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AI Capability and Sustainable Performance: Unveiling the Mediating Effects of Organizational Creativity and Green Innovation with Knowledge Sharing Culture as a Moderator

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Abstract: The purpose of this study is to investigate the role of AI capability (AIC) on organizational creativity (OC), green innovation (GI), and sustainable performance (SP). It also aims to investigate the mediating roles of OC and GI, as well as the moderating role of knowledge sharing culture (KNC). This study used quantitative methodology and utilized a survey to collect data from 421 employees in different organizations in Bangladesh. We used the structural equation modeling (SEM) technique to analyze the data. This study finds that AI capability significantly influences OC, GI, and SP. OC and GI work as mediators, and KNC serves as a moderator among the suggested relationships. This study is notable for its novelty in examining multiple unexplored aspects in the current body of research. This research also provides valuable insights for policymakers and practitioners regarding the effective integration of AI to enhance organizational competitiveness.

Keywords: AI capability; green innovation; organizational creativity; sustainable performance; knowledge sharing culture; sustainable development

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1. Introduction

Over the past few years, organizations have prioritized artificial intelligence (AI) as a top technological priority, primarily due to the advent of sophisticated techniques and infrastructure and the availability of big data [1,2]. According to the Gartner [3] report, the number of organizations that have implemented AI has increased by 270 percent over the last four years and trebled in the past year. Although there is anticipation about the potential economic benefits of AI, firms that are implementing AI solutions are confronting many challenges that inhibit performance improvements [1,4]. The lack of predicted benefits from AI is attributed to delays in implementation and restructuring, according to researchers [2]. Organizations must allocate resources to improve and make the most of their AI investments [5,6]. Understanding and effectively deploying the necessary complementary resources (such as human resources) is crucial for achieving performance improvements from AI. Put simply, it is now necessary to analyze how organizations develop an AI capacity [7–9].

The correlation between artificial intelligence capabilities and sustainable performance is intricate and diverse [10]. By streamlining procedures, using advanced data analytics, and fostering innovative ideas, artificial intelligence (AI) has the potential to greatly enhance organizational performance [11,12]. Nevertheless, the journey from AI skills to sustained performance is not a straightforward and linear one [13]. The impact of AI on sustainability is contingent upon enterprises effectively utilizing its potential through creative processes and new practices [14–17]. Organizational creativity pertains to the capacity of people and teams to produce original and valuable concepts, which is essential for properly harnessing AI technologies [18–20]. Green innovation, the acceptance of methods, and the creation of goods advance environmental sustainability [21–23]. Businesses striving to align with global sustainability goals especially depend on this, so AI capacity will help them [24,25]. By use of data, recommendations, and experiences, a culture of knowledge sharing improves artificial intelligence capacity and long-term performance [13,26,27]. In March 2020, Bangladesh put its AI strategy into action [6]. The strategy is centered around seven priority sectors: public service delivery, manufacturing, agriculture, smart mobility and transportation, skill and education, finance and trade, and health. The strategy outlines key goals and actions for each sector and identifies six strategic pillars: research and development, skilling and reskilling the AI workforce, data and digital infrastructure, ethics and data privacy, funding and accelerating AI start-ups, and industrialization of AI technologies. Each pillar includes a strategic brief, roadmap, action plan, relevant stakeholders, and lead ministries, forming a roadmap for building a sustainable AI ecosystem in the country [6,28,29]. Bangladesh can profit from AI by utilizing its scientific ability to build the required technical infrastructure. Top talent is being drawn to organizations that specialize in AI research [6].

Despite the growing interest in these subjects, certain areas of inquiry remain unexplored. Firstly, there is a scarcity of studies on this topic, especially in the context of a developing country like Bangladesh and in the quantitative realm. Furthermore, there is a dearth of studies on the influence of AI capabilities on green innovation. Furthermore, there has been a dearth of research regarding the influence of AI capabilities on both the creative output and long-term effectiveness of organizations. Additionally, it is necessary to do a more in-depth investigation of the intermediary function of green innovation and organizational creativity. Currently, the presence of a knowledge sharing culture as a moderating factor in the indicated correlations is uncommon. Lastly, to the best of the authors' knowledge and understanding, there are no individual studies that employ a second-order framework to investigate the proposed association. To fill this gap, we want to find out the answer to three research questions: RQ1: Does AI capability influence organizational creativity, green innovation, and sustainable performance? RQ2: Does organizational creativity and green innovation mediate the relationship between AI capability and sustainable performance? RQ3: Does a knowledge sharing culture serve as a moderator in our model?

