **H11: BS has an influence in BI towards the adoption of AI-based tools; H12: CR has an influence in BI towards the adoption of AI-based tools; H13: CI has an influence in BI towards the adoption of AI-based tools; H14: RE has an influence in BI towards the adoption of AI-based tools; H15: ES has an influence in BI towards the adoption of AI-based tools; H16: BT has an influence in BI towards the adoption of AI-based tools; H17: HL has an influence in BI towards the adoption of AI-based tools; H18: EX has an influence in BI towards the adoption of AI-based tools; and H19: AG has an influence in BI towards the adoption of AI-based tools.**

Right after, a linear model was used to test the effect of the 8 control variables (between [ ]s) and the 5 independent variables constructs (between { }s) in BI. Then, the model $BI = \beta 0 + \{\beta 1' * FC + \beta 2' * PE + \beta 3' * EE + \beta 4' * SI + \beta 5' * SE\} + [\beta 6' * BS + \beta 7' * CR + \beta 8' * CI + \beta 9' * RE + \beta 10' * ES + \beta 11' * BT + \beta 12' * HL + \beta 13' * EX + \beta 14' * AG]$ + Error was tested. The model's adjusted R^2 was 0.48 with a p-value < 0.015. The residual error was 0.778 on 270 degrees of freedom. Supplementary Table 9 shows the results for the βs and the p-values. For the nominal variables, only the β, std error, t-value, and p-value corresponding to the lowest p-values found are indicated in Supplementary Table 9 because a p-value was computed for each possible nominal value. The model also encompassing the control variables achieved a higher R^2 (0.48) than the previous one (R^2=0.36). As expected, except for EE, the original independent variables (FC, PE, SI, and SE) are significant at a 5% level in this new model. BS, ES, and BT control variables are non-significant at the 5% level. Therefore, hypotheses H11, H15, and H16 were rejected. The business size, economic sector, and type do not influence the behavior intention. The control variables CR, CI, HL, and EX are significant at a 5% level. Thus, hypotheses H12, H13, H17, and H18 were accepted.

Consequently, the company industry and its reach influenced the BI. Moreover, the level in the hierarchy of the participants and their experience were found to influence the behavior intention. Finally, the control variables RE and AG are significant at the 6% level. Therefore, hypotheses H14 and H19 were accepted. Hence, the geographic region in Brazil where the company is located and the participant's age influenced the behavioral intention.

The companies whose business coverage belongs to one of those groups presented a statistically significant difference in the behavior intention when each group was compared to the remaining CR in the sample: state, nation, Latin America, or global. Also, companies located in Brazil's northeast region presented a statistically significant difference in the BI when the region was compared to the remaining regions in the sample. Finally, the companies belonging to one of the following industries also presented statistically significant differences when each group was compared to the remaining industries in the sample: capital goods, consumer goods, durable goods, education, engineering & consulting, entertainment & sport, healthcare, logistics, mining, real estate, utilities, civil construction, processes manufacturing (e.g., chemical industry), and other professional services.

Moreover, the higher the participant's position in the company's hierarchical level, the higher the BI of adopting an AI-based system. Also, the participants' age presented a statistically significant influence on the BI. Thirty-six or older participants presented higher behavioral intention than the other ages.

Moderation Analysis

As previously explained, no statistically significant effect of the business size on the behavior intention was found. Then, an exploratory analysis was performed by segmenting the sample by business size. Although the power analysis for each segment was not ideal, when testing the linear model with the mediation, the effect of the variables on BI changed considerably for each business size. That was an indication of a potential moderation effect.

