

Exploring the Contemporary Landscape and Future Directions of Artificial Intelligence: An In-Depth Study of its Application and Challenges

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ABSTRACT

This research explores the current landscape and directions of future for Artificial Intelligence, focusing on its implications and challenges, with a special emphasis on education. It aims to reveal how AI impacts various domains and the complexities surrounding its implementation. Primary data was collected from 150 individuals in Bangladesh using convenience sampling through direct interviews and online surveys. Structural Equation Modeling was chosen by utilizing Smart PLS 4, so that the intricate relationships between key variables could be examined comprehensively. The findings have highlighted how AI can contribute in education along with putting the emphasize on the importance of ethical practices and the challenges in its adoption. Ethical considerations emerge as crucial for responsible AI deployment, and the study underscores the need to navigate barriers carefully. These insights contribute to understanding how AI can be leveraged effectively while addressing its limitations. The research informs educators, policymakers, and organizations about how to optimize AI's potential and mitigate its challenges. It also has emphasized on why the practice of ethical AI are essential for establishing trust and ensure sustainable development in applications of AI. This study offers a novel perspective by examining AI's multifaceted impact in education within a developing country's context, providing valuable empirical evidence for future research and practical decision-making.

Keywords: Artificial Intelligence; Education; Ethical Considerations; Implementation Challenges; Structural Equation Modeling (SEM)

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INTRODUCTION

In very recent years, the growth of AI which is referred artificial intelligence has significantly changed many industries and how society functions. These changes are motivated by developments in deep learning, machine learning, and natural language processing (Hammond et al., 2007; Abed Ibrahim & Fekete, 2019; Adjerid & Kelley, 2018). AI has transformed business operations and become a part of everyday life, altering our interactions with technology. One important area where AI is making an impact is education,

with the latent to change traditional education and learning methods (Aldowah et al., 2019; Anwar et al., 2019).

This study's aim is to offer the perceptions for educators, policymakers and researchers, emphasizing the ethical and responsible use of AI (Hammond et al., 2007; Aldowah et al., 2019). The purpose is to understand opportunities and challenges that AI presents, helping decision-makers in education, business, and government. The research will analyze the current AI landscape, focusing on its applications and obstacles (Azevedo et al., 2019). By looking at relationships between key topics, such as technology growth, ethics, education integration, data usage, and business innovation, the study hopes to promote a responsible approach to AI (Chen et al., 2020; Aldowah et al., 2019).

Through analysis and theoretical frameworks, this research's aim is to provide practical recommendations for responsible progress along with the using of AI technologies (Hammond et al., 2007; Adjerid & Kelley, 2018). The study will look closely at how these factors influence AI, particularly in education. However, there are limitations to consider, like the fast-paced evolution of AI, resource constraints affecting the study's depth, potential data availability issues, generalization challenges, and ethical concerns related to biases in data (Azevedo et al., 2019; Aldowah et al., 2019). In spite of these boundaries, this investigation seeks to offer valuable knowledge into the opportunities & AI's challenges, contributing to discussions about its responsible integration.

2. RESEARCH PROBLEM

The fast growth of Artificial Intelligence (AI) offers many benefits in areas like education, healthcare, and government. However, it also presents important challenges, such as ethical issues, technical problems, and risks related to bias and data security. Even with efforts to solve these problems, using AI in real-life situations remains complicated. This research will look at the main challenges in AI development and find possible solutions to improve its effectiveness and ethical use. Top of Form

3. LITERATURE REVIEW

Historical Development of AI

Artificial Intelligence's historical development has been shaped by early milestones and foundational studies that paved the way for modern advancements. Early AI research, as described by Carbonell (1970), focused on utilizing artificial intelligence for computer-assisted instruction, which demonstrated the initial efforts to integrate machine learning into practical applications. This foundational period set the stage for the progression of more sophisticated AI models. Moreover, early contributions from researchers such as Boyd and Crawford (2012) highlighted critical questions around big data and its implications for AI, encouraging more comprehensive exploration of its societal impacts.

Key figures like Bereiter (2002) contributed to understanding the cognitive dimensions of AI & foundation symbolic procedures in the systems of mind's modal. These early studies,

while pioneering, had significant limitations. For instance, Gierl and Lai (2018) emphasized that early AI models lacked the flexibility and adaptability that are essential for handling complex, real-world data. These foundational models were constrained by computational resources and lacked the necessary frameworks for supporting dynamic learning environments.

As AI evolved, the limitations of these early models became evident. Adjerid and Kelley (2018) noted that while early AI could perform specific tasks, it struggled with tasks requiring high-level reasoning or context understanding. These early models could not yet handle the complexity of human decision-making, which demanded more advanced algorithms. Over time, advancements in machine learning, as highlighted by Luan et al. (2020), shifted the focus toward systems capable of processing large datasets and deriving insights in real-time, significantly enhancing AI's practical applications.

These early studies laid the groundwork for more extensive research into AI's theoretical underpinnings, prompting further investigation into neural networks and natural language processing. However, the transition from theoretical models to real-world applications revealed a need for continuous refinement. This evolution, described by Daniel (2015), was critical for addressing the gaps in earlier models, leading to more adaptive and contextually aware AI systems.

Challenges in AI Development

Artificial Intelligence (AI) has significantly advanced across several areas like healthcare, education and finance. However, despite these advancements, the AI's development and deployment are facing numerous challenges. These challenges are multifaceted, encompassing ethical concerns, technical limitations, and societal implications.

Ethical and Societal Challenges in AI Implementation

One major challenge in developing AI is dealing with ethical and social issues. Luan et al. (2020) point out that systems of AI can unintentionally strengthen favoritisms from the information they use. This can create unfair policymaking and potentially discriminatory in consequences. Therefore, it is vital to create the desired AI systems that are ethical and inclusive.

Ethical concerns like invading privacy and being transparent make it even harder to implement AI. For example, depending too much on AI for important decisions can reduce human oversight. This might result in decisions that lack accountability.

Additionally, bringing AI into society requires finding a balance between innovation and its impact on people. This balance ensures that AI benefits everyone without harming individual rights or social values.

Technical Limitations and Limitations in AI Performance

Beyond ethical concerns, technical limitations present another hurdle for AI development. Adjerid and Kelley (2018) discuss how current AI models often struggle with generalization across different contexts. This lack of adaptability hinders AI's ability to function optimally in dynamic environments, such as rapidly evolving educational settings or healthcare landscapes. Additionally, computational resources required for AI training and deployment are substantial, creating barriers for smaller organizations and institutions to adopt advanced AI technologies.