The study's value rests in its contribution to both theoretical and practical fields. In theory, this study intends to fill important gaps in research by examining how AI capabilities, green innovation, and organizational creativity interact in the specific setting of a developing country such as Bangladesh. This study will enhance the current body of research by offering a second-order paradigm that emphasizes the intricacies of these relationships. Essentially, the discoveries will provide significant knowledge for companies aiming to use AI to promote environmentally friendly innovation and improve long-term effectiveness. Businesses can cultivate a sustainable and inventive work environment by understanding the mediating effects of green innovation and organizational creativity, as well as the moderating sway of a knowledge sharing culture. This understanding allows them to develop specific tactics to promote such an environment. This research will provide policymakers and practitioners with information on the significance of incorporating AI capabilities into organizational practices to enhance sustainability and competitiveness.

2. Literature Review and Hypotheses Development

2.1. Underpinning Theory

Resources, which an organization owns or controls, can affect industry performance. The resource-based view (RBV) is a popular theoretical framework for understanding this [30]. The strategic management literature underpins RBV. It implies that companies compete by exploiting their resources. These resources can improve performance if they are rare, valuable, difficult to duplicate, and non-replaceable [31]. Subsequent studies on the RBV differentiate between the two main components of the theory, competence development and resource acquisition [1]. According to Wade and Hulland [32], RBV is a crucial theoretical framework for comprehending how IT investments generate value and assist businesses in performing better. This theoretical perspective is relevant to our work because it is essential to understanding the AI resources that businesses must develop in order to profit from investments. RBV has demonstrated that human and complementary organizational resources are also required to optimize expenditures; technology alone is insufficient [33,34]. Empirical evidence from numerous studies supports the RBV's description of how organizational resources impact company success. For more than thirty years, researchers have extensively tested the RBT as the primary paradigm for theoretical reasoning and empirical research on organizational resources and firm performance [1,30,31]. Numerous studies have utilized the RBV to explore how IT and other complementary resources enhance the performance of management information systems (MIS) [35]. The RBV, according to Wade and Hulland [32], offers a precise framework for evaluating the strategic relevance of information system resources. Mikalef and Gupta [1] investigated how AI capabilities impact organizational creativity and performance using the RBV theory. Because the RBV attempts to identify the organizational resources required to create AI capabilities—which are believed to boost performance, creativity, and innovation—it is appropriate for this study. By applying RBV theory, we can evaluate organizational resources' strategic importance and establish connections between their independent factors and their effects on long-term performance.

2.2. AI Capability

AI capability is a firm's ability to effectively select, coordinate, and utilize its resources specifically dedicated to AI [1]. According to Ransbotham et al. [36], one of the main obstacles to fully utilizing AI is a lack of technical skills. Their analysis showed that roughly 20% of organizations do not understand AI's data requirements and the technologies needed to store and transport data. Davenport and Ronanki [37] found that integrating AI projects with current processes and systems is the biggest impediment to AI success. Mikalef et al. [33] found that combining systems and data and using high-quality data to train AI are the biggest challenges in the public sector. Unique data properties are necessary for AI, necessitating innovative technological solutions to overcome emerging challenges. However, AI technology has advanced significantly in recent years [7].

The above research and other scientific and commercial reports emphasize the need for organizations to nurture a wide range of resources to effectively extract corporate value from AI investments. There is little theoretical study on how businesses might develop AI capabilities. This gap benefits both research and practice because it identifies the core topics firms should prioritize when deploying AI projects. It also aids in determining commercial value and value-generation strategies. Based on the RBV theory [30,33], empirical research in information systems (IS) that has used the RBV [32,35]. We propose three categories of resources (human, tangible, and intangible) that form an AI capability based on the existing literature. Prior research has similarly utilized the resources of three categories, as outlined by Grant [38]. In a recent study, Mikalef et al. [1] used these three categories of resources to examine the impact of AI capabilities on firm performance. Human resources include business and technical experience, while tangible resources include data, technology, and foundational resources. Inter-departmental cooperation, organizational change capacity, and risk proclivity are intangible resources needed to build AI.

2.3. AI Capability and Organizational Creativity

Organizational creativity refers to the collective capability of an organization to generate novel and useful ideas, processes, products, or solutions [1]. It encompasses the creative potential of employees and the supportive systems, culture, and practices that nurture innovative thinking [39]. The automation of routine tasks by AI technologies frees employees from mundane activities, allowing them to focus on creative and strategic endeavors [12]. This reallocation of time and cognitive resources facilitates the exploration of new ideas and innovative solutions [40]. Furthermore, AI systems analyze vast amounts of data to identify patterns and insights that may not be immediately apparent to human analysts [13]. These data-driven insights serve as a foundation for creative thinking, enabling employees to develop novel approaches based on robust information [1,39].