Then, the next step encompassed an investigation of the effect of the business size on the relationship between each of the five independent variables (PE, EE, FC, SI, and SE) on the behavior intention. Therefore, the following hypotheses were formulated to test whether the business size moderates the effect of each one of the independent variables on the behavior intention of adopting an AI-based system: **H20: The influence of FC in BI is moderated by BS; H21: The influence of PE in BI is moderated by BS; H22: The influence of EE in BI is moderated by BS; H23: The influence of SI in BI is moderated by BS; and H24: The influence of SE in BI is moderated by BS.**

The hypotheses H20-H24 were tested individually using the function *lm,* and the charts were plotted using the function *plotSlopes* from the R Studio package *rockchalk*. Supplementary Table 10 shows the results for each hypothesis: βs, std errors, t-values, and p-values. The hypotheses H20, H21, and H22, were rejected, and H23 and H24 were accepted at a 5% significant level.

The business size has a bigger moderation effect size (absolute value of 0.414) on the relationship between SI and BI than on SE and BI. It is almost twice more significant. Figure 3 shows the plot of the slopes of the linear relationship between SE and BI moderated by the business size. In small businesses (1 – blue dashed line), the linear relationship has the steepest slope, indicating a higher effect size of SE on BI. In bigger businesses (3 – continuous dark line), the linear relationship has the slightest slope, indicating a smaller effect size of SE on BI. Finally, in medium businesses (2 – dotted dark line), the linear relationship has an intermediary slope compared to the other two business sizes, which indicates an intermediary effect size of SE on BI. Therefore, self-efficacy has a more significant effect size in the behavior intention of adopting an AI-based system in small businesses when compared to medium and large businesses. In large businesses, self-efficacy has a smaller effect on behavior intention. In medium businesses, self-efficacy has an intermediary effect size in the behavior intention compared to small and large businesses.

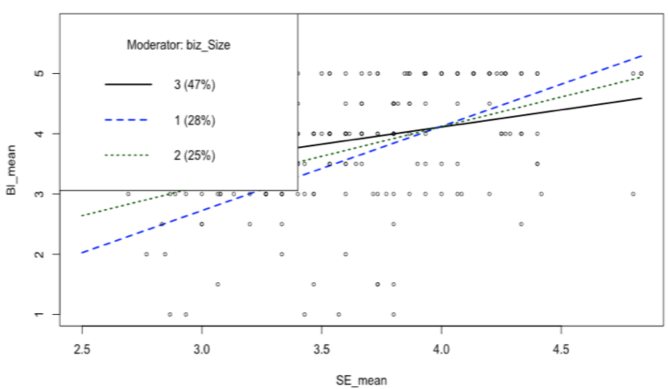

Figure 3. Business size as a moderator between SE and BI

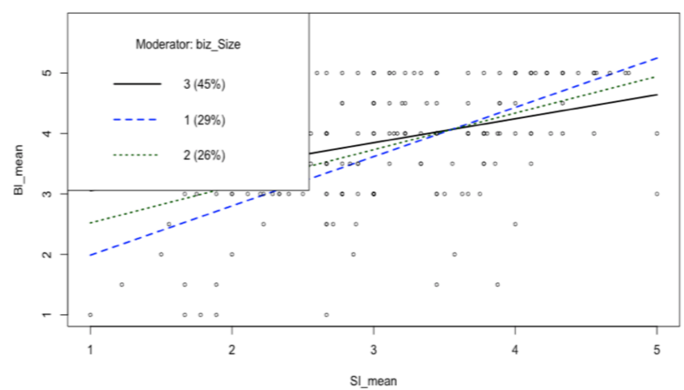

Figure 4. Business size as a moderator between SI and BI

Figure 4 shows the plot of the slopes of the linear relationship between SI and BI moderated by the business size. In small businesses (1 – blue dashed line), the linear relationship has the steepest slope, indicating a higher effect size of SI on BI. In bigger businesses (3 – continuous dark line), the linear relationship has the slightest slope, indicating a smaller effect size of SI on BI. Finally, in medium businesses (2 – dotted dark line), the linear relationship has an intermediary slope compared to the other two business sizes, which indicates an intermediary effect size of SI on BI. Therefore, social influence has a more significant effect size in the behavior intention of adopting an AI-based system in small businesses compared to medium and large businesses. In large businesses, social influence has a smaller effect on behavior intention. In medium businesses, the social influence has an intermediary effect size in the behavior intention compared to small and large businesses.

