Factors Affecting the Attitude Towards AI Learning: Moderating Role of Information Management

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Abstract

Artificial intelligence integrated with technology has evolved into a domain offering both challenges and opportunities. Artificial intelligence (AI) has enhanced learning and aided human intelligence, but it is solely dependent upon several associated factors. By using the structural equation modeling techniques, this study examines the direct relationships between factors like digital divide, cognitive absorption, AI anxiety, AI self-efficacy, and AI learning, and the moderating role of information management. Additionally, this study also examined how all these factors influence the employees working in the service sector of China. A questionnaire was used to observe the respondents' feedback on a five-point Likert scale. The descriptive results revealed that responses have a mixed mean trend, while the standard deviation in the average scores was also less than 1. Further analysis showed that the average variance extracted for all of variables was above 0.50; the composite reliability was above 0.80 but items having less loadings were deleted, thus confirming the reliability of items. The final results show that the digital divide and information management promoted AI learning, whereas AI Anxiety impedes all types of learning among employees in the service sector. The moderating effect of information management also exists between AI self-efficacy and AI learning and between the digital divide and AI learning in this cohort of respondents.

Keywords

AI Learning, AI Self-efficacy, Digital Divide, Information Management, Cognitive Absorption.

1. Introduction

Artificial intelligence (AI) is a fast and evolving field in the computer science domain. Due to its integration with technology, it has penetrated into all aspects of our daily-life; hence, linked with numerous benefits (**Khaleel *et al.***, 2024). People interact with AI unknowingly, viz., when searching for information on Google or receiving video recommendations on video platforms like YouTube (**Celik *et al.***, 2022; **Lee *et al.***, 2021). In the upcoming duration, it is expected that there will be more advanced AI systems like self-driving cars and robots available to the larger part of our community (**Lugano**, 2017; **Pisarov; Mester**, 2021). Technology has made life very much easier, yet at the same Time, its rapid growth also raises some anxiety regarding how it might affect the thinking and interactions of the humans with others (**Usmani *et al.***, 2024). AI anxiety is defined as the apprehension and stress that individuals may feel about AI's increasing presence and influence in various aspects of life (**Li; Huang**, 2020). People wonder that AI might make certain jobs obsolete, AI's impact is far-reaching and often uncertain, leading to a sense of unease for many people (**Wang; Wang**, 2022).

Deep involvement with AI technology is also often termed as cognitive absorption, which is a kind of loss of consciousness or control, and can have both positive and negative consequences. Cognitive absorption is a critical factor for AI users, particularly when they have to design technologies to meet their specific requirements (**Celik**, 2023). It requires a high level of concentration, cognitive engagement, and absorption, to influence an individual's creativity and innovativeness (**Jumaan *et al.***, 2020). AI self-efficacy is another factor that refers to individual's perception of their ability to use AI technologies and products to accomplish tasks. It is the belief in one's ability to successfully perform a technologically sophisticated new task. AI self-efficacy is closely related to AI learning, which is a more formal approach to learn how to perform tasks that require the application of AI enabled tools (**Ali; Abdel-Haq**, 2021). Hence, AI learning opens new avenues to learners by identifying patterns and relationships in large amounts of data. AI learning is also about making use of algorithms to analyze complex situations and discover relationship between data to effect decision-making (**Zhou *et al.***, 2020). AI learning makes individual adept at performing specific high-volume, computerized tasks without fatigue that requires both AI self-efficacy and adaptation.

This entails that AI is changing the way individuals gather information, create linkages, and communicate with each other. Technological advancements are shaping daily lives, hence there is a need to manage this flow of information. Information management system helps capture, store, retrieve, and use information in a structured and optimal way, at both individual and organizational levels (**Rainer *et al.***, 2020). It is a framework that directs and guides how to collect, store, organize, and distribute information. A well-placed information management system improves operational efficiency and helps individuals make better decisions (**Collins *et al.***, 2021). However, it is important to understand that technology can influence the minds and relationships of individuals resulting in both social and ethical implications (**Usmani *et al.***, 2024). The unequal access to technology may often leads to what is known as the digital divide, a significant issue identified by **Van Dijk** (2020). The digital divide not only limits access to AI-based technologies like social robots and virtual assistants but also restricts opportunities for AI learning (**van der Zeeuw *et al.***, 2019). Owing to these barriers, it becomes challenging to get proper access to digital technologies and devices, causing individuals less likely to use and benefit from these technologies. Such barriers create further gaps in AI literacy and individuals' learning.

Research suggests that factors like cognitive absorption, AI self-efficacy and AI learning can significantly affect individual's intention to use a new information management system, and thus reduce the digital divide as well as inequalities in the skills and expertise needed for effective learning through artificial intelligence and its literacy (**Van Dijk**, 2020). Additionally, the confidence in using artificial intelligence also reduces AI anxiety and improves attitude and perception toward AI. This study, therefore, attempts to address the correlation between the study constructs like digital divide, cognitive absorption, AI anxiety, AI self-efficacy, Information management, and AI learning, to examine how their confluence affects the employees working in the service sector of China.

2. Literature Review

It is observed that the rise of artificial intelligence holds some significant promise for boosting economic productivity at the global level. However, its growing impact on individuals has sparked widespread concerns about their continued development and use. In front of some experts like **Brynjolfsson and McAfee** (2014), there has been a valid argument that automation technologies will profoundly disrupt the workforce. These studies warn that unchecked adoption of AI could destabilize society at large. Moreover, with the evolving stages of automation and computerization, there is an experience of reshaping the nature of the work by altering or eliminating certain jobs while also creating new opportunities (**Wang; Wang**, 2022). Such outcomes are no doubt creating some serious level of anxiety among different individuals. A 2017 report by the McKinsey Global Institute highlighted this shift, estimating that by 2030, between 75 million and 375 million workers, roughly 3% to 14% of the global workforce, might be in need towards the transition into new occupations or acquiring additional skills (**Manyika *et al.***, 2017). The concept of artificial intelligence anxiety in information systems research dates back to the early days of computers. At the time, many feared that computers would seriously threaten "being human". While researchers have extensively studied computer anxiety, traditional measures of it fall short when applied to the field of artificial intelligence. Unlike these other anxieties, AI anxiety often stems from misunderstandings about technology, confusion over autonomy, and a lack of awareness about the interaction between technology and society as a whole (**Wang; Wang**, 2022).

Cognitive absorption is a deep state of engagement and immersion in technology use (**Reychav; Wu**, 2015). The given concept is further marked by focused attention, losing track of time, enjoyment, a sense of control, and curiosity (**Agarwal; Karahanna**, 2000). Recent research has highlighted its role in shaping user behaviour across various technological settings. For example, **Acharya *et al.*** (2023b) explored how cognitive absorption influences online shoppers' decisions to continue using recommender systems. It further reveals that different aspects of cognitive absorption play distinct roles in shaping behavioral intentions. Similarly, **Acharya *et al.*** (2023a) studied how cognitive absorption affects users' commitment to AI-driven recommender systems in e-commerce.