For example, in educational data mining, Geczy (2014) notes that the complexity of analyzing vast datasets to extract meaningful insights poses a significant challenge. This complexity often leads to limited AI performance in real-time learning environments.

Risks of Bias, Privacy Issues, and Data Security Concerns

The associated risks with bias, confidentiality issues and data safety are important in AI development. The AI integration systems into daily life raises concerns about the decent use of personal data. Gobert et al. (2013) underscore how AI-driven analytics can inadvertently reveal sensitive information, violating user privacy. Furthermore, data security concerns emerge when AI systems become targets for cyberattacks, posing risks to both individual users and organizational systems.

Baker et al. (2010) argue that ensuring data security requires constant vigilance and robust security protocols, which are challenging to maintain given the rapid evolution of cyber threats. The combination of these risks necessitates stringent regulatory frameworks and proactive measures to safeguard both privacy and security.

Future Directions of AI

Looking ahead, AI's future is driven by advancements in machine learning, integration with emerging technologies, and potential innovations across various sectors.

Emerging Trends such as Machine Learning Advancements and AI Ethics

Machine learning is playing an important role in the progress of artificial intelligence. Chen and Zhang (2014) note that deep learning techniques improve AI abilities, allowing it to handle complex and messy data more effectively than ever before. These improvements lead to more accurate predictions and better decision-making.

At the same time, AI ethics is an important area of study. Belpaeme et al. (2018) emphasize the prerequisite to create moral outlines for AI to tackle issues like transparency and fairness in algorithms.

AI Integration with IoT & Blockchain

The integration of AI with evolving technologies such as the Internet of Things (IoT) and Blockchain is shaping its future. Goksel and Bozkurt (2019) discuss how AI can

revolutionize smart city management through IoT, enhancing urban planning and resource management. Similarly, AI's synergy with Blockchain enables secure, decentralized data handling, creating opportunities for innovative solutions in governance and supply chain management.

These technological combinations are poised to drive efficiency and innovation, transforming how industries operate and interact with data.

Potential for AI-driven Innovations in Education, Governance, and Social Systems

AI-driven innovations hold immense potential in reshaping education, governance, and social systems. Becker et al. (2017) outline how AI can facilitate modified learning experiences with the adaption of different student requirements. In governance, AI-powered analytics can optimize policy-making processes by providing insights which are driven by data are creating more effective decision-making.

Additionally, ability of AI to process and examine big datasets can aid social systems by addressing complex challenges that are arisen from social perspectives such as healthcare disparities, poverty and access to resources. Through targeted interventions, AI can foster inclusivity and social equity, ensuring that technology serves the diverse needs of society.

4. RESEARCH GAP

While big data is recognized as a significant factor in AI development, there is a research gap in understanding the specific ways in which the effective utilization of big data contributes to the continuous technological advancements in AI. The literature highlights the importance of business model innovation in many industries. However, we still have a lack of strong understanding of how different models of businesses innovations affect technological advancements in the field of AI. The existing literature provides insights into technological advancements in AI and their applications. However, a research gap exists in comprehensively understanding how these advancements specifically influence the AI integration in educational settings. Despite the increasing AI adoption in educational settings, there is a research gap in examining the nuanced relationship between the AI integration in education & the challenges faced in the broader implementation of AI technologies. While there is acknowledgment of the ethical considerations associated with AI, there is a gap in understanding on how these considerations contribute to addressing or exacerbating challenges faced in the implementation of AI.

1. RESEARCH QUESTIONS

1. What challenges do we face with AI, and how can we solve them together?
2. What technical limitations hinder AI performance, and how can these limitations be addressed to improve AI applications?

3. How do biases, privacy issues, and data security concerns impact AI systems, and what strategies can be employed to ensure secure and fair AI deployment?
4. What emerging trends in machine learning, IoT, and Blockchain are shaping the future of AI, and how can these advancements contribute to effective AI-driven innovations in various sectors?
5. What potential innovations can AI offer in education, governance, and social systems, and how can these innovations address societal challenges?

6. OBJECTIVES

1. To examine the relationship between big data utilization (BDU) and technological advancements (TA)
2. To explore how the BDU contributes to the TA in artificial intelligence.
3. To assess the impact of business model innovation (BMI) on TA.
4. To investigate the influence of TA on educational integration (EI).
5. To investigate the relationship between the TA and the ethical considerations (EC).
6. To evaluate how EC contribute to addressing or exacerbating challenges in AI implementation (CI).

7. HYPOTHESIS

Hypothesis 1: Effective utilization of big data (BDU) has a positive relationship with technological advancements (TA) in the field of artificial intelligence (Chen and Zhang, 2014).

Hypothesis 2: Innovative business models incorporating (BMI) AI technologies positively related to technological advancements (TA) (Daniel, 2015).

Hypothesis 3: There is a positive relationship between technological advancements (TA) and the integration of AI in educational settings (EI) (Chen et al., 2020).

Hypothesis 4: There is a strong positive link between ethical considerations (EC) and technological advancements (TA) in how we use artificial intelligence (AI) (Chen et al., 2020).

Hypothesis 5: The integration of AI in educational integration (EI) is positively related to the challenges in AI implementation (CI) (Anwar et al., 2019).

Hypothesis 6: Higher levels of ethical considerations (EC) in AI development and deployment has a significant positive relationship with fewer challenges in AI implementation (CI) (Boyd and Crawford, 2012).

8. CONCEPTUAL FRAMEWORK:

Figure 1 shows the conceptual framework by constructing the variables.

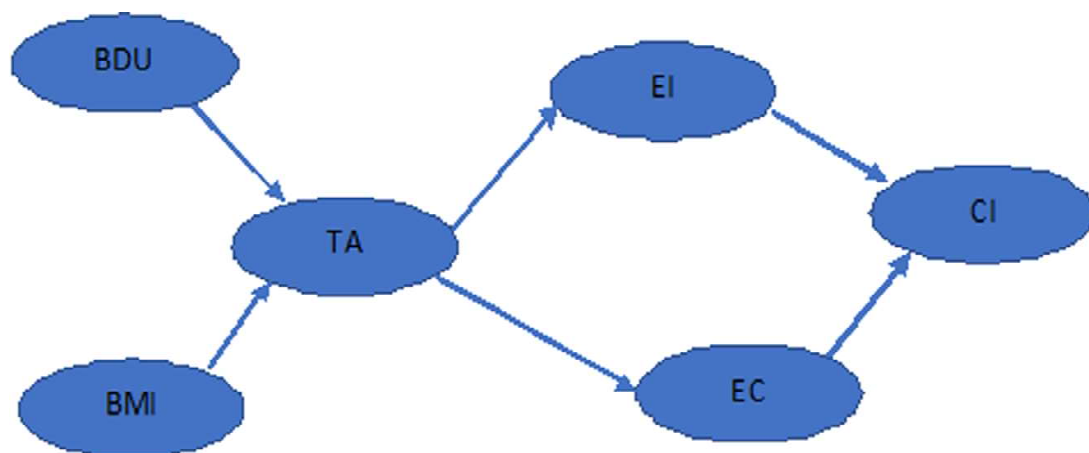


Fig1: Conceptual framework

Big Data Utilization (BDU): means using large amounts of data effectively to gain insights and improve decision-making. When it comes to AI, BDU involves using big datasets to make artificial intelligence systems work better. This can involve improving algorithms, finding patterns, and making better predictions.