AI improves decision-making with accurate predictions and recommendations. This AI-powered assistance encourages unusual techniques and new approaches by making decisions more informed and confident [24,25]. It streamlines project management, communication, and information sharing, enhancing teamwork. Collaboration brings new viewpoints and information, boosting company innovation [41]. By meeting employee needs, AI-enabled individualized learning and development programs improve skills and knowledge [1]. A culture of continual learning and curiosity enhances creativity because well-equipped employees innovate. AI generates multiple answers, simulates scenarios, and predicts results, fostering creativity. AI promotes ideation and refinement to enhance creativity [16]. Li et al. [2] found that AI positively affects knowledge sharing, which in turn positively impacts organizational creativity. Furthermore, their study showed that knowledge sharing mediates the relationship between artificial intelligence and organizational creativity. Thus, we propose the following hypothesis:

Hypothesis 1. *AIC positively influences OC.*

2.4. AI Capability and Organizational Green Innovation

Organizational green innovation refers to the development and implementation of new products, processes, or practices that reduce environmental impacts and promote sustainability [42]. This covers energy efficiency, waste reduction, carbon footprint reduction, and renewable resource advancements [22]. AI technologies can boost an organization's green innovation. AI optimizes resource and energy usage through advanced analytics and predictive modeling [24,25]. In massive datasets, AI algorithms can find inefficiencies and suggest energy and waste reductions, making processes and goods greener [43]. According to the findings of Wang et al. [44], there are significant direct, indirect, and total effects of AI on green innovation. AI-driven insights help develop sustainable materials and technology [7]. AI can speed research and development by modeling material qualities and performance under multiple scenarios to find the most sustainable solutions [44]. This feature speeds up the creation of green technologies by cutting down on the time and money needed for testing [45]. Advanced AI algorithms can monitor the environment in real time using sensors and IoT data. This capability helps organizations swiftly identify and fix environmental issues, ensuring they meet environmental laws [7,9]. Additionally, AI encourages sharing information and working together, both of which are important parts of green creation [25]. AI-powered platforms allow teams to share ideas and the best ways to do things. This method, by working together and sharing different ideas and information, leads to better and more complete green inventions [46]. Subsequently, we propose the following hypothesis:

Hypothesis 2. *AIC positively influences GI.*

2.5. AI Capability and Sustainable Performance

Sustainable performance is the capacity of a company to satisfy social and environmental responsibilities while also succeeding economically [22]. It guarantees long-term profitability and social and environmental impact by combining sustainability into corporate strategy, operations, and outcomes [7]. Using advanced data analytics and predictive modeling, AI can find inefficiencies and save energy, waste, and pollution [47]. Optimizations reduce costs and environmental impact by improving resource efficiency. AI provides practical data analysis insights for better decision-making [11,12]. AI systems process massive volumes of data from numerous sources to provide real-time information and predicted insights for strategic planning and operational modifications [4]. This competence helps businesses make educated decisions that balance economic, environmental, and social goals for sustainable growth [48].

Organizations can monitor environmental conditions and identify problems early with AI-powered sensors and IoT devices [26,47]. This proactive approach reduces legal and reputational risks by following environmental regulations [48]. AI-driven monitoring ensures long-term sustainability by implementing environmental stewardship best practices [7,9]. AI promotes sustainable product and service innovation [49]. Simulations and projections can speed up sustainability research and development with AI [4]. This proficiency allows companies to innovate environmental solutions and meet changing customer and regulatory needs [50]. AI improves employee and community well-being, promoting social sustainability [4]. AI-driven HR systems optimizing workforce management boost employee productivity and happiness [4,51]. AI can identify CSR community participation opportunities from social impact data. These events encourage social responsibility and sustainability [22]. In light of this, we put forward the following hypothesis:

Hypothesis 3. *AIC positively influences SP.*

2.6. Mediating Role of Organizational Creativity and Green Innovation

AI helps organizations come up with new ideas by giving them advanced tools and information that encourage creative thought [40]. Automation and AI technologies free up workers to focus on more important and creative tasks [43]. AI systems also look at big sets of data to find patterns and trends. This gives them data-driven insights that help them come up with new ideas and ways of doing things [24]. This information and automation base makes higher-level creative processes possible, which helps staff members come up with new and useful ideas [52]. By encouraging the development of novel approaches, goods, and procedures that address social and environmental issues, organizational creativity improves long-term success [1]. According to Grilli and Pedota [12], innovative organizations are better able to reduce negative impacts on the environment, increase social justice, and promote economic stability in the long run. Examples of innovative thinking that can lead to sustainable outcomes include energy-efficient procedures, waste-reduction programs, and socially responsible corporate strategies [1,42]. AI improves the ideation process by giving creative organizations access to new tools and insightful data. Drawing from this, we propose the following hypothesis:

Hypothesis 4. *OC positively mediates the relationship between AIC and SP.*

AI enhances organizations' ability to innovate towards sustainability by providing advanced tools and insights. These tools optimize resource use and energy consumption through analytics and predictive modeling, pinpointing inefficiencies and proposing improvements [22]. Such capabilities enable the creation of processes and products that significantly reduce environmental impact [42]. Green innovation, powered by AI, supports economic and ecological objectives by fostering solutions that reduce energy consumption, waste, and emissions [25]. This lowers operational costs and ensures compliance with environmental regulations, enhancing organizational reputation and competitiveness over the long term [53]. AI replicates different environmental circumstances to quickly test products and procedures for sustainability. This fast-paced innovation cycle helps firms launch green innovations faster and improve sustainability. Through AI-driven insights, firms stay ahead in sustainable innovation and solve environmental issues [48]. Thus, we propose the following hypothesis:

Hypothesis 5. *GI positively mediates the relationship between AIC and SP.*

2.7. Knowledge Sharing Culture as a Moderator

Knowledge sharing culture refers to the organizational norms, practices, and systems that facilitate the exchange and dissemination of knowledge among employees [9,54,55]. However, there is no single study that uses knowledge sharing culture as a moderator between the suggested variables, several studies have used this construct as a moderator in technology and different relations [54,56,57]. Studies on AI and its impact on business value suggest that businesses need to foster a culture of collaboration, common objectives, and shared resources to fully leverage the benefits of AI technologies [16]. Authors believe that a knowledge sharing culture positively moderates the relationship between AI capability and organizational creativity, green innovation, and sustainable performance.

In workplaces where employees are encouraged to openly exchange information, organizational innovation flourishes [9,18]. Facilitating the flow of varied viewpoints, ideas, and insights, a knowledge sharing culture increases the influence of AI capabilities on organizational innovation [9,58]. AI can spark new ideas by providing cutting-edge tools and data-driven insights [51]. These technologies, when combined with a culture of knowledge sharing, allow employees to work together more efficiently, make use of insights produced by AI, and expand upon each other's ideas [59,60]. A knowledge sharing culture improves organizational innovation by enabling open communication and learning to maximize AI's creative potential [61,62]. Green innovation demands cross-functional collaboration and various expertise. Knowledge sharing enhances AI and green innovation by exchanging environmental insights, technology skills, and sustainable practices [10,63]. AI optimizes resource management and provides predictive analytics for ecologically sustainable solutions [44]. These capabilities and a knowledge sharing culture allow enterprises to exploit AI-driven insights, discuss best practices, and co-create innovative green initiatives [13,51]. Information sharing across departments and teams accelerates green innovation development and implementation, boosting sustainability [56,64]. A knowledge sharing culture promotes AI capabilities and sustained performance by sharing information, best practices, and lessons learned [5,13,18]. AI optimizes operations, improves decision-making, and monitors the environment to promote sustainability [65]. These competencies enable firms to use AI-driven insights, collaborate on sustainability efforts, and adjust fast to changing environmental and market situations when combined with a knowledge sharing culture [9]. In light of this, we put forward the hypotheses that:

Hypothesis 6. *KNC moderates the relationship between AIC and OC.*

Hypothesis 7. *KNC moderates the relationship between AIC and GI.*

Hypothesis 8. *KNC moderates the relationship between AIC and SP.*

We offered the following framework based on the foregoing discussion (Figure 1):