While focusing on individuals' learning capabilities, AI self-efficacy reflects the belief in one's ability to perform specific tasks successfully while achieving goals in a specific domain. However, the given concept has been well explained using artificial intelligence. As **Wang and Chuang** (2024) explain, AI self-efficacy is referred to as the individual's ability to use and interact with artificial intelligence. In modern literature, the notion of AI self-efficacy has widely been studied from the context of the educational sector. Unlike the general concept of self-efficacy, AI-self efficacy is the level of confidence in a specific task or situation faced by an individual involved in artificial intelligence. Therefore, it is expressed that AI self-efficacy is primarily linked with the ability to utilize and interact with the AI (**Chen *et al.***, 2024).

As expressed earlier, artificial intelligence is an ongoing phenomenon that has created several learning opportunities for societies and business groups (**Shepherd; Majchrzak**, 2022). AI learning involves recent developments in artificial intelligence leading towards a system capable of autonomously designing and conducting experiments (**Michalski *et al.***, 2013). Such an act has marked significant steps towards AI learning. Moreover, authors like **Dahri *et al.*** (2024) express that AI-based tools have the potential for metacognitive self-regulation in learning. Meanwhile, the research work of **Chen *et al.*** (2024) also signifies the need and role of learning through artificial intelligence by using an innovative framework. It is suggested that AI learning is based on personality and demographic-related dynamics.

Although there is a growing trend in learning through AI, there is a very little-known area in terms of theoretical and empirical contributions by the researchers. To explore this, **Celik** (2023) developed a research model based on past studies and various theories linked with learning artificial intelligence. The model included factors like cognitive absorption and the digital divide. Moreover, it further helped people while using, recognizing, and evaluating AI technologies. The study further found that having access to information and communication technologies (ICTs) increases the likelihood of using and understanding artificial intelligence. Besides, factors like motivation and technical skills further enable individuals to critically assess outcomes through artificial intelligence. The additional findings also highlighted that easy access to information and communication technologies fosters greater engagement with AI, leading to deeper involvement. Moreover, it is further noted that people with more motivation and skills in using artificial intelligence tend to have more positive and enjoyable experiences with these technologies.

Observing the modern technological changes, OpenAI has developed AI-based tool which provides a remarkable learning experience to several users (**Azaria *et al.***, 2024). The AI-based tool is powered by latent technologies such as natural language processing and large language models. Such technological tools and techniques help enable it to engage in conversations with users. It can assist with various tasks, including writing essays and generating code (**Lo**, 2023). Despite its usefulness, concerns remain about the quality and accuracy of its responses, which can sometimes limit its effectiveness (**Lund *et al.***, 2023). AI learning provides several meaningful insights, which open path for strategic decision-making in this modern era of technological advancement (**Celik**, 2023). To effectively use AI-related technologies, it is quite obvious that individuals need to achieve specific knowledge and skills about AI. Such skills provide a path for the learning through artificial intelligence.

Chen *et al.* (2024) also aim to review on empirical grounds regarding the role of AI in second language learning. It has been inferred that earlier studies have claimed that AI can play an important role in improving the process of learning a second language, which is widely known as L2. However, some specific factors' impact on learning through AI by s Moreover, with the advancement in digital devices that are widely available to college students, they are uniquely positioned to benefit from artificial intelligence-based language learning. Their study explores the key motivation behind college learners learning L2 with the help of several AI-based tools. The study also focuses on self-efficacy and anxiety from AI and the overall attitude towards learning L2. Regarding the theoretical foundation, the authors have covered their debate with the help of an extended version of the Technology Acceptance Model (TAM). Regarding the empirical estimations, the study has collected data from 429 learners of a second language. The study uses Chinese universities regarding the data collection with the help of an online survey that included four established measurement scales. The data analysis includes the Structural equation modeling (SEM) approach by using AMOS 24 versions. The results provide outstanding output. For example, students with higher confidence in using artificial intelligence were less anxious. The same students had more positive attitudes toward artificial intelligence and were likelier to use its tools.

On the other hand, Anxiety about AI is a key indicator in reducing the utilization of AI-related tools. Additionally, the confidence in using artificial intelligence also indirectly increased AI use by reducing such type of anxiety, improving attitudes toward AI, or both. At the end of the debate, the study covered valuable insights into both theory and teaching practices. The debate further suggests areas for future research to support second language learners better using artificial intelligence tools on effective grounds. Similarly, **Zhou *et al.*** (2024) deals with the concept of artificial intelligence which can actually encourage the employees to learn. Instead of viewing artificial intelligence-related stress as purely negative indicator, the study looks at how workers use it as an opportunity and good chance in order to build new skills and knowledge. Using a well-known idea about how people balance job demands and control, the research aims to explore why and how artificial intelligence-related stress can push employees to learn and find ways to handle challenges better. The study suggests that this stress can create opportunities for the growth and development of the employees, along with assisting the workers to perform better and support during the Time of digital changes in their relative organization. It also shows that employees who trust AI are more likely to take active steps to learn when stressed. The findings are based on surveys of 224 workers from a motor vehicle testing company in China and interviews with 32 of these workers. The study has a major objective to explore how the stress related to the AI learning can be transformed into a better opportunity for employees.

Additionally, the idea of AI has the potential to significantly improve how people perform their duties and spend their day-to-day life (**Pan**, 2016). However, along with potential benefits, the utilization of artificial intelligence brings several ethical concerns, including issues related to data privacy, biases in the decision-making process, and spread of wrong information among different age groups and members (**Gedrimiene *et al.***, 2023; **Wang; Siau**, 2019). In addition, access to technology is presumed critical for individuals to develop skills and knowledge (**Aydin**, 2021). For instance, increased access to the Internet enables people to become more proficient in using it; similarly, access to AI tools is essential for fostering AI learning (**Rajam *et al.***, 2021). When people regularly use technology, they begin to understand its advantages and integrate it into their daily routines, which is vital for enhancing AI learning as well (**Wang; Wu**, 2022).

3. Methodology

3.1. Instruments

Table 1 mentions sources from where instruments were retrieved in each of the domains of digital divide, cognitive absorption, artificial intelligence anxiety, artificial intelligence self-efficacy, artificial intelligence learning, and information management. Table 1 also presents items for these variables along with the measurement scale for all variables. For example, the measurement for the digital divide is based on four items, and the sample items include physical access, motivational access, skills access and usage access. Four items for cognitive absorption were selected, including the sample items time, curiosity, focus of attention, and pleasure. Similarly, the sample items for AI anxiety include taking AI classes, learning how to use AI, and understanding its functions. All of these make me feel anxious. Lastly, AI self-efficacy is measured through assistance, anthropomorphic interaction, comfort with AI, and technological skills. In the next step, a questionnaire was constructed by using a few demographics and the scale of the given variables. The questionnaire was distributed among the employees and managers of service organizations registered in China. The final sample consisted of 206 respondents covering both genders with different educational and age-related characteristics.

Table 1: Layout of the Variables.