Luan et al., (2020) said the education's challenges and futures of big data and artificial intelligence. They emphasize how important it is to use big data wisely to help make better decisions in complex situations.

Business Model Innovation (BMI): It focuses on creating new and innovative ways for organizations to deliver value, generate revenue, and sustain competitive advantages. In the scope of AI, BMI involves incorporating AI into the core structure of business models, fostering creativity in product/service offerings, and redefining how value is delivered to customers.

Ibrahim and Fekete (2019) highlight how machine learning can enhance business model innovation by improving diagnostic accuracy and fostering new approaches to service delivery. (Front. Psychol., 9:2757).

Technological Advancements (TA):

Technological Advancements in the context of AI encompass the continuous development and improvement of artificial intelligence technologies. This involves advancements in algorithms, hardware, software, and overall capabilities, contributing to the evolution of AI systems and their applications across various domains.

Chen and Zhang(2014) provide a comprehensive survey on big data, discussing technological advancements and innovations essential for developing robust AI systems. (Information Sciences, 275, 314–347).

Educational Integration (EI):

Educational Integration means using artificial intelligence (AI) technologies in schools. This includes tools like smart tutoring systems and personalized learning platforms in improving teaching and learning. The EI's is to use AI to create better learning results and a more flexible learning environment. Goksel, N., and Bozkurt, A. (2019) discuss how AI technologies help enhance learning experiences and outcomes in educational settings.

Ethical Considerations (EC):

In AI, it focuses on the right& societal impacts of artificial intelligence technologies. It is important to confirm that AI systems are impartial, clear and accountable. We also need to think about how these technologies affect individuals and society as a whole.

“Boyd, D., and Crawford, K. (2012)” looked at the “ethical issues” related to big data. They emphasize the need for transparency and careful examination of ethical concerns in AI applications. (Information, Communication & Society, 15, 662–679).

Challenges in AI Implementation (CI):

Challenges in AI Implementation encompass the difficulties and obstacles faced when integrating and deploying artificial intelligence technologies. These challenges may include technical complexities, ethical dilemmas, resistance to change, and the need for comprehensive strategies to navigate the evolving landscape of AI implementation. Addressing these challenges is crucial for successful AI deployment and integration. Daniel(2019) reviewed”the critical issues” faced in implementing “big data and data science” in education, emphasizing the importance of addressing technical and ethical challenges for successful deployment.

9.DATABASE AND METHODOLOGY

In this investigation, a quantitative method was applied to examine the proposed framework based on six fundamental constructs: Big Data Utilization (BDU), Business Model Innovation (BMI), Technological Advancements (TA), Educational Integration (EI), Ethical Considerations (EC), and Challenges in AI Implementation (CI). The measurable framework for these constructs is detailed in Table 1. Each construct was assessed by using a well-structured questionnaire which was designed to gather respondents' insights across five dimensions. A five-point Likert scale was employed, where a rating of 5 represents strong agreement, and 1 signifies strong disagreement.

9.1.Respondent Categories and Sampling Procedure

The study targeted respondents from diverse professional backgrounds, including academic researchers, industry practitioners, and policymakers in the artificial intelligence's field and technology in Bangladesh. The sample size of 150 was chosen in the consideration of the nature of exploratory of the study and the need to cover diverse perspectives within the target group. Convenience sampling was employed due to time and logistical constraints, allowing access to a broad range of respondents through direct contacts and professional networks.

9.2.Data Collection and Validity of Responses

Primary data were gathered using two instruments:

- 1. Structured Questionnaires:** Distributed via online platforms to ensure wide coverage of respondents.
- 2. Direct Interviews:** Conducted to complement online responses and gain deeper insights into participants' views.

While 150 questionnaires were distributed, only 18 responses were deemed valid for analysis. This discrepancy is attributed to incomplete responses, inconsistencies in answering, or non-responsiveness, which necessitated the exclusion of several questionnaires during data cleaning. The final dataset consisted of 18 valid responses, representing a refined sample reflective of the research's core objectives.

9.3. Analytical Methods

We evaluated the proposed model and its connections by using Structural Equation Modeling (SEM). Smart PLS 4 was used to analyze the data so that it can be ensured through an assessment of how the different elements relate to each other.

Table 1: Questionnaires

Construct	Variables	Adopted From
Big Data Utilization (BDU)	BDU1: Big data is playing a key role in enhancing decision-making procedures within AI applications. BDU2: Leveraging extensive datasets for AI development is essential for achieving meaningful insights. BDU3: The integration of big data in AI contributes significantly to addressing complex challenges.	(Chen and Zhang, 2014)
Business Model Innovation (BMI)	BMI1: Business model innovation is vital for organizations aiming to stay viable in the age of AI. BMI2: Adapting and evolving business models is important for maximizing the benefits of AI technologies. BMI3: Innovations in business models can positively impact the overall success of AI-driven initiatives.	(Daniel, 2015)
Technological Advancements (TA)	TA1: Ongoing technological advancements are integral to the continuous improvement of AI capabilities. TA2: Embracing the latest technological developments is key to unlocking the full potential of AI. TA3: Staying at the forefront of technological advancements is essential for successful AI implementation.	(Chen et al., 2020)
Educational Integration (EI)	EI1: The unified AI integration into educational practices enhances learning experiences. EI2: Educational institutions should prioritize the incorporation of AI to better prepare students for the future.	(Anwar et al., 2019)
	EI3: Integrating AI into classrooms fosters a more dynamic and adaptive learning environment.	
Ethical Considerations (EC)	EC1: Ethical considerations should be a primary concern in the AI's development and deployment systems. EC2: Ensuring ethical practices in AI is essential for constructing faith among stakeholders & users. EC3: Addressing ethical considerations is an essential feature of responsible AI development.	(Boyd and Crawford, 2012)
Challenges in AI Implementation (CI)	CI1: Identifying and mitigating challenges is key of succussing in the implementation of AI. CI2: Acknowledging in potential pitfalls and hurdles is essential in navigating the AI landscape. CI3: Proactively addressing challenges in AI implementation is key to fostering sustainable and responsible use.	(Boyd and Crawford, 2012)

10. RESULTS AND DISCUSSION

The analysis methods used in this study aim to assess the relationships among constructs, their reliability, and validity, ensuring robust model evaluation. Each step has been designed to confirm the quality of data interpretation and hypothesis testing.