The AI-systems Adoption Intention Model (AI2M)

Finally, the proposed model is shown in Figure 5. The AI-systems Adoption Intention Model (AI2M) states that the behavior intention of adopting an AI-based system influences conditions, performance expectancy, effort expectancy, self-efficacy, and social influence. The last two variables are the mediator of the influence of the first three ones on the behavior intention. The business size moderates the effect of self-efficacy and social influence on the behavior intention. The user demographics are also included because they improve the model's explanation to 48%. The dotted line from FC to SE indicates the coefficient is lower than 0.10.

The hypothesis stating SE mediates the effect of EE on BI could have emerged from the theory instead of from the observed statistical effect. According to Bandura (1997), SE has an essential role in the context of behavior's intention, learning, adoption, and persistence. According to the author, expectations of personal efficacy (self-efficacy) determine whether a behavior will be initiated, how much effort will be invested, and how long a person will persist when seeking success when facing adversities. Therefore, even when the expected effort was considered low (creating a positive effect on the behavior intention), low self-efficacy could reduce this effect on the behavior intention of adopting the AI system. Furthermore, vice-versa, since a higher self-efficacy can positively affect the behavioral intention. According to Usher and Pajares (2008), when people consider themselves capable of learning and mastering a specific activity, they face the challenges more positively. They tend to be more persistent in mastering the activity when compared to those who consider themselves incapable of trying or mastering it. Therefore, higher self-efficacy leads to reduced defensive and aversive behavior and higher persistence. When dealing with new technology adoption (e.g., AI), people face challenges, and people with higher self-efficacy would persist and engage more than those with lower self-efficacy.

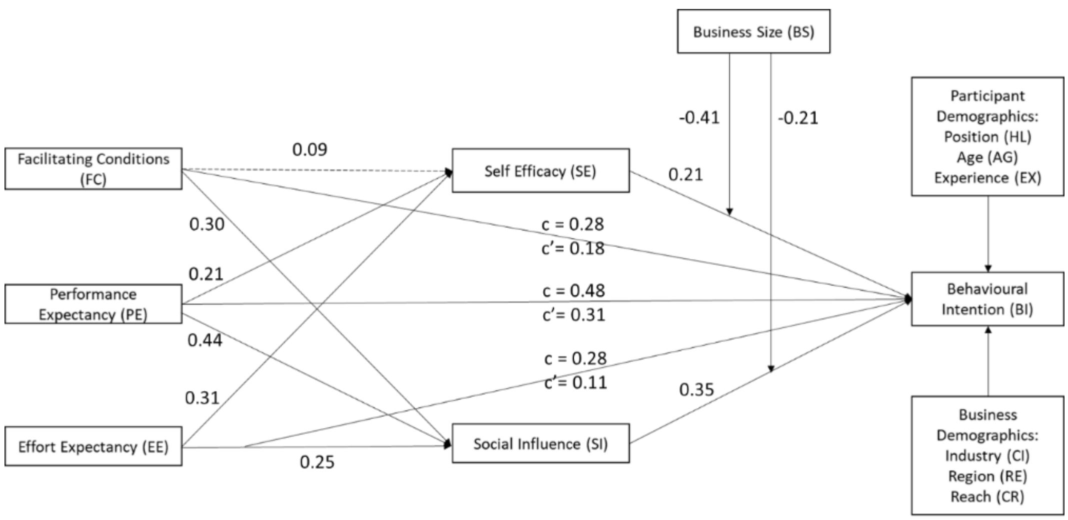

Figure 5. The proposed AI Systems Adoption Intention model (AI2M)

Fewer facilitating conditions available create more challenges people will need to face in the adoption process, and people with low self-efficacy could struggle even with reasonably good facilitating conditions. Hence, it was reasonable to expect some interplay between those constructs. Therefore, a hypothesis stating SE mediates the effect of FC on BI was also proposed.