Variable	Nature	Scale Items	Source
Digital divide	Independent variable	• Physical Access • Motivational Access • Skills Access • Usage Access (1 = very low, 5 = very high)	(**Celik**, 2023)
Cognitive absorption	Independent variable	• Measure Time • Curiosity • Focus of Attention • Pleasure (1 = very low, 5 = very high)	(**Agarwal; Karahanna**, 2000)
AI anxiety	Independent variable	• Taking AI training sessions makes me anxious. • Learning AI use makes me anxious. • Understanding AI functions makes me anxious. • Knowing how AI works makes me anxious. • Using specific AI functions makes me anxious. • Interacting with AI makes me anxious. • Keeping up with AI advances makes me anxious. • Reading AI manuals makes me anxious. • Fear AI will replace jobs. • Working with AI makes me anxious. (1 = Strongly Disagree, 5 = Strongly Agree)	(**Wang; Wang**, 2022)
AI self-efficacy	Independent variable	• Assistance • Anthropomorphic Interaction • Comfort with AI • Technological Skills. (1 = very low, 5 = very high)	**Wang and Chuang** (2024)
AI learning	Dependent variable	• The AI system demonstrates a clear understanding of my preferences and adapts accordingly. • The AI system provides accurate and relevant responses to my queries. • The AI system has improved over time based on my interactions with it. (1 = Strongly Disagree, 5 = Strongly Agree)	(**Brusilovsky; Millán**, 2007; **Goodfellow**, 2016; **Sutton; Barto**, 2018)
Information Management	Moderating variable	• Accuracy: "The data in our system is accurate and error-free." (1 = Strongly Disagree, 5 = Strongly Agree) • Completeness: "All necessary data is included and available for our needs." (1 = Strongly Disagree, 5 = Strongly Agree) • Timeliness: "Data is always up to date when needed." (1 = Strongly Disagree, 5 = Strongly Agree) • Consistency: "Data in our system is consistent across sources." (1 = Strongly Disagree, 5 = Strongly Agree) • Relevance: "The data we access is relevant to our tasks." (1 = Strongly Disagree, 5 = Strongly Agree)	(**Wang; Strong**, 1996; **Eppler; Helfert**, 2004)

3.2. Research Methods of Analysis Approaches.

The empirical method of this study includes several estimation techniques. Considering the research methods, the study first developed a questionnaire using the scale from past studies (See Table 1). In the next step, the questionnaires were distributed among the relevant respondents (Step 2, Figure 1). Initially, the respondents were evaluated using their relative share in gender, age, and education. The bar charts were also presented to give a graphical presentation of the respondents' dimensions. The data quality regarding the average trends and deviation was examined using descriptive statistics as suggested in the past literature (**Shan *et al.***, 2021; **Yu *et al.***, 2023; **Katrakazas *et al.***, 2020). The study also used the two-stage approach. The first stage considered reliability and validity. Cronbach alpha and composite reliability have been suggested in the available primary data literature (**Haji-Othman; Yusuff**, 2022; **Kennedy**, 2022). The discriminant validity clarifies that in a given model, the variables are truly distinct (**Voorhees *et al.***, 2016; **Franke; Sarstedt**, 2019; **Rönkkö; Cho**, 2022). The second stage used the structural equation modelling technique to test the relationships between the variables. The technique given helped the researchers to investigate the direct and indirect (moderating or mediating) relationships between the set of variables as measured through relative items in the questionnaire. Notable research studies exploring the relationships using the structural equation modelling techniques are (**Thakkar**, 2020; **Moshagen; Bader**, 2024; **Ringle *et al.***, 2023).

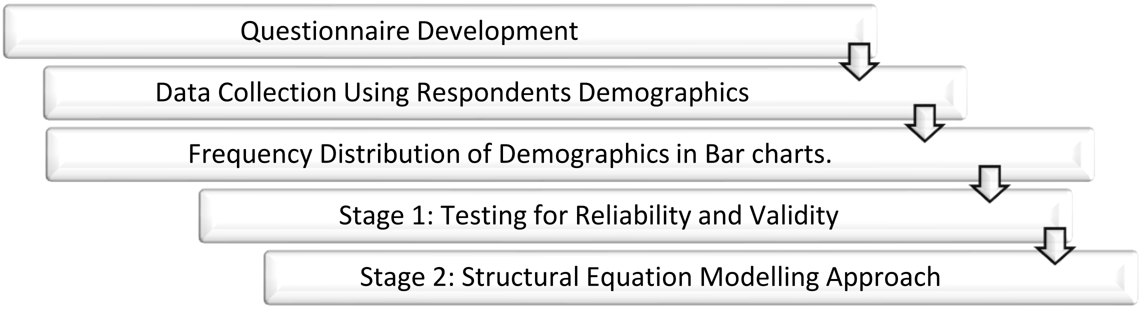

Figure 1: Methodological Sequence Applied.

3.3. Sample

The sample of this study comprised 206 employees working in the service sector of China. The respondents varied in gender, age and education, which were the key demographic factors. Table 2 presents both the frequency and percentage share of these factors. For instance, there were 169 male respondents (82%) and 37 female respondents (18%). Regarding age, 65 respondents were between 18-25 years, 24 respondents were between 26 and 30 years, and 47 respondents were above 30 years of age. The highest participation in this study was by respondents aged 18-25 years (65.53%). In the educational factor, 96 respondents were graduates, 39 respondents had master's qualifications, and 71 respondents stated that they had some other type of education. Table 2 and Figure 2 present the profiles of respondents.

Table 2: Profile of Respondents (n=206).

Description	Frequency	Percentage
Gender		
Male	169	82.04
Female	37	17.96
Age		
18-25 years	135	65.53
26-30 years	24	11.65
Above 30 years	47	22.82
Education		
Graduation	96	46.60
Master	39	18.93
Other	71	34.47

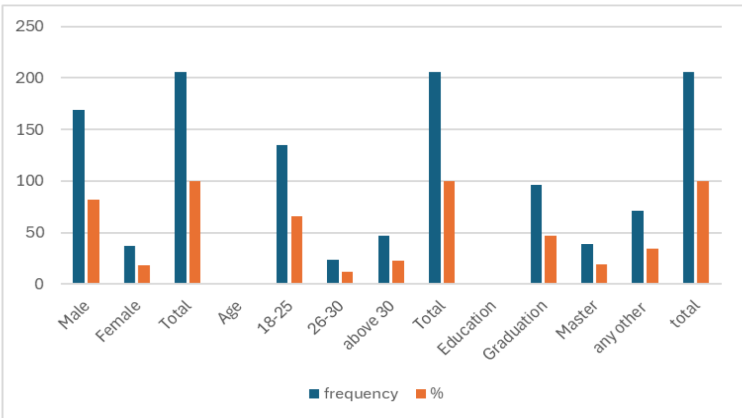

Figure 2: Study Demographics.

4. Results and Discussion

4.1. Descriptive Results

The descriptive results aim to cover the layout of the data trends, like the average scores and the deviation in the average scores. Table 1 reports Mean and SD of all statements covered in the questionnaire for each of the variables. The Mean scores were measured by using the five-point scale from Strongly disagree to Agree. All mean values approaching or above four show that, on average, respondents agree with the given statements. Regarding the standard deviation, the given values show that there is no concern related to the higher deviation or the risk in the average scores of items. All deviation values are less than 1, which suggests that data characteristics are good when accounting for the mean and standard deviation.

Table 3: Descriptive Results.