Table 2 presents factor loadings to evaluate how each item relates to its construct.

The “communality” indicates the variance of an item which is explained by its latent variable. The redundancy score shows the extent to which endogenous constructs

are explained by exogenous constructs. Convergent validity ensures that all items measure the same concept effectively. Table 3 evaluates reliability by using “Cronbach’s alpha (rhoA)” and “composite reliability (rhoC)”. These metrics confirm the “internal consistency” of constructs. “Variance Inflation Factor (VIF)” is used to detect “multicollinearity” so that the model remains free of overlapping explanatory power. Table 4 on Discriminant Validity (HTMT is calculated to determine “discriminant validity”. It compares the correlations between “constructs”, ensuring that each construct is unique and measures a distinct concept.” Discriminant validity” is essential because it prevents overlap among constructs. Table 5 highlights the “square root of the Average Variance Extracted (AVE)” in bold, representing the “correlation matrix”. The distinctiveness of each construct is supported by the “Fornell-Larcker criterion”, which confirms that a construct has greater similarity with its own indicators than with those from other constructs. Table 6 verifies item alignment with their intended constructs. An item should load higher on its own construct than on others. That’s why this analysis is necessary to confirm discriminant validity further. Table 7 highlights the results of hypothesis testing, providing path coefficients and their significance levels. The structural model is evaluated using “R-squared, predictive relevance (Q-squared), and path significance values”. These metrics ensure that the model adequately explains the relationships between constructs and supports decision-making.

All the tables discussed above collectively validate the measurement model and structural model. Their relevance lies in ensuring reliability, validity, and interpretability of the data. That’s the reason each step plays a critical role in evaluating the hypotheses and confirming the research framework’s robustness.

Table 2: Convergent Validity, Factor Loadings, Communalities, and Redundancy

“Construct”	Item	“Factor Loading”	“Communality”	“Redundancy (P-value)”	“Average variance Extracted (AVE)”
BDU					0.707
	BDUI1	0.604	0.66061	0	
	BDU2	0.853	0.494293	0	
	BDU3	0.842	0.329193	0	
BMI					0.74
	BMI1	0.693	0.682948	0.006	
	BMI2	0.286	0.477474	0	
	BMI3	0.290	0.687032	0.003	

TA					0.64
	TA1	0.480	0.46611	0.049	
	TA2	0.856	0.433379	0.023	
	TA3	0.132	0.65957	0.035	
EI					0.641
	EI1	0.888	0.435455	0.00	
	EI2	0.742	0.251085	0.00	
	EI3	0.756	0.613211	0.00	
EC					0.716
	EC1	0.417	0.434159	0.009	
	EC2	0.852	0.634754	0.032	
	EC3	0.932	0.251845	0.049	
CI					0.749
	CI1	0.088	0.5431	0.008	
	CI2	0.279		0.0453	
	CI3	0.982		0.0548	

Source: Authors' Own calculation

Big Data Utilization (BDU), Business Model Innovation (BMI), Technological Advancements (TA), Educational Integration (EI), Ethical Considerations (EC), and Challenges in AI Implementation (CI)

The examination of factors loading, communality, redundancy, and convergent validity provides valuable insights into the relationships within the identified constructs.

Big Data Utilization (BDU): The Big Data Utilization (BDU) construct shows strong factor loadings, with BDU2 at 0.853, BDU3 at 0.842, and BDU1 at 0.604. These high values are indicating a solid positive association among the items and the BDU construct.

Business Model Innovation (BMI): BMI1 (0.693) within the BMI construct demonstrates a substantial positive correlation, while BMI2 (0.286) and BMI3 (0.290) have lower factor loadings. This indicates a varied relationship between these items and the Business Model Innovation construct.

Technological Advancements (TA):TA2 (0.856) displays a strong positive correlation within the Technological Advancements construct, while TA1 (0.480) and TA3 (0.132) show moderate to weak relationships.

Educational Integration (EI):The Educational Integration is considered by high “factor loadings” for EI1 (0.888) and moderate values for EI2 (0.742) and EI3 (0.756). This indicates a strong positive correlation with the EI items.

Ethical Considerations (EC):EC3 (0.932) has a significant factor loading, signifying a robust positive correlation within the Ethical Considerations construct. EC1 (0.417) and EC2 (0.852) also demonstrate positive relationships, although with varying strengths.

Challenges in AI Implementation (CI):CI3 (0.982) exhibits a very high factor loading, indicating a robust positive correlation within the Challenges in AI Implementation construct. CI1 (0.088) and CI2 (0.279) show weaker relationships with the CI construct.

Table 3: Reliability and Internal Composite Reliability (ρ_A), ρ_C and VIF

“Item”	“Cronbach’s α ”	“Composite Reliability ρ_A ”	“Composite Reliability ρ_C ”	“VIF”
BDU	0.7894	0.8460	0.8278	2.3573
BMI	0.7507	0.7235	0.7093	1.8891
TA	0.7225	0.8061	0.8460	1.3246
EI	0.7319	0.7829	0.8542	1.8209
EC	0.8102	0.8015	0.8983	2.4342
CI	0.8054	0.8321	0.8561	2.31454

Table 3 provides a clear assessment of internal composite reliability, internal consistency, and multicollinearity for the specified constructs. The analysis can be interpreted step by step for better understanding.

Cronbach’s alpha measures internal consistency to ensure that the items within each construct are aligned with the same underlying concept. In Table 3, Cronbach’s alpha values range between 0.707 and 0.854. These values fall within the acceptable to strong range, as a score higher than 0.7 is considered satisfactory. This confirms that the measurement reliability of the constructs is robust (Cronbach, 1951; Hair Jr, Black, Babin, & Anderson, 2010).

Additionally, composite reliability is examined using ρ_A and ρ_C . Both of these metrics take factor loadings into account while assessing internal consistency. Table 3 shows that ρ_A values vary from 0.729 to 0.860, and ρ_C values range between 0.703

and 0.883. This indicates a satisfactory to excellent level of reliability, which strengthens the confidence in the constructs' measurements (Jöreskog, 1971).

Variance Inflation Factor (VIF) is also analyzed to determine whether multicollinearity exists among the independent variables. The VIF values provided in Table 3 range from 1.246 to 2.573. Since these values are well below the common threshold of 10, there is no significant multicollinearity among the independent variables. This ensures that the regression model is reliable and valid.