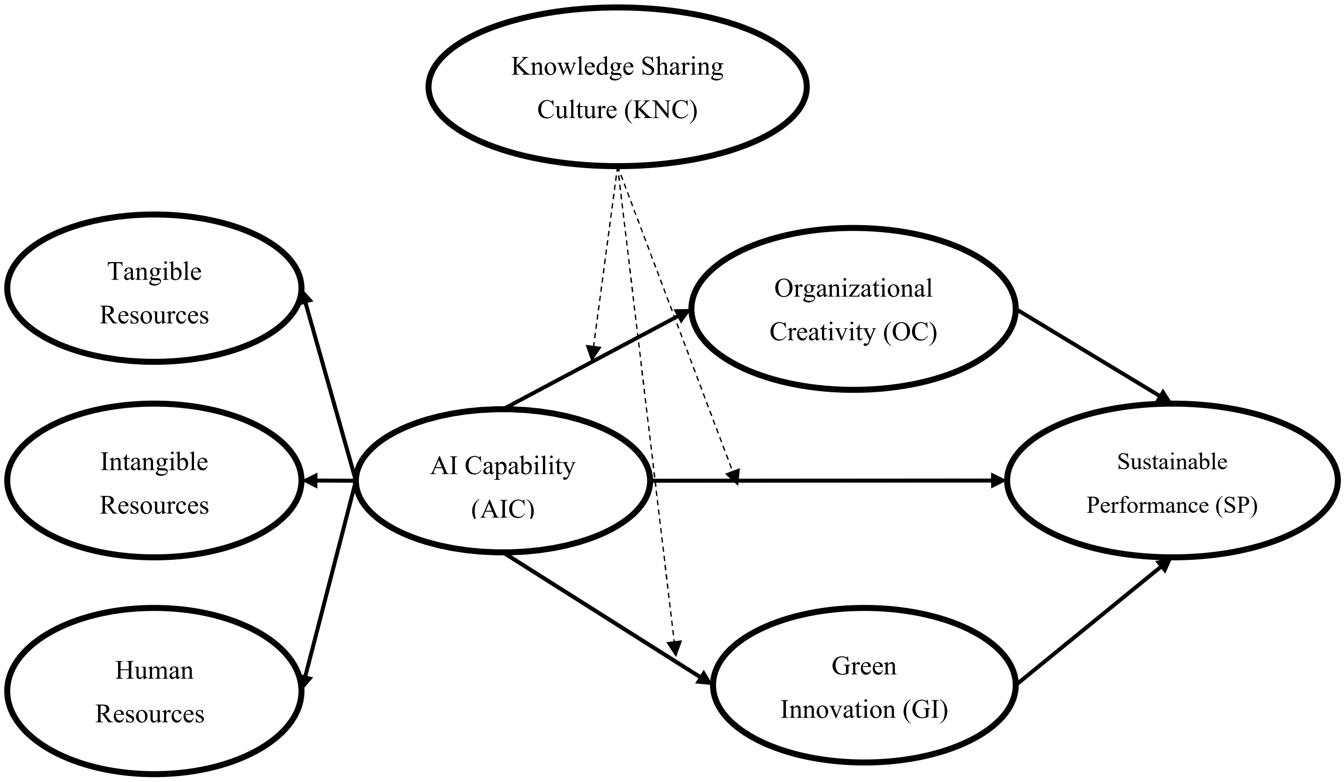

Figure 1. Conceptual framework.

3. Research Methodology

3.1. Sample Selection

This study utilized snowball sampling to recruit 421 employees from various industries in Bangladesh. Respondents were chosen based on their organization's technological advancement and their experience and knowledge about technology and AI. Due to the emerging interest in AI tools and the challenge of finding qualified participants, this approach was effective in reaching the targeted individuals.

3.2. Instruments Design

The survey questionnaire was designed through a three-stage process. Initially, we conducted a thorough examination of the existing literature to identify the items for the questionnaire. Subsequently, we created self-administered questionnaires. A group of five experienced research academics specializing in business and technology conducted a focus group analysis to enhance and clarify the questions, ensuring they were balanced and clear while avoiding unnecessary repetition. Subsequently, we carried out a preliminary investigation with 30 people who were picked at random in order to assess the appropriateness of the measuring questions. We conducted tests to assess the normality and multicollinearity of the data, which confirmed its suitability for further investigation. We conducted reliability testing using Cronbach's alpha, implementing slight adjustments to enhance the legibility and comprehensibility of the questions prior to finalizing them. The ultimate survey questionnaire consisted of two pieces. The initial section of our study delineates the research goals and provides participants with the assurance that their replies will be gathered solely for research purposes. The objective of the second portion was to assess the respondents' perceptions regarding the indicated items. We assessed the level of AI capacity by employing second-order reflective structures. We utilized and enhanced the question items for the three domains of AI capabilities, deriving inspiration from prior research [1,2,9]. The items for green innovation and organizational creativity were derived from previous studies conducted by Ullah et al. [22] and Wang et al. [44]. We utilized the metrics of organizational creativity derived from previous research [12,16]. We derived the elements of a culture that promotes the sharing of knowledge from the works of Guo [56], Thu et al. [57], and Zhang [54]. A seven-point Likert scale was employed to rate all the items, where 1 indicated “strongly disagree” and 7 indicated “strongly agree”.