Variable	Code	Items	Mean	SD
Digital divide	DDV1	• Physical Access	3.985	0.336
	DDV2	• Motivational Access	4.021	0.405
	DDV3	• Skills Access	4.672	0.541
	DDV4	• Usage Access	4.005	0.365
Cognitive absorption	COA1	1. Measure Time	3.995	0.392
	COA2	2. Curiosity	3.913	0.483
	COA3	3. Focusing of Attention	3.892	0.403
	COA4	4. Pleasure	4.708	0.724
AI anxiety	AIA1	• Taking AI class makes me anxious.	3.951	0.464
	AIA2	• Learning AI use makes me anxious.	3.895	0.508
	AIA3	• Understanding AI functions makes me anxious.	3.949	0.504
	AIA4	• Knowing how AI works makes me anxious.	3.949	0.467
	AIA5	• Using specific AI functions makes me anxious.	3.959	0.451
	AIA6	• Interacting with AI makes me anxious.	3.931	0.409
	AIA7	• Keeping up with AI advances makes me anxious.	4.764	0.633
	AIA8	• Reading AI manual makes me anxious.	4.756	0.607
	AIA9	• Fear AI will replace jobs.	3.897	0.398
	AIA10	• Working with AI makes me anxious.	3.908	0.443
AI self-efficacy	AIS1	1. Assistance	3.908	0.394
	AIS2	2. Anthropomorphic Interaction	3.931	0.389
	AIS3	3. Comfort with AI	3.821	0.544
	AIS4	4. Technological Skills.	3.836	0.51
AI learning	AIL1	• The AI system demonstrates a clear understanding of my preferences and adapts accordingly.	3.859	0.529
	AIL2	• The AI system provides accurate and relevant responses to my queries.	4.718	0.681
	AIL3	• The AI system improves over Time based on my interactions with it.	3.892	0.49
Information Management	INM1	• Accuracy: "The data in our system is accurate and error-free." (1 = Strongly Disagree, 5 = Strongly Agree)	4.738	0.659
	INM2	• Completeness: "All necessary data is included and available for our needs." (1 = Strongly Disagree, 5 = Strongly Agree)	3.928	0.608
	INM3	• Timeliness: "Data is always up to date when needed." (1 = Strongly Disagree, 5 = Strongly Agree)	4.731	0.666
	INM4	• Consistency: "Data in our system is consistent across sources." (1 = Strongly Disagree, 5 = Strongly Agree)	3.872	0.422
	INM5	• Relevance: "The data we access is relevant to our tasks." (1 = Strongly Disagree, 5 = Strongly Agree)	4.721	0.669

4.2. Measurement Model

In Figure 3, the DDV items, DDV1, DDV2, and DDV4 show the loadings of 0.951, 0.863, and 0.927, with the third item DDV3 deleted due to lower loadings in the model presentation. The three COA items show the loadings score as 0.862, 0.915, and 0.913, with COA1 deleted due to lower loading. The three AIS items show the loadings score of 0.794, 0.900, and 0.912 with AIS2 deleted from the model due to showing low value of factor loadings. The additional findings show that INM and AIL items also have loadings above 0.80 and less than 0.95, with INM2 deleted from the model due to low factor loading.

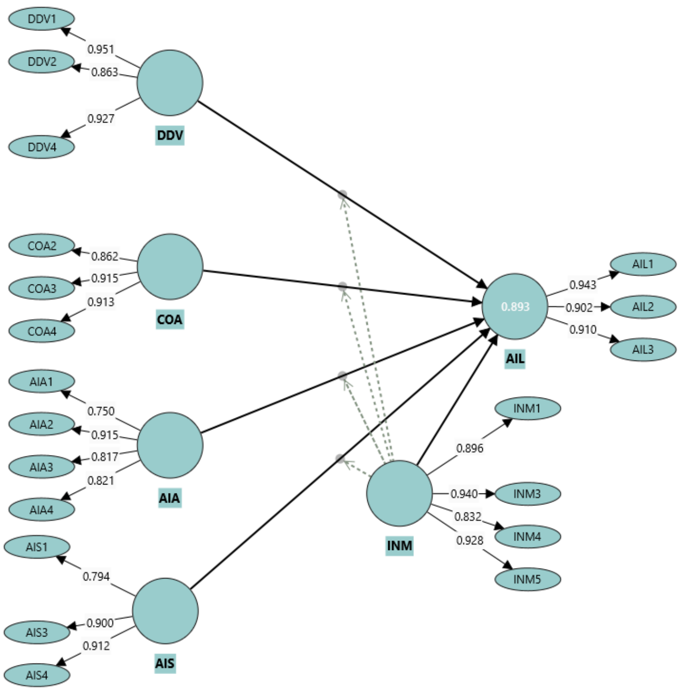

Figure 3: Loadings of the Item as above 0.80.

Note: DDV: Digital Divide, COA: Cognitive Absorption, AIA: AI Anxiety, AIS; AI Self-Efficacy, AIL; AI Learning, INM; Information Management.

Table 4 reports results for the variables confirming the presence of reliability. The alpha scores are in the range of 0.838 to 0.907 for all variables. These values confirm that items in the first stage of the data analysis play an excellent role in generating reliable findings. The results of the second measure of composite reliability show that all values are above 0.80 which further confirms the reliability of the items under each variable. The lowest value under rho_a is found to be 0.847 for AIS and under rho_c, it is 0.897 for AIA. The highest rho_a and rho_c values are linked with DDV and INM with scores 0,981 and 0.944 respectively. The average variance extracted (AVE) value should be greater than 0.50, which can be seen for all the variables, with AIL showing the highest value of 0.845 and AIA showing the lowest AVE of 0.686. It is important to analyze that all values presented in Table 4 cover the reliability results, which further open the paths for the next level estimations either through the measurement model or through the structural model.

Table 4: Alpha and other Reliability Values.

	Cronbach's Alpha	Composite Reliability (rho_a)	Composite Reliability (rho_c)	Average Variance Extracted (AVE)
AIA	0.849	0.900	0.897	0.686
AIL	0.907	0.908	0.942	0.843
AIS	0.838	0.847	0.903	0.758
COA	0.881	0.916	0.925	0.805
DDV	0.905	0.981	0.938	0.835
INM	0.921	0.931	0.944	0.810
Note: DDV: Digital Divide, COA: Cognitive Absorption, AIA: AI Anxiety, AIS; AI Self-Efficacy, AIL; AI Learning, INM; Information Management.				

Figure 3 and Table 5 reflect the outer loadings for each of the single items observed in this study.

Table 5: Outer Loadings of the Items.

Items	Outer Loadings
AIA1 <- AIA	0.750
AIA2 <- AIA	0.915
AIA3 <- AIA	0.817
AIA4 <- AIA	0.821
AIL1 <- AIL	0.943
AIL2 <- AIL	0.902
AIL3 <- AIL	0.910
AIS1 <- AIS	0.794
AIS3 <- AIS	0.900
AIS4 <- AIS	0.912
COA2 <- COA	0.862
COA3 <- COA	0.915
COA4 <- COA	0.913
DDV1 <- DDV	0.951
DDV2 <- DDV	0.863
DDV4 <- DDV	0.927
INM1 <- INM	0.896
INM3 <- INM	0.940
INM4 <- INM	0.832
INM5 <- INM	0.928
Note: DDV: Digital Divide, COA: Cognitive Absorption, AIA: AI Anxiety, AIS; AI Self-Efficacy, AIL; AI Learning, INM; Information Management.	