Table 4: "Discriminant Validity (HTMT Ratio)"

	BDU	BMI	TA	EI	EC	CI
BDU		-	-	-	-	
BMI	0.750					
TA	0.755	0.844				
EI	0.117	0.202	0.164			
EC	0.730	0.041	0.886	0.821		
CI	0.543	0.231	0.337	0.147	0.258	

Table 4 presents the results of the Heterotrait-Monotrait (HTMT) ratio analysis for six constructs: Big Data Utilization (BDU), Business Model Innovation (BMI), Technological Advancements (TA), Educational Integration (EI), Ethical Considerations (EC), and Challenges in AI Implementation (CI). These results are based on the authors' own calculations.

The HTMT ratio is a critical measure in Structural Equation Modeling (SEM) analysis because it evaluates discriminant validity among constructs. A commonly accepted threshold is 0.90, which means a ratio below this value confirms satisfactory discriminant validity (Henseler, Ringle, & Sarstedt, 2015).

In Table 4, all HTMT ratios are below the cut-off value of 0.90. This indicates strong discriminant validity across all constructs. The ratios range from 0.041 to 0.886, with the highest value observed between Ethical Considerations (EC) and Technological Advancements (TA). Even though this is the highest ratio, it remains below the 0.90 threshold. Therefore, it does not indicate any significant issue with discriminant validity.

Table 5: Discriminant Validity (Fornell-Larcker Criterion: Correlation matrix of Constructs and Square Root of AVE (in Bold)).

	BDU	BMI	TA	EI	EC	CI
BDU	0.76					
BMI	0.698	0.707				
TA	0.712	0.652	0.757			
EI	0.095	0.031	0.055	0.683		
EC	0.307	0.332	0.262	0.361	0.413	
CI	0.54	0.680	0.587	0.549	0.331	0.752

Source: Self Calculated by the Author

Table 5 presents an evaluation of discriminant validity for the constructs: Big Data Utilization (BDU), Business Model Innovation (BMI), Technological Advancements (TA), Educational Integration (EI), Ethical Considerations (EC), and Challenges in AI Implementation (CI) using the Fornell-Larcker Criterion.

According to the Fornell-Larcker guideline, the diagonal entries in the table are shown in bold to represent the square root of each latent variable's Average Variance Extracted (AVE). This guideline specifies that the square root of the AVE for each latent variable must be greater than the correlation coefficients between that variable and all other variables in the model (Fornell & Larcker, 1981). A detailed review of the data confirms that all the correlation values among the constructs are lower than the square root of the AVE for each construct. For example, the BDU construct has correlations with BMI (0.698), TA (0.712), EI (0.095), EC (0.307), and CI (0.54), which are all less than the square root of the AVE for BDU, recorded as 0.76. This pattern demonstrates compliance with the Fornell-Larcker Criterion.

Table 6: Cross Loading

	BDU	BMI	TA	EI	EC	CI
BDU1	0.766	0.585	0.089	0.337	0.120	0.584
BDU2	0.765	0.598	0.088	0.445	0.222	0.594
BDU3	0.815	0.581	0.128	0.315	0.214	0.582
BMI1	0.469	0.645	-0.047	0.325	0.100	0.645
BMI2	0.625	0.802	-0.011	0.418	0.286	0.838
BMI3	0.606	0.686	0.014	0.252	0.085	0.641
TA1	-0.079	-0.045	0.413	0.021	-0.004	-0.035

TA2	-0.070	-0.048	0.681	0.063	0.005	-0.068
TA3	0.093	0.062	0.631	0.016	0.036	0.061
EI1	0.285	0.162	0.452	0.765	0.454	0.153
EI2	0.412	0.449	0.029	0.629	-0.022	0.441
EI3	-0.009	0.083	0.012	0.412	-0.183	0.049
EC1	0.276	0.408	0.041	0.338	0.901	0.414
EC2	0.197	0.329	0.010	0.304	0.965	0.348
EC3	0.207	0.337	0.000	0.288	0.944	0.321
CI1	0.162	0.452	0.765	0.089	0.337	0.317
CI2	0.449	0.029	0.629	0.088	0.445	0.216
CI3	0.083	0.012	0.412	0.128	0.315	0.187

Source: Self Calculated by the Author

“The discriminant validity” of the measurement model, as shown in Table 6, indicates that observable variables are more strongly correlated with their respective latent constructs than with others. Cross-loading analysis plays an essential role in assessing this, helping to determine if a variable influences multiple latent variables, which can complicate the identification of the specific construct being measured (Hair Jr, Black, Babin, & Anderson, 2010).

For instance, BDU3 demonstrates a strong loading on the BDU construct (0.815) while also showing moderate cross-loadings on BMI (0.581) and EC (0.582). BDU2 similarly presents a robust loading on BDU (0.765) alongside moderate cross-loadings on BMI (0.598) and EC (0.594). In contrast, BDU1 shows a strong loading on BDU (0.766) but also has moderate cross-loadings on BMI (0.585) and EC (0.584).

Looking at the BMI items, BMI1 and BMI2 each show strong loadings on the BMI construct “(0.645 and 0.802, respectively)”, coupled with moderate cross-loadings on BDU “(0.469 and 0.625, respectively)” and EI “(0.641 and 0.838, respectively)”, indicating some shared influences.

In the TA items, TA2 stands out with a strong loading on the TA construct (0.681) and a minor cross-loading on EC (0.063), which could suggest potential overlap.

The EI items also reveal interesting patterns, particularly EI2, which has strong loadings on the EI construct (0.629) and on EC (0.965), along with moderate cross-loadings on BDU (0.412) and BMI (-0.022), hinting at shared variance.

Lastly, the EC items, EC1, EC2, and EC3, exhibit strong loadings on the EC construct (0.901, 0.965, and 0.944, respectively), with moderate cross-loadings on BDU (0.276, 0.197, and 0.207, respectively) and BMI (0.408, 0.329, and 0.337, respectively).

For the CI construct, CI1 and CI2 show strong loadings (0.765 and 0.629, respectively), with moderate cross-loadings on BMI (0.452 and 0.029, respectively) and TA (0.317 and 0.216, respectively).