3.3. Overview of Analyses

The data were obtained through an online platform using a well-organized questionnaire. The data collection period spanned from December 2023 to June 2024. Although 448 surveys were collected, some were discarded owing to incomplete responses, missing data, outliers, and other issues. This left us with 421 valid samples for investigation. We conducted exploratory factor analysis (EFA), descriptive statistics, and demographic analysis using IBM SPSS Statistics 24. Subsequently, we used Amos 24 software to perform confirmatory factor analysis (CFA) and assess the reliability and validity of the measurement model, as well as to evaluate the relevance of the paths. Structural equation modeling (SEM) was also conducted with Amos 24 to investigate hypothetical pathways and test the proposed relationships. Additionally, bootstrapping was used to assess the model’s mediating effects. This method was chosen because SEM can generate distinct construct relationships and accurately predict exogenous variables [66,67].

3.4. Common Method Variance (CMV)

This study evaluated CMV using Harman’s single-factor test. Podsakoff et al. [68] state that CMV concerns may exist if all items load onto one factor or if one factor explains more than 50% of variance. This test shows that the first factor explains 45.36% of the variation. Few components have eigenvalues greater than 1, indicating no CMV concerns in the data [68,69].

4. Analysis and Results

4.1. Demographic Analysis

The demographics of the respondents are shown in Table 1. Out of the 421 participants, 61.0% are men and 39.0% are women. When it comes to marriage, 51.1% are single and 48.9% are married. A total of 21.6% of the respondents are between the ages of 20 and 25, 25.7% are between the ages of 26 and 30, 23.3% are between the ages of 31 and 35, 21.6% are between the ages of 35 and 40, and 7.8% are over the age of 40. A total of 2.4% of them have an undergraduate degree, 60.1% have a graduate degree, 35.4% have a professional degree, and 2.1% have a PhD. In terms of monthly income, 9.3% make between 10,000 and 20,000 BDT, 21.4% make between 20,000 and 30,000 BDT, 50.4% make between 30,000 and 40,000 BDT, 11.6% make between 40,000 and 50,000 BDT, and 7.4% make more than 50,000 BDT. Finally, 25.7% have less than 5 years of work experience, 49.6% have 5 to 10 years, 17.1% have 10 to 15 years, and 7.6% have more than 15 years.

Table 1. Demographic profile.

Variables (n = 421)		Frequency	%
Gender	Male	257	61.0
	Female	164	39.0
Marital status	Single	215	51.1
	Married	206	48.9
Age	21–25	91	21.6
	26–30	108	25.7
	31–35	98	23.3
	35–40	91	21.6
	Above 40	33	7.8

Table 1. *Cont.*

Variables (n = 421)		Frequency	%
Level of Education	Undergraduate	10	2.4
	Graduate	253	60.1
	Post Graduate	149	35.4
	PhD	9	2.1
Monthly income (BDT)	10,000–15,000	39	9.3
	20,000–30,000	90	21.4
	30,000–40,000	212	50.4
	40,000–50,000	49	11.6
	Above 50,000	31	7.4
Experience	Below 5 years	108	25.7
	5 to 10 years	209	49.6
	10 to 15 years	72	17.1
	Above 15 years	32	7.6

4.2. Measurement Model Analysis

Figure 2 displays the measurement model, while Table 2 describes its validity and reliability. The results show that the composite reliability (CR) scores are higher than the suggested cutoff value of 0.70, running from 0.970 to 0.980. This means that the tests are very consistent with each other [70]. The average variance extracted (AVE) numbers, which range from 0.870 to 0.909, are also higher than the acceptable level of 0.50. The items on the test have excellent factor loading, with values between 0.918 and 0.968, and all of the Cronchabach's alpha numbers are above 70. According to Hair et al. [70] and Fornell and Larcker [71], there is also divergent and discriminant validity because the inter-construct correlation value is less than the square root of the AVEs. We use the variance inflation factor (VIF) to check for multicollinearity and make sure it does not go over 10. The VIF scores of 1.688 to 2.537 show that the model does not have any problems with multicollinearity. When it comes to model fit, this one is great. These numbers demonstrate how well the model fits: $X^2/df = 2.113$, GFI = 0.843 AGFI = 0.843, CFI = 0.975, TLI = 0.973, IFI = 0.976, NFI = 0.955, RMSEA = 0.051, and PClose = 0.283.

Table 2. First-order model validity and reliability statistics.