4.3. Direct Effects

As seen in Table 6, the direct results between variables show some sort of mixed scenarios. For example, AIA -> AIL path shows a coefficient of -0.443 with a standard deviation of 0.181. This deviation shows that on average, the risk in the value of the coefficient is 0.181, which supports the calculation of T-statistics and, finally, the p-value. The negative direction of the coefficient shows that AIA is leading to a change of 0.443% in AI learning. This means that anxiety related to AI is not productive rather it is something causing an adverse effect on the learning using the artificial intelligence. It is believed that AI anxiety, or the fear and discomfort about learning and using AI can make the learning process much harder by creating mental and emotional roadblocks. When individuals see AI as overly complicated by how fast its advancing, they often avoid engaging with it in terms of learning new ideas and concepts. This fear usually comes from not knowing enough about the basic and advanced knowledge related to artificial intelligence, therefore, having wrong ideas about what it can do, or worrying about being left behind as technology evolves. Therefore, such individuals start to skip the AI-related tasks or approach them with reluctance rather than interest. Such type of anxiety also affects how the brain works when trying to learn, because anxiety takes up mental energy, like attention and memory, to understand new things. It is also harder to focus and to understand or remember key concepts. As a result, instead of paying attention to what they are actually learning, they might worry about failing or not being good enough. Over Time, this avoidance and lack of focus can leave gaps in their understanding, making AI seem even more intimidating. Therefore, this direct result infers that a higher level of anxiety related to artificial intelligence means lower level of learning abilities; hence proving the direct relationship.

The second path (AIS -> AIL) shows AI self-efficacy positively but insignificantly linked to AI learning. The coefficient for this impact is 0.181, which leads to a t-value as 1.254, far less than the minimum score of 1.96. It is easy to explain that AI self-efficacy does not have a significant impact on AI learning for similar respondents. As the results have no significant findings, hence no statistical and empirical discussion can be made based on such results. Therefore, it is concluded that AI self-efficacy is an insignificant determinant of AI learning. Regarding the third path (COA -> AIL) showing relationship between Cognitive Absorption and AI learning, the results also report lower t-statistics and higher p-values which confirm insignificant output. This insignificance reflects that the effect of Cognitive Absorption on AI learning is not permissible when tested through the current sample. This also indicates that a better and bigger sample size in future studies may lead to significant output, when productive effect of Cognitive Absorption on AI learning of respondents can be predicted.

Table 6: Direct Impact of IVs on DV.

Directions	Original Sample (O)	Standard Deviation (STDEV)	T Statistics (O/STDEV)	P Values
AIA -> AIL	-0.443	0.181	-2.455	0.014
AIS -> AIL	0.181	0.144	1.254	0.21
COA -> AIL	-0.074	0.161	0.461	0.645
DDV -> AIL	-0.191	0.026	-7.346	0.000
INM -> AIL	0.462	0.131	3.536	0.000

In the fourth path (DDV -> AIL), the construct Digital Divide shows a coefficient of -0.191 with a lower standard deviation of 0.026. This leads to evidence of statistically significant results because of higher t-value and lowest p-value, as seen in Table 6. This connection between the coefficient and the p-value shows that significant and negative impact of Digital Divide on AI learning exists. This also suggests that keeping all of the factors into the model and the error term as constant, as well as the current sample, a one percent increase in the Digital Divide means an overall and average change of -0.191% in the AI learning. This validates the adverse connection between the Digital Divide and AI learning for the same sample. This notion linked with the Digital Divide reflects some type of unequal access to technology and online resources, which further aims to bring challenges for learning about the latest technologies as available in the market. Therefore, the efforts to bridge this gap, such as expanding internet availability and providing affordable devices, would like to enable the individuals in the economy, specifically those entitled as underserved communities to gain the tools they need to explore and understand new technologies. Moreover, by providing better access to the set of available technologies and products, these individuals can develop skills, expertise and capabilities in the field of information and digital technologies, along with broadening their knowledge. Such efforts would be reflected in the form of better learning. At the same Time, another view claims that technology itself can play a role in closing the Digital Divide, which further supports education and skill-building. This can be expressed by using the idea that technology-driven platforms can offer better learning experiences for people having low learning exposure from the technology. For example, the available online tutorials by using the advanced technologies, interactive applications, and adaptive learning programs help in making complex concepts easier. Therefore, it is important to note that when people gain access to these resources and overcome barriers linked with learning, they are better equipped to engage with and benefit from technology. Therefore, we finally infer that such a relationship creates a productive and positive cycle of growth that supports learning and inclusion for all.

The last direct path (INM -> AIL) aims to cover the impact of Information Management on the learning through AI learning. This relationship seems good enough on statistical grounds due to the significant trend in the p-value. The coefficient shows the direction and strength of the relationship between Information Management and AI Learning. The value of the coefficient shows that considering the impact of all of the independent and error terms into the model as constant, an increase in the INM by one unit aims to improve AI learning by 0.462, with the standard deviation of 0.131. Explaining the relationship between INM and AI learning has several dimensions. Information management helps organize and store data in a way that is easy to utilize and access. Therefore, when individuals aim to learn about modern technologies, they often need a lot of information. Considering this point, dealing with the information on proper grounds make it easier for learners to find what they need without wasting Time. Additionally, organized data helps the individuals to focus on learning new skills and expertise comparatively to the struggling to search for resources. This can make the learning process very much easier and faster, hence helping a diversified audience regarding how to use and benefit from modern tools like artificial intelligence.

4.4. Moderating Effect of the INM

Regarding the moderating effect of the information management, structural equation modelling technique unveiled the findings as shown in Table 7. For instance, the first path, (INM x COA -> AIL) shows a coefficient of -0.157 by using the interaction term between INM and COA, which have an influence on AIL. This path indicates that interaction term is negatively linked with AIL when observed with the help of COA. As the value of t-score is 1.561, and p-value is above 0.10%; therefore, this path has been regarded as insignificant, showing that there is no moderating effect of INM between COA and AIL when analyzed with the help of full sample of this research work. Therefore, no further investigation is needed. The second path (INM x AIA -> AIL) examined the interaction effect of INM between AI anxiety and AI learning. The coefficient value is positive but the value of higher standard deviation comparatively to this coefficient is leading to a lower t-statistics which is 0.832 and a p-value of 0.405. This means that the overall trend in the moderating effect of the INM between AIA and AIL is not admitted when using the threshold level of t and p-values. The t and p values are not approaching to the relative threshold level. Therefore, once again, the it cannot be accepted that INM significantly moderates the association between the AIA and AIL in this study.