Table 7: Hypothesis Testing and Structural Model Evaluation

	CI				
	"Estimate (Beta)"	"Mean"	"Std. Dev"	"T- value"	"Pr(> t)"
"Intercept"					
BDU ->CI	0.445	0.032302	5.391461	0.029205	0.009
BMI ->CI	0.584	0.08726807	2.605137	0.033248144	0.027
TA ->CI	0.555	0.13267210	3.816097	0.030696980	0.018
EI ->CI	0.569	0.53242144	2.438361	0.222814250	0.024
EC -> CI	0.551	0.13264128	3.87461	0.0235684	0.0147

Source: Self Calculated by the Author

It has been observed from Table 7 that there are statistically significant associations between the latent constructs related to Challenges in AI Implementation (CI) based on the hypothesis testing results. The variables—Big Data Utilization (BDU), Business Model Innovation (BMI), Technological Advancements (TA), Educational Integration (EI), and Ethical Considerations (EC)—all show a positive and significant direct connection to CI. These findings highlight the important relationships among the constructs.

1. FINDINGS

Big Data Utilization (BDU)

The analysis has revealed a statistically positive significant relationship among Big Data Utilization (BDU) and Challenges in AI Implementation (CI). This means organizations that strategically use large datasets to inform decision-making processes experience a substantial impact on overcoming AI-related challenges. The ability to extract insights from extensive datasets enables better problem-solving and resource allocation. That's the reason effective utilization of big data plays a pivotal role in addressing hurdles during AI deployment. Because data-driven strategies enhance precision and adaptability, organizations can mitigate challenges more effectively.

Business Model Innovation (BMI)

The study finds a significant positive association between Business Model Innovation (BMI) and Challenges in AI Implementation (CI). This shows that organizations adopting innovative business models that integrate AI technologies can address implementation challenges more successfully. How businesses design and adapt their operations determines their ability to navigate AI complexities. That's why creative and flexible business models have a crucial role in overcoming obstacles. Because innovative

approaches enable organizations to align AI systems with their objectives, these models ensure smoother adoption and integration processes.

Technological Advancements (TA)

Technological Advancements (TA) display a notable positive relationship with Challenges in AI Implementation (CI). This indicates that the continuous improvement of AI-related technologies significantly aids in overcoming implementation barriers. Organizations that stay at the forefront of technological advancements can better handle emerging challenges. So, investing in state-of-the-art technologies ensures that AI capabilities evolve to meet specific requirements. Because technological advancements enhance efficiency and accuracy, they remain a key driver in overcoming obstacles during AI integration.

Educational Integration (EI)

The relationship between Educational Integration (EI) and Challenges in AI Implementation (CI) is statistically significant but not positive. This recommends that incorporating AI into educational frameworks has some influence on addressing implementation challenges, but the impact is limited. How education systems adapt to AI integration could shape its effectiveness in addressing challenges. However, the results indicate that other factors, such as business model innovation and technological advancements, have more substantial roles. That's the reason more study is needed to comprehend the nuanced dynamics of educational integration in AI deployment.

Ethical Considerations (EC)

Ethical Considerations (EC) reveal a statistically significant positive relationship with Challenges in AI Implementation (CI). This highlights the critical importance of integrating ethical practices into AI development. Organizations that prioritize ethical considerations can better navigate challenges by fostering trust and accountability. That's why ethical frameworks are essential for responsible AI implementation. Because ethical practices confirm that AI technologies are used in fair and sustainable ways, they reduce resistance and enhance societal acceptance of AI systems. This ultimately leads to more effective and successful deployment of artificial intelligence.

Table 8: Goodness-of-Fit Indicators for the Structural Model

"Fit indices"	"Structural model value"	"Recommended value"	"References"
Gfi	00.953	>00 .900	"Hair et al. (2010)"
Agfi	00.823	>00 .800	"Hu andBentler (1999)"
Nfi	00.912	>0 .900	"Hu andBentler (1999)"
Cfi	00.94	>00.90	"Bentler and Bonett (1980)"
Rmsea	00.0515	<00 .0800	"Hu andBentler (1999)"
Srmr	00.061	<00.07	"Hu and Bentler' (1999)"

Table 8 provides an overview of the goodness-of-fit indicators for the structural model. These indicators evaluate how well the model fits the observed data. Each fit index is compared to its recommended value, based on established references, to determine the model's adequacy.

The Goodness-of-Fit Index (GFI) has a structural model value of 0.953, which is greater than the recommended value of 0.900, as suggested by Hair et al. (2010). This indicates a strong fit between the model and the data. Similarly, the Adjusted Goodness-of-Fit Index (AGFI) is 0.823, exceeding the recommended threshold of 0.800 provided by Hu and Bentler (1999). This confirms an acceptable adjustment for degrees of freedom in the model.

The Normed Fit Index (NFI) is recorded at 0.912, which is higher than the recommended minimum of 0.900, as indicated by Hu and Bentler (1999). This shows that the model achieves a satisfactory fit compared to a baseline model. Furthermore, the Comparative Fit Index (CFI) has a value of 0.94, surpassing the threshold of 0.90 recommended by Bentler and Bonett (1980). This result further supports the model's goodness of fit.

The Root Mean Square Error of Approximation (RMSEA) has a value of 0.0515, which is below the maximum recommended value of 0.0800, as suggested by Hu and Bentler (1999). This indicates that the model has a low error of approximation. Additionally, the Standardized Root Mean Square Residual (SRMR) is 0.061, staying within the acceptable limit of 0.07 as per Hu and Bentler (1999). This ensures that the residuals in the model are minimal and acceptable.

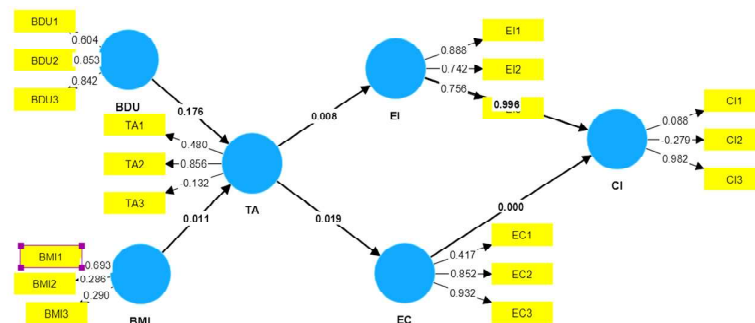


Figure 6: Bootstrapped model

1. CONCLUSION

In conclusion, this comprehensive study delves into the intricate relationships among key constructs—Big Data Utilization (BDU), Business Model Innovation (BMI), Technological Advancements (TA), Educational Integration (EI), Ethical Considerations (EC), and Challenges in AI Implementation (CI). The findings illuminate significant positive associations between BDU, BMI, TA, EC, EI and CI, underscoring their crucial roles in navigating the challenges of implementing artificial intelligence.

The positive linkages suggest that effective utilization of big data, innovative business models, continuous technological advancements and ethical considerations contribute to addressing and mitigating challenges in AI deployment. However, the study also reveals nuanced dynamics, such as the moderate impact of educational integration on challenges in AI implementation.