	CR	AVE	MSV	MaxR (H)	IR	OC	HR	SP	GI	TR	KN	VIF
IR	0.980	0.909	0.392	0.981	**0.953**							1.858
OC	0.978	0.900	0.396	0.980	0.527 ***	**0.949**						1.905
HR	0.975	0.888	0.462	0.975	0.576 ***	0.596 ***	**0.942**					2.121
SP	0.978	0.899	0.436	0.978	0.609 ***	0.630 ***	0.614 ***	**0.948**				
GI	0.972	0.872	0.371	0.973	0.514 ***	0.548 ***	0.533 ***	0.609 ***	**0.934**			1.688
TR	0.971	0.870	0.462	0.972	0.626 ***	0.621 ***	0.680 ***	0.660 ***	0.576 ***	**0.933**		2.537
KN	0.970	0.891	0.453	0.972	0.576 ***	0.551 ***	0.590 ***	0.614 ***	0.532 ***	0.673 ***	**0.944**	2.002

Model Fit Measures: $X^2/df = 2.113$, GFI = 0.843, AGFI = 0.843, CFI = 0.975, TLI = 0.973, IFI = 0.976, NFI = 0.955, RMSEA = 0.051, and PClose = 0.283; Note: Bold diagonal values are the square root of AVE value. Significance of Correlations: † $p < 0.100$; * $p < 0.050$; ** $p < 0.010$; *** $p < 0.001$.

4.3. Higher Order Measurement Model

A new framework (refer to Figure 3) has been developed, incorporating a second-order reflective construct known as AIC. The subdimensions of AIC are TR, IR, and HR. The sub-dimensions are examined by assessing their factor loads on AIC and their level of importance.

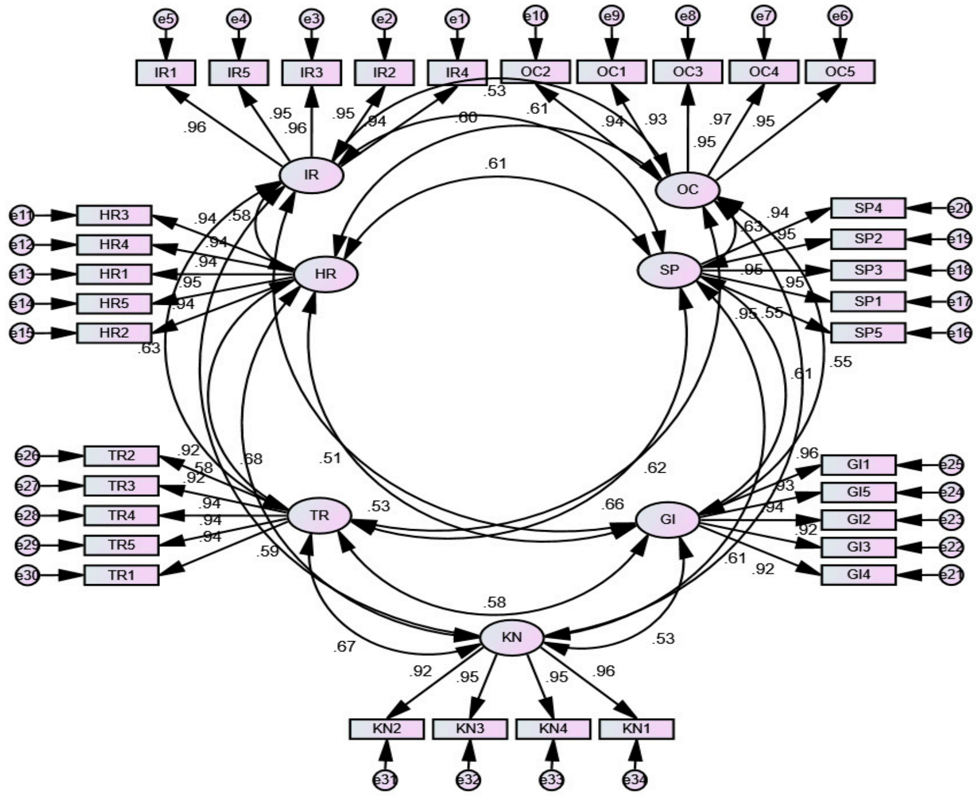

Figure 2. First-order measurement model (Table 3).