The third path (INM x AIS -> AIL) shows a coefficient of 0.184 with deviation recorded as 0.048, and a t-score of 3.833. The positive direction of this coefficient reveals that the interaction term has a direct impact on AI learning. The p-value of this path is 0.000, reflecting that there is a significant moderating effect of the INM and AIS on AI learning. The relationship between the confidence of a respondent in his/her ability to learn AI (self-efficacy) and the success in learning AI is strongly influenced by their ability to manage information. More specifically, the idea of AI self-efficacy explains the belief in one's capability while understanding and using some artificial intelligence-based tools, which can motivate and encourage engagement in the in the overall learning process. However, on the other hand, confidence alone does not reflect some effective learning. Additionally, information management, which involves organizing, processing and effectively using the information, plays a crucial role in determining how well AI self-efficacy translates into successful AI learning of individuals. When individuals possess better skills in terms of information management, their confidence in AI learning is supported by their ability to locate, organize, and apply resources effectively. This combination enables individuals to focus and overcome the linked obstacles and apply their body of knowledge in practical ways. One possible example indicates that a person who is confident in their ability to learn AI but lacks the skills to manage information may struggle to comprehend or integrate the material. Conversely, individuals with some type of the strong INM abilities are more likely to transform their relative confidence into meaningful learning outcomes. In this way, they tend to improve their understanding and mastery of AI concepts. Conversely, on the other hand, poor INM skills can diminish the effect of self-efficacy on learning through artificial intelligence. Even if individuals believe in their abilities and capabilities, the issues like disorganized or inefficient information-handling practices can create obstacles, making it harder to access, understand, or apply AI-related knowledge. Therefore, the interaction between self-efficacy and information management determines how effectively individuals can achieve higher learning outcomes. Moreover, INM aims to serve as a key factor that bridges confidence and successful learning, highlighting the importance of both belief in one's abilities and the ability to manage learning resources effectively. Therefore, we finally state that the presence of INM as a moderator between the AI self-efficacy and AI learning is logical by all means.

The last path (INM x DDV -> AIL) examines the moderating role of Information Management between Digital Divide and AI learning for the same sample of respondents. The coefficient for this interaction effect is 0.227 which is the second highest value in the analysis of the moderating effect. This last interaction term is significant at 5%, for which the p-value is 0.008. Therefore, we infer that the interaction effect has been accepted with a significant p-value.

Table 7: Moderating Role of INM.

Directions	Original Sample (O)	Standard Deviation	T Statistics	P Values
INM x COA -> AIL	-0.157	0.100	1.561	0.119
INM x AIA -> AIL	0.049	0.059	0.832	0.405
INM x AIS -> AIL	0.184	0.048	3.833	0.000
INM x DDV -> AIL	0.227	0.085	2.663	0.008

5. Conclusion

This study investigated the dynamic trends in AI learning as linked with Digital Divide, AI self-efficacy, Cognitive Absorption, and information Management. The study was carried out with a sample of employees in the service sector of China. This quantitative study resulted in several statistical estimation techniques on data collected through a survey questionnaire. The demographic variables show a good diversification in the profile of the respondents, whereas the descriptive values reflect that results data as collected using the survey questionnaire is showing a good layout in terms of average and deviation from the average values. The other results using the measurement model determine the good outer loadings for the items of the dependent, independent and moderating variable into the model. However, few items were deleted due to their adverse effect on the reliability and validity results using the predefined criteria about the factor loading. The subsequent results aim that alpha values of variables and average variance extracted were perfect, hence the study focused on testing the impact of direct effect from the AI Self-efficacy, AI Anxiety, Cognitive Absorption, Digital Divide, and Information Management through data quality on the AI learning horizon. The results by using the empirical methods show that the AI anxiety is reducing learning through AI, whereas the Digital Divide and Information Management via data quality as productively connected with such learning horizon. The next step provided the moderating impact of Information Management towards the relationship between the Digital Divide, AI Anxiety, AI self-efficacy, Cognitive Absorption and AI Learning. The results of the moderation show that only two paths namely (INM x AIS -> AIL) and (INM x DDV -> AIL) are significant when accounted for checking the t-value and p-value. This means that out of four explanatory variables, the moderation term only exists between two variables, which are AI Self-efficacy and Information Management towards AI Learning.

The first and foremost policy implication of the study suggests that to help people regarding AI learning in more effective manner, it is important to reduce the AI anxiety. The policymakers linked with the service sector organizations can take steps to make AI learning free from anxiety. One way to achieve this is by introducing artificial intelligence concepts to employees in the service sector through simple and easy-to-understand method. For instance, training and development of employees regarding the demonstrations of how AI-powered tools, such as chatbots or recommendation systems, can provide an environment of better learning. Beginner-friendly workshops tailored to the service industry can make AI less intimidating and provide employees with a clear understanding of how it can benefit their roles. A supportive workplace environment would be of great support towards reducing the anxiety linked with AI and creating a learning atmosphere.

The second suggestion aims to focus on the relationship between the Digital Divide and AI learning. To help employees in the service sector learn more about AI, it is essential to tackle the Digital Divide. The reason is that the Digital Divide makes it harder for some people to access the tools and knowledge they need, which can facilitate the learning perspective. Closing this gap means ensuring everyone within the context of the service firms has fair access to technology, resources both physical and non-physical, and support so they can take part in artificial intelligence training, regardless of their background. Moreover, several service sector workers are lacking with access to the necessary devices or a stable internet connection for AI training. Therefore, both employers and policymakers can address this by providing basic facilities like computers, the Internet and other digital devices so that the employee can gain better and advance knowledge using artificial intelligence tools.

The last suggestion indicates the significance of the need of Information Management in terms of data quality for learning through AI. It reflects that for improvement in AI learning, it is essential to focus on data quality along with its integrity within the service sector domain. The employees should be trained to ensure that the data they input or manage is accurate, consistent, and up to date, because poor-quality data can lead to misleading the output in the form of learning through AI. Additionally, the provision of tools or guidelines for organizing and validating data can make this process easier and reduce errors at different stages not only for the employees but alto for the organization. Moreover, creating a culture of responsibility around data management, where employees understand how clean, well-structured data would reflect a direct improvement in the AI learning outcomes.

One of the limitations of this study was that it utilized quantitative research design. Future studies need to focus on implementing mixed method of research. Second, this research was confined to the sample solely from the service industry; however, future studies may investigate other sectors like manufacturing and automobile. The third limitation determines that the study consider only the first order measures for the variables. Future studies can expand on other implications while focusing on different regional settings.

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References

Acharya, Nirmal; Sassenberg, Anne-Marie; Soar, Jeffrey. (2023a). "Effects of cognitive absorption on continuous use intention of AI-driven recommender systems in e-commerce". *Foresight,* v. 25, n. 2, pp. 194-208. *https://doi.org/10.1108/FS-10-2021-0200*

Acharya, Nirmal; Sassenberg, Anne-Marie; Soar, Jeffrey. (2023b). "The Role of Cognitive Absorption in Recommender System Reuse". *Sustainability,* v. 15, n. 5, pp. 3896. *https://doi.org/10.3390/su15053896*

Agarwal, Ritu; Karahanna, Elena. (2000). "Time Flies When You're Having Fun: Cognitive Absorption and Beliefs about Information Technology Usage". *MIS Quarterly,* v. 24, n. 4, pp. 665-694. *https://doi.org/10.2307/3250951*

Ali, Mohammed; Abdel-Haq, Mohammed Kayed. (2021). "Bibliographical Analysis of Artificial Intelligence Learning in Higher Education: Is the Role of the Human Educator and Educated a Thing of the Past?" In: *Fostering Communication and Learning With Underutilized Technologies in Higher Education.* Ali, Mohammed Banu; Wood-Harper, Trevor (Eds.), pp. 36-52. Hershey, PA, USA:IGI Global. *https://doi.org/10.4018/978-1-7998-4846-2.ch003*