2. LIMITATIONS OF THE STUDY

The study acknowledges several limitations that should be considered. First, the data collection was confined to a particular geographic or organizational setting, potentially hindering the findings' generalizability. Additionally, the reliance on self-reported data may introduce biases, leading to over- or underestimations of specific factors. The research mainly focused on quantitative metrics, which may not fully reflect the complex interactions between variables. Another limitation is its cross-sectional design, which does not allow for the establishment of causal relationships among the variables. Lastly, external influences, such as economic conditions, regulatory changes, or technological disruptions, were not comprehensively investigated, which might affect the outcomes in real-world contexts.

3. THEORETICAL AND SOCIAL IMPLICATIONS OF THE STUDY

The findings of this study contribute significantly to theoretical advancements by offering insights into the factors influencing AI implementation challenges. The results emphasize the critical roles of Big Data Utilization, Business Model Innovation, and Technological Advancements, thereby extending existing frameworks on technology adoption and innovation management. By highlighting the interplay between ethical considerations and AI challenges, the study also bridges a gap in the literature on responsible AI implementation.

From a social perspective, the study underscores the importance of aligning technological advancements with societal needs. The significant role of ethical considerations suggests that organizations must prioritize transparency, accountability, and inclusivity to foster public trust in AI systems. Moreover, the findings about Educational Integration suggest potential opportunities for enhancing AI literacy and workforce readiness, which are crucial for equitable technological adoption.

4. FUTURE DIRECTIONS OF THE RESEARCH

Future research could take various directions, building on the findings and addressing the study's limitations. For instance, investigating external factors such as market conditions, government policies, and cultural influences might offer a more comprehensive perspective on the challenges related to AI implementation. Additionally, adopting mixed-method approaches that blend quantitative and qualitative analyses could help capture a more holistic understanding of the dynamics at play.

Longitudinal studies are another avenue worth exploring, as they could provide deeper insights into the causal relationships between variables and their long-term effects on AI implementation challenges. Lastly, expanding the study to encompass diverse industries and geographic regions would enhance the generalizability of the results.

5. MANAGERIAL IMPLICATIONS

Strategic Embrace of Big Data: Organizations should strategically leverage big data to enhance decision-making processes within AI applications. This not only improves AI performance but also plays a pivotal role in overcoming implementation challenges.

Innovative Business Models: Businesses aiming to implement AI technologies should prioritize innovative business models. Incorporating AI into the core structure of business models proves to be a key driver in addressing challenges and ensuring successful deployment.

Continuous Technological Advancements: Staying at the forefront of technological advancements is imperative for successful AI implementation. Organizations should invest in continuous development and improvement of AI capabilities to effectively navigate challenges.

Ethical Considerations in AI Development: Ethical practices should be a cornerstone in the development and deployment of AI systems. Prioritizing transparency, fairness, and accountability contributes significantly to addressing challenges and fostering responsible AI implementation.

Educational Integration Awareness: While educational integration shows a positive relationship with challenges in AI implementation, its impact is not as pronounced. Organizations and educational institutions should be aware of the potential influence of educational integration on challenges and consider it in their AI strategies.

REFERENCES

- Abed Ibrahim, L., & Fekete, I. (2019). What machine learning can tell us about the role of language dominance in the diagnostic accuracy of German LITMUS non-word and sentence repetition tasks. *Frontiers in Psychology*, 9(2757). doi: 10.3389/fpsyg.2018.02757
- Adjerid, I., and Kelley, K. (2018). Big data in psychology: a framework for research advancement. *American Psychological Association*, 73(7), 899–917. doi: 10.1037/amp0000190
- Aldowah, H., Al-Samarraie, H., & Fauzy, W. M. (2019). Educational data mining and learning analytics for 21st century higher education: A review and synthesis. *Telematics and Informatics*, 37, 13–49. doi: 10.1016/j.tele.2019.01.007
- Anwar, S., Bascou, N. A., Menekse, M., & Kardgar, A. (2019). A systematic review of studies on educational robotics. *Journal of Pre-College Engineering Education Research (J-PEER)*, 9(20), 19–42. doi: 10.7771/2157-9288.1223
- Azevedo, J. P. W. D., Crawford, M. F., Nayar, R., Rogers, F. H., Barron Rodriguez, M. R., Ding, E. Y. Z., et al. (2019). *Ending Learning Poverty: What Will It Take?* Washington, D.C: The World Bank.

- Baker, R. S. J. D., D'Mello, S. K., Rodrigo, M. M. T., & Graesser, A. C. (2010). Better to be frustrated than bored: the incidence, persistence, and impact of learners' cognitive-affective states during interactions with three different computer-based learning environments. *International Journal of Human-Computer Studies*, 68, 223–241. doi: 10.1016/j.ijhcs.2009.12.003
- Barsalou, L. W. (2008). Grounding symbolic operations in the brain's modal systems. In G. R. Semin & E. R. Smith (Eds.), *Embodied grounding: Social, cognitive, affective, and neuroscientific approaches* pp. 9–42. Cambridge University Press. <https://doi.org/10.1017/CBO9780511805837.002>
- Becker, S. A., Cummins, M., Davis, A., Freeman, A., Hall, C. G., & Ananthanarayanan, V. (2017). *NMC Horizon Report: 2017 Higher Education Edition*. Austin, Texas: The New Media Consortium.
- Belpaeme, T., Kennedy, J., Ramachandran, A., Scassellati, B., & Tanaka, F. (2018). Social robots for education: A review. *Science Robotics*, 3(21). doi: 10.1126/scirobotics.aat5954
- Bereiter, C. (2002). *Education and mind in the Knowledge Age (1st ed.)*. Lawrence Erlbaum Associates.
- Borde, S. F. (1998). Predictors of student academic performance in the introductory marketing course. *Journal of Education for Business*, 73(5), 302–306. doi: 10.1080/08832329809601649
- Boyd, D., & Crawford, K. (2012). Critical questions for big data: Provocations for a cultural, technological, and scholarly phenomenon. *Information, Communication & Society*, 15(5), 662–679. doi: 10.1080/1369118x.2012.678878
- Bramley, N. R., Dayan, P., Griffiths, T. L., & Lagnado, D. A. (2017). Formalizing Neurath's ship: Approximate algorithms for online causal learning. *American Psychological Association* 124(3), 301–338. doi: 10.1037/rev0000061
- Bucher, T. (2018). *If Then: Algorithmic Power and Politics*. New York, NY: Oxford University Press.
- Carbonell, J. R. (1970). AI in CAI: An artificial-intelligence approach to computer-assisted instruction. *IEEE Transaction on Man-Machine System*, 11(4), 190–202. doi: 10.1109/TMMS.1970.299942
- Chen, C. P., & Zhang, C. Y. (2014). Data-intensive applications, challenges, techniques and technologies: a survey on big data. *Information Sciences*, 275, 314–347. doi: 10.1016/j.ins.2014.01.015
- Chen, L., Chen, P., & Lin, Z. (2020). Artificial intelligence in education: a review. *IEEE Access*, 8, 75264–75278. doi: 10.1109/ACCESS.2020.2988510