Moreover, self-efficacy was also expected to mediate the effect of performance expectancy on behavior intention, which became another formulated hypothesis. That is because self-efficacy is related to the individual's beliefs about their own performance in specific tasks or topics, which could be using a new technological tool such as an AI-based system. Hence, adapting Bandura's (1977) statement in adopting an AI system, when users believe they cannot perform the required behavior, their actions towards the behavior will not be influenced even when they believe the AI-system usage could produce the desired result outcome.

The business size moderation effect acts such as the smaller the business is, the higher the effect of SE and SI on BI. Therefore, social influence showed a significantly more important role in the adoption intention in small businesses than in medium or large ones. Moreover, self-efficacy also showed a significantly more important role in adopting intention in small businesses than in medium or large ones. The higher importance of self-efficacy in small businesses compared to large businesses might be related to the fact the small businesses owners play multiple roles in those organizations, differently than what happens in medium and large organizations where the challenges of the adoption may be felt by a different person than the one who decided for the adoption. Therefore, in small companies, the potential overlap between the decision-maker and user roles might influence the importance of the self-perception about the user's efficacy in using the AI tool. Finally, because of the moderation effect of the business size on SE, the effect of SE on BI is considerably diminished for large businesses. This effect could explain why Venkatesh et al. (2013) found no significant effect of SE on BI since the authors used data from large companies.

Moreover, since self-efficacy can be influenced by mastery experiences, vicarious experiences, verbal persuasion, and physiological and affective states (Bandura, 1997), AI2M can help managers design strategies to enhance the behavior intention when their teams need to face the adoption of AI-based systems. For example, practical training, role model speech, and immersive technical visits can potentially boost self-efficacy.

Finally, observing the final model makes it possible to perform additional reflections on the findings. BI can be considered as the result of a combination of the decision maker's different expectations. That is the combination of self-expectation (self-efficacy), expectations about other people (social influence), expectations about organizational (environmental) factors (facilitating conditions), and expectations about the technology (performance and effort expectancies). In smaller businesses, the self-expectations and the expectations about others become more relevant, while in larger businesses, they seem to play a less critical role accordingly to the moderation effects.

Conclusions

This study proposed and tested a model to support AI adoption intention in any business size. The model explained 48% of BI variance from PE, EE, and FC, mediated by SI and SE. This model was named AI-systems Adoption Intention Model (AI2M). The model extends UTAUT by adding self-efficacy and uncovering mediations and moderations relationships. Moreover, AI2M remarkably generalizes UTAUT (Venkatesh et al., 2003) for distinct firm sizes because the variable business size adjusts SE and SI's effect on behavior intention. In fact, for example, because AI2M considers SE as a mediator of the effect of EE on BI and it has the business size moderating the effect of SE on BI, it could explain why Okafor et al. (2016) found the perceived ease of use did not have any influence on the adoption of online multimedia technologies for Malaysian SMEs. However, more research is needed to verify if the model valid can encompass other technologies besides AI systems.

Moreover, the companies' demographics, industry, reach, and region influence the behavior intention. From the respondent's demographics, their position level in the hierarchy, experience, and age influenced their behavioral intention.

Additional investigation is needed to understand the effect of the technology maturity and diffusion stage on the SE and SI. Those constructs may play a more important role as mediators when a new technology has not been widely adopted. Novelty could strengthen SE and SI effects because the new technology is not well known yet. If this is the case, it could explain why self-efficacy was found relevant to computer adoption by Compeau and Higgins (1995a) in the 1990s, and later on, in 2013, it was found not relevant by Venkatesh et al. (2013). Finally, additional investigation is needed to validate AI2M in other geographies.

References

Alia, A. (2017). *An investigation of the application of the Technology Acceptance Model (TAM) to evaluate instructors' perspectives on E-Learning at Kuwait University*. Dublin City University.

Bandura, A. (1977). Self-efficacy: toward a unifying theory of behavioral change. *Psychological Review*, *84*(2), 191.

Bandura, A. (1986). The explanatory and predictive scope of self-efficacy theory. *Journal of Social and Clinical Psychology*, *4*(3), 359–373.