Aydin, Mustafa. (2021). "Does the digital divide matter? Factors and conditions that promote ICT literacy". *Telematics and Informatics,* v. 58, pp. 101536. *https://doi.org/10.1016/j.tele.2020.101536*

Azaria, Amos; Azoulay, Rina; Reches, Shulamit. (2024). "ChatGPT is a Remarkable Tool—For Experts". *Data Intelligence,* v. 6, n. 1, pp. 240-296. *https://doi.org/10.1162/dint_a_00235*

Brusilovsky, Peter; Millán, Eva. (2007). "User Models for Adaptive Hypermedia and Adaptive Educational Systems." In: *The Adaptive Web: Methods and Strategies of Web Personalization.* Brusilovsky, Peter; Kobsa, Alfred; Nejdl, Wolfgang (Eds.), pp. 3-53. Berlin, Heidelberg:Springer Berlin Heidelberg. *https://doi.org/10.1007/978-3-540-72079-9_1*

Brynjolfsson, Erik; McAfee, Andrew. (2014). *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*. WW Norton & Company. *https://wwnorton.com/books/the-second-machine-age*

Celik, Ismail. (2023). "Exploring the Determinants of Artificial Intelligence (AI) Literacy: Digital Divide, Computational Thinking, Cognitive Absorption". *Telematics and Informatics,* v. 83, pp. 102026. *https://doi.org/10.1016/j.tele.2023.102026*

Celik, Ismail; Dindar, Muhterem; Muukkonen, Hanni; Järvelä, Sanna. (2022). "The Promises and Challenges of Artificial Intelligence for Teachers: a Systematic Review of Research". *TechTrends,* v. 66, n. 4, pp. 616-630. *https://doi.org/10.1007/s11528-022-00715-y*

Chen, Dayou; Liu, Wentao; Liu, Xinyu. (2024). "What drives college students to use AI for L2 learning? Modeling the roles of self-efficacy, anxiety, and attitude based on an extended technology acceptance model". *Acta Psychologica,* v. 249, pp. 104442. *https://doi.org/10.1016/j.actpsy.2024.104442*

Collins, Christopher; Dennehy, Denis; Conboy, Kieran; Mikalef, Patrick. (2021). "Artificial intelligence in information systems research: A systematic literature review and research agenda". *International Journal of Information Management,* v. 60, pp. 102383. *https://doi.org/10.1016/j.ijinfomgt.2021.102383*

Dahri, Nisar Ahmed; Yahaya, Noraffandy; Al-Rahmi, Waleed Mugahed; Aldraiweesh, Ahmed; Alturki, Uthman; Almutairy, Sultan; Shutaleva, Anna; Soomro, Rahim Bux. (2024). "Extended TAM based acceptance of AI-Powered ChatGPT for supporting metacognitive self-regulated learning in education: A mixed-methods study". *Heliyon,* v. 10, n. 8, pp. e29317. *https://doi.org/10.1016/j.heliyon.2024.e29317*

Eppler, Martin; Helfert, Markus. (2004). "A Classification and Analysis of Data Quality Costs." In: *Proceedings of the Ninth International Conference on Information Quality (ICIQ-04).* pp. 311-325. MIT Cambridge. *http://mitiq.mit.edu/ICIQ/Documents/IQ%20Conference%202004/Papers/AClassificationandAnalysisofDQCosts.pdf*

Franke, George; Sarstedt, Marko. (2019). "Heuristics versus statistics in discriminant validity testing: a comparison of four procedures". *Internet Research,* v. 29, n. 3, pp. 430-447. *https://doi.org/10.1108/IntR-12-2017-0515*

Gedrimiene, Egle; Celik, Ismail; Mäkitalo, Kati; Muukkonen, Hanni. (2023). "Transparency and Trustworthiness in User Intentions to Follow Career Recommendations from a Learning Analytics Tool". *Journal of Learning Analytics,* v. 10, n. 1, pp. 54-70. *https://doi.org/10.18608/jla.2023.7791*

Goodfellow, Ian. (2016). *Deep Learning*. MIT Press. *https://mitpress.mit.edu/9780262035613*

Haji-Othman, Yusuf; Yusuff, Mohd Sholeh Sheh. (2022). "Assessing Reliability and Validity of Attitude Construct Using Partial Least Squares Structural Equation Modeling (PLS-SEM)". *International Journal of Academic Research in Business and Social Sciences,* v. 12, n. 5, pp. 378-385. *https://doi.org/10.6007/IJARBSS/v12-i5/13289*

Jumaan, Ibrahim A.; Hashim, Noor Hazarina; Al-Ghazali, Basheer M. (2020). "The role of cognitive absorption in predicting mobile internet users' continuance intention: An extension of the expectation-confirmation model". *Technology in Society,* v. 63, pp. 101355. *https://doi.org/10.1016/j.techsoc.2020.101355*

Katrakazas, Christos; Michelaraki, Eva; Sekadakis, Marios; Yannis, George. (2020). "A descriptive analysis of the effect of the COVID-19 pandemic on driving behavior and road safety". *Transportation Research Interdisciplinary Perspectives,* v. 7, pp. 100186. *https://doi.org/10.1016/j.trip.2020.100186*

Kennedy, Imasuen. (2022). "Sample size determination in test-retest and Cronbach alpha reliability estimates". *British Journal of Contemporary Education,* v. 2, n. 1, pp. 17-29. *https://doi.org/10.52589/BJCEFY266HK9*

Khaleel, Mohamed; Jebrel, Abdullatif; Dunia, M. Shwehdy. (2024). "Artificial Intelligence in Computer Science". *International Journal of Electrical Engineering and Sustainability (IJEES),* v. 2, n. 2, pp. 01-21. *https://doi.org/10.5281/zenodo.10937515*

Lee, Irene; Ali, Safinah; Zhang, Helen; DiPaola, Daniella; Breazeal, Cynthia. (2021). "Developing Middle School Students' AI Literacy." In: *Proceedings of the 52nd ACM Technical Symposium on Computer Science Education.* pp. 191-197. Association for Computing Machinery. *https://doi.org/10.1145/3408877.3432513*

Li, Jian; Huang, Jin-Song. (2020). "Dimensions of artificial intelligence anxiety based on the integrated fear acquisition theory". *Technology in Society,* v. 63, pp. 101410. *https://doi.org/10.1016/j.techsoc.2020.101410*

Lo, Chung Kwan. (2023). "What Is the Impact of ChatGPT on Education? A Rapid Review of the Literature". *Education Sciences,* v. 13, n. 4, pp. 410. *https://doi.org/10.3390/educsci13040410*

Lugano, Giuseppe. (2017). "Virtual assistants and self-driving cars." In: *2017 15th international conference on ITS telecommunications (ITST).* pp. 1-5. IEEE. *https://doi.org/10.1109/ITST.2017.7972192*

Lund, Brady D.; Wang, Ting; Mannuru, Nishith Reddy; Nie, Bing; Shimray, Somipam; Wang, Ziang. (2023). "ChatGPT and a new academic reality: Artificial Intelligence-written research papers and the ethics of the large language models in scholarly publishing". *Journal of the Association for Information Science and Technology,* v. 74, n. 5, pp. 570-581. *https://doi.org/10.1002/asi.24750*

Manyika, James; Lund, Susan; Chui, Michael; Bughin, Jacques; Woetzel, Jonathan; Batra, Parul; Ko, Ryan; Sanghvi, Saurabh. (2017). *Jobs Lost, Jobs Gained: What the Future of Work Will Mean for Jobs, Skills, and Wages*. McKinsey Global Institute. *https://apo.org.au/node/199751*

Michalski, R. S.; Carbonell, J. G.; Mitchell, T. M. (2013). *Machine Learning: An Artificial Intelligence Approach*. Berlin, Heidelberg: Springer.