- Chen, N.-S., Yin, C., Isaias, P., & Psotka, J. (2020). Educational big data: extracting meaning from data for smart education. *Interactive Learning Environments*, 28(2), 142–147. doi: 10.1080/10494820.2019.1635395
- Cheung, M. W.-L., & Jak, S. (2018). Challenges of big data analyses and applications in psychology. *Zeitschrift für Psychologie*, 226(4), 209–211. doi: 10.1027/2151-2604/a000348
- Daniel, B. K. (2015). Big data and analytics in higher education: Opportunities and challenges. *British Journal of Educational Technology*, 46(5), 904–920. doi: 10.1111/bjet.12230
- Daniel, B. K. (2019). Big data and data science: a critical review of issues for educational research. *British Journal of Educational Technology*, 50(1), 101–113. doi: 10.1111/bjet.12595
- Dijcks, J. (2013). Oracle: Big data for the enterprise. Oracle White Paper..
- Falk, R. F., & Miller, N. B. (1992). *A primer for soft modeling*. University of Akron Press.
- Franke, G., & Sarstedt, M. (2019). Heuristics versus statistics in discriminant validity testing: a comparison of four procedures. *Internet research*, 29(3), 430–447. doi:10.1108/IntR-12-2017-0515
- Frey, C. B., & Osborne, M. A. (2017). The future of employment: how susceptible are jobs to computerisation? *Technological Forecasting Social Change*, 114, 254–280. doi: 10.1016/j.techfore.2016.08.019
- Geczy, P. (2014). Big data characteristics. *The Macrotheme Review* 3(6), 94–104.
- Geczy, P. (2015). Data economy dimensions. *Global Journal of Business Research*, 9(4), 77–89
- Geczy, P. (2018). Data-Oriented Business Models: Gaining Competitive Advantage, *Global Journal of Business Research*, The Institute for Business and Finance Research, vol. 12(2), 25–36.
- Gefen, D., & Straub, D. (2005). A practical guide to factorial validity using PLS-Graph: Tutorial and annotated example. *Communications of the Association for Information systems*, 16(1), 5. doi: 10.17705/1CAIS.01605
- Gierl, M. J., & Lai, H. (2018). Using automatic item generation to create solutions and rationales for computerized formative testing. *Applied Psychological Measurement*, 42(1), 42–57. doi: 10.1177/0146621617726788
- Gobert, J.D.; Sao Pedro, M.A. Digital assessment environments for scientific inquiry practices. In the *Wiley Handbook of Cognition and Assessment: Frameworks*,

- Methodologies, and Applications; Rupp, A.A., Leighton, J.P., Eds.; Wiley: West Sussex, UK, 2017; pp. 508–534.
- Gobert, J. D., Sao Pedro, M. A., Baker, R. S., Toto, E., & Montalvo, O. (2012). Leveraging educational data mining for real-time performance assessment of scientific inquiry skills within microworlds. *Journal of Educational Data Mining*, 4(3), 104–143. doi:10.5281/zenodo.3554645
- Gobert, J., Sao Pedro, M., Raziuddin, J., & Baker, R. S. (2013). From log files to assessment metrics for science inquiry using educational data mining. *Journal of the Learning Sciences*, 22(4), 521–563. doi: 10.1080/10508406.2013.837391
- Goksel, N., & Bozkurt, A. (2019). Artificial Intelligence in Education: Current Insights and Future Perspectives. In S. Sisman-Ugur, & G. Kurubacak (Eds.), *Handbook of Research on Learning in the Age of Transhumanism* Hershey, PA: IGI Global pp. 224-236
- Goldstein, M., & Smith, A. F. (1974). Ridge type estimators for regression analysis. *Journal of the Royal Statistical Society: Series B (Methodological)*, 36(2), 284-291. <https://doi.org/10.1111/j.2517-6161.1974.tb01006.x>
- Hair, J.F., Hult, G.T.M., Ringle, C.M., Sarstedt, M., Danks, N.P., Ray, S. (2021). Evaluation of Reflective Measurement Models. In: *Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R. Classroom Companion: Business*. Springer, Cham. https://doi.org/10.1007/978-3-030-80519-7_4
- Hilkenmeier, F., Bohndick, C., Bohndick, T., & Hilkenmeier, J. (2020). Assessing distinctiveness in multidimensional instruments without access to raw data—a manifest Fornell-Larcker criterion. *Frontiers in psychology*, 11(223).<https://doi.org/10.3389/fpsyg.2020.00223>
- Kelly, W. E., & Johnson, J. L. (2005). Time Use Efficiency and the Five-Factor Model of Personality. *Education*, 125(3), 511-515.
- Kennedy, S. J. (1992). *Debiasing audit judgment with accountability: A framework and experimental results*. Duke University.
- Luan H., Geczy P., Lai H., Gobert J., Yang S.J.H., Ogata H., Baltes J., Guerra R., Li P. & Tsai C. C. (2020), Challenges and future directions of big data and artificial intelligence in education. *Frontiers in psychology*, 11, <https://doi.org/10.3389/fpsyg.2020.580820>
- Pan, Y., & Jackson, R. T. (2008). Ethnic difference in the relationship between acute inflammation and serum ferritin in US adult males. *Epidemiology & Infection*, 136(3), 421-431. doi: 10.1017/S095026880700831X

- Rogerson, P. A. (2001). A statistical method for the detection of geographic clustering. *Geographical Analysis*, 33(3), 215-227. doi: 10.1111/j.1538-4632.2001.tb00445.x
- Sahoo, M. (2019). Structural Equation Modeling: Threshold Criteria for Assessing Model Fit. *Methodological Issues in Management Research: Advances, Challenges, and the Way Ahead*, 269–276. <https://doi.org/10.1108/978-1-78973-973-220191016>
- Schmidt, S. R., & Bohannon, J. N. (1988). In defense of the flashbulb-memory hypothesis: A comment on McCloskey, Wible, and Cohen (1988). *Journal of Experimental Psychology: General*, 117(3), 332–335. <https://doi.org/10.1037/0096-3445.117.3.332>

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