Bandura, A. (1997). Self Eflicacy. The Exercise of Control, New York: W H. *Freeman \& Co. Student Success*, *333*, 48461.

Compeau, D., Higgins, C. A., & Huff, S. (1999). Social cognitive theory and individual reactions to computing technology: A longitudinal study. *MIS Quarterly*, 145–158.

Compeau, D. R., & Higgins, C. A. (1995a). Application of social cognitive theory to training for computer skills. *Information Systems Research*, *6*(2), 118–143.

Compeau, D. R., & Higgins, C. A. (1995b). Computer self-efficacy: Development of a measure and initial test. *MIS Quarterly*, 189–211.

Davis, F. D. (1986). A technology acceptance model for testing new end-user information systems: Theory and results. *Sloan School of Management*, 291.
Dellinger, A. B., & Leech, N. L. (2007). Toward a unified validation framework in mixed methods research. *Journal of Mixed Methods Research*, *1*(4), 309–332.
Farooq, M. S., Salam, M., Jaafar, N., Fayolle, A., Ayupp, K., Radovic-Markovic, M., & Sajid, A. (2017). Acceptance and use of lecture capture system (LCS) in executive business studies. *Interactive Technology and Smart Education*.
Garrett, H. E. (1937). Statistics in psychology and education.
MacKinnon, D. P., Fairchild, A. J., & Fritz, M. S. (2007). Mediation analysis. *Annu. Rev. Psychol.*, *58*, 593–614.
Mnih, V., Kavukcuoglu, K., Silver, D., Graves, A., Antonoglou, I., Wierstra, D., & Riedmiller, M. (2013). Playing atari with deep reinforcement learning. *ArXiv Preprint ArXiv:1312.5602*.
Nascimento, A.M., Cunha, M. A. V. ., Meirelles, F. S., Scornavacca, E., & Melo, V. V. (2018). A Literature Analysis of Research on Artificial Intelligence in Management Information System (MIS).
Nascimento, Alexandre Moreira, & Bellini, C. G. P. (2018). Artificial intelligence and industry 4.0: The next frontier in organizations. *BAR - Brazilian Administration Review*, *15*. Retrieved from http://www.scielo.br/scielo.php?script=sci_arttext&pid=S1807-76922018000400100&nrm=iso
Okafor, D. J., Nico, M., & Azman, B. B. (2016). The influence of perceived ease of use and perceived usefulness on the intention to use a suggested online advertising workflow. *Canadian International Journal of Science and Technology*, *6*(14), 162–174.
Russell, S. J., & Norvig, P. (2016). *Artificial intelligence: a modern approach*. Malaysia; Pearson Education Limited,.
Silver, D., Huang, A., Maddison, C. J., Guez, A., Sifre, L., Van Den Driessche, G., … others. (2016). Mastering the game of Go with deep neural networks and tree search. *Nature*, *529*(7587), 484–489.
Simon, H. A. (1995). Artificial Intelligence Artificial intelligence : an empirical science, *77*, 95–127.
Staff, V. B. (2019). Why do 87\% of data science projects never make it into production. *URL: Https://Venturebeat. Com/2019/07/19/Why-Do-87-of-Data-Scienceprojects-Never-Make-It-into-Production*.
Tuan*, H.-L., Chin, C.-C., & Shieh, S.-H. (2005). The development of a questionnaire to measure students' motivation towards science learning. *International Journal of Science Education*, *27*(6), 639–654.
Usher, E. L., & Pajares, F. (2008). Sources of self-efficacy in school: Critical review of the literature and future directions. *Review of Educational Research*, *78*(4), 751–796.
Venkatesh, V. (2022). Adoption and use of AI tools: a research agenda grounded in UTAUT. *Annals of Operations Research*, *308*(1), 641–652.
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.
Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. *MIS Quarterly*, *36*(1), 157–178.

Appendix – Supplementary Materials

Due to the restriction on the maximum number of pages, all the supplementary materials (research instrument, the supplementary tables, and supplementary figures) are in the Appendix file downloadable **<here>.**