Moshagen, Morten; Bader, Martina. (2024). "semPower: General power analysis for structural equation models". *Behavior Research Methods,* v. 56, n. 4, pp. 2901-2922. *https://doi.org/10.3758/s13428-023-02254-7*

Pan, Yunhe. (2016). "Heading toward Artificial Intelligence 2.0". *Engineering,* v. 2, n. 4, pp. 409-413. *https://doi.org/10.1016/J.ENG.2016.04.018*

Pisarov, Jelena; Mester, Gyula. (2021). "Implementing New Mobility Concepts with Autonomous Self-Driving Robotic Cars". *IPSI Transactions on Advanced Research (TAR),* v. 17, n. 2, pp. 41-49. *https://ipsitransactions.org/journals/papers/tar/2021jul/p9.pdf*

Rainer, R Kelly; Prince, Brad; Sanchez-Rodriguez, Cristobal; Splettstoesser-Hogeterp, Ingrid; Ebrahimi, Sepideh. (2020). *Introduction to information systems*. John Wiley & Sons.

Rajam, Vaidehi; Reddy, A. Bheemeshwar; Banerjee, Sudatta. (2021). "Explaining caste-based digital divide in India". *Telematics and Informatics,* v. 65, pp. 101719. *https://doi.org/10.1016/j.tele.2021.101719*

Reychav, Iris; Wu, Dezhi. (2015). "Are your users actively involved? A cognitive absorption perspective in mobile training". *Computers in Human Behavior,* v. 44, pp. 335-346. *https://doi.org/10.1016/j.chb.2014.09.021*

Ringle, Christian M.; Sarstedt, Marko; Sinkovics, Noemi; Sinkovics, Rudolf R. (2023). "A perspective on using partial least squares structural equation modelling in data articles". *Data in Brief,* v. 48, pp. 109074. *https://doi.org/10.1016/j.dib.2023.109074*

Rönkkö, Mikko; Cho, Eunseong. (2022). "An Updated Guideline for Assessing Discriminant Validity". *Organizational Research Methods,* v. 25, n. 1, pp. 6-14. *https://doi.org/10.1177/1094428120968614*

Shan, Shan; Genç, Sema Yılmaz; Kamran, Hafiz Waqas; Dinca, Gheorghita. (2021). "Role of green technology innovation and renewable energy in carbon neutrality: A sustainable investigation from Turkey". *Journal of Environmental Management,* v. 294, pp. 113004. *https://doi.org/10.1016/j.jenvman.2021.113004*

Shepherd, Dean A.; Majchrzak, Ann. (2022). "Machines augmenting entrepreneurs: Opportunities (and threats) at the Nexus of artificial intelligence and entrepreneurship". *Journal of Business Venturing,* v. 37, n. 4, pp. 106227. *https://doi.org/10.1016/j.jbusvent.2022.106227*

Sutton, Richard S.; Barto, Andrew G. (2018). *Reinforcement Learning: An Introduction*. MIT Press, Cambridge, MA. *https://mitpress.mit.edu/9780262039246*

Thakkar, Jitesh J. (2020). *Structural Equation Modelling: Application for Research and Practice (with AMOS and R)*. Springer Singapore. *https://doi.org/10.1007/978-981-15-3793-6*

Usmani, Usman Ahmad; Happonen, Ari; Watada, Junzo. (2024). "The Digital Age: Exploring the Intersection of AI/CI and Human Cognition and Social Interactions". *Procedia Computer Science,* v. 239, pp. 1044-1052. *https://doi.org/10.1016/j.procs.2024.06.268*

van der Zeeuw, Alex; van Deursen, Alexander JAM; Jansen, Giedo. (2019). "Inequalities in the social use of the Internet of things: A capital and skills perspective". *New Media & Society,* v. 21, n. 6, pp. 1344-1361. *https://doi.org/10.1177/1461444818821067*

Van Dijk, Jan. (2020). *The Digital Divide*. John Wiley & Sons.

Voorhees, Clay M.; Brady, Michael K.; Calantone, Roger; Ramirez, Edward. (2016). "Discriminant validity testing in marketing: an analysis, causes for concern, and proposed remedies". *Journal of the Academy of Marketing Science,* v. 44, n. 1, pp. 119-134. *https://doi.org/10.1007/s11747-015-0455-4*

Wang, Cheng-Hui; Wu, Chih-Lun. (2022). "Bridging the digital divide: the smart TV as a platform for digital literacy among the elderly". *Behaviour & Information Technology,* v. 41, n. 12, pp. 2546-2559. *https://doi.org/10.1080/0144929X.2021.1934732*

Wang, Richard Y.; Strong, Diane M. (1996). "Beyond Accuracy: What Data Quality Means to Data Consumers". *Journal of Management Information Systems,* v. 12, n. 4, pp. 5-33. *https://doi.org/10.1080/07421222.1996.11518099*

Wang, Weiyu; Siau, Keng. (2019). "Artificial Intelligence, Machine Learning, Automation, Robotics, Future of Work and Future of Humanity: A Review and Research Agenda". *Journal of Database Management (JDM),* v. 30, n. 1, pp. 61-79. *https://doi.org/10.4018/JDM.2019010104*

Wang, Yu-Yin; Chuang, Yu-Wei. (2024). "Artificial intelligence self-efficacy: Scale development and validation". *Education and Information Technologies,* v. 29, n. 4, pp. 4785-4808. *https://doi.org/10.1007/s10639-023-12015-w*

Wang, Yu-Yin; Wang, Yi-Shun. (2022). "Development and validation of an artificial intelligence anxiety scale: an initial application in predicting motivated learning behavior". *Interactive Learning Environments,* v. 30, n. 4, pp. 619-634. *https://doi.org/10.1080/10494820.2019.1674887*

Yu, Zhichao; Kamran, Hafiz Waqas; Amin, Azka; Ahmed, Bilal; Peng, Sun. (2023). "Sustainable synergy via clean energy technologies and efficiency dynamics". *Renewable and Sustainable Energy Reviews,* v. 187, pp. 113744. *https://doi.org/10.1016/j.rser.2023.113744*

Zhou, Qiwei; Chen, Keyu; Cheng, Shuang. (2024). "Bringing employee learning to AI stress research: A moderated mediation model". *Technological Forecasting and Social Change,* v. 209, pp. 123773. *https://doi.org/10.1016/j.techfore.2024.123773*

Zhou, Xiaofei; Van Brummelen, Jessica; Lin, Phoebe. (2020). "Designing AI Learning Experiences for K-12: Emerging Works, Future Opportunities and a Design Framework". *arXiv preprint arXiv:2009.10228*. *https://doi.org/10.48550/arXiv.2009.10228*