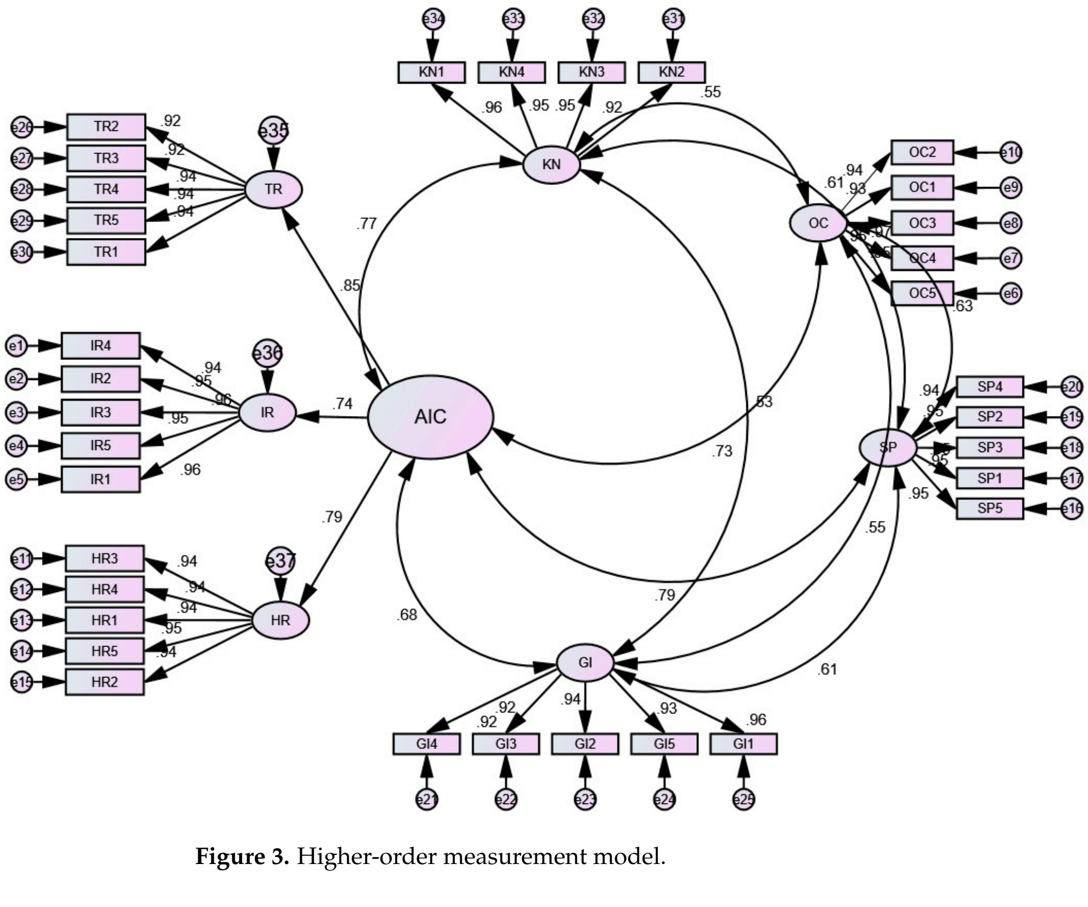

Figure 3. Higher-order measurement model.

Table 3. Standardized regression weight.

Variable	Item	Loading	S. E.	t-Value	Cronbach's Alpha
TR	TR1	0.942	0.029	36.065	0.971
	TR2	0.920			
	TR3	0.918	0.032	33.132	
	TR4	0.942	0.031	36.063	
	TR5	0.941	0.030	35.901	
IR	IR1	0.960	0.022	44.332	0.980
	IR2	0.950	0.024	42.040	
	IR3	0.963	0.024	45.002	
	IR4	0.944			
	IR5	0.951	0.023	42.226	
HR	HR1	0.942	0.024	41.025	0.975
	HR2	0.944			
	HR3	0.936	0.027	35.065	
	HR4	0.940	0.028	35.026	
	HR5	0.949	0.026	42.027	
OC	OC1	0.929	0.023	39.115	0.978
	OC2	0.943	0.024	41.806	
	OC3	0.953	0.021	44.110	
	OC4	0.968	0.022	47.984	
	OC5	0.950			
GI	FS1	0.959	0.030	38.332	0.972
	FS2	0.940	0.030	35.692	
	FS3	0.920	0.031	33.187	
	FS4	0.918			
	FS5	0.931	0.031	34.490	
KNC	KNC1	0.956	0.027	38.205	0.970
	KNC2	0.921			
	KNC3	0.953	0.028	37.833	
	KNC4	0.945	0.028	36.621	
SP	SP1	0.945	0.024	42.253	0.978
	SP2	0.951	0.023	43.513	
	SP3	0.950	0.023	43.159	
	SP4	0.944	0.024	41.985	
	SP5	0.950			

Table 4 and Figure 3 demonstrate that all of these sub-dimensions effectively represent AIC. However, evaluating a higher-order measurement model involves using second-order reflective constructs and three additional psychometric variables. The findings indicate that the reliability, divergent and discriminant validity, multicollinearity, and model fit indices all meet the desired criteria, as demonstrated in Table 4.

Table 4. Higher-order measurement model validity reliability.

	CR	AVE	MSV	MaxR (H)	OC	SP	GI	KN	AIC
OC	0.978	0.900	0.537	0.980	**0.949**				
SP	0.978	0.899	0.619	0.978	0.630 ***	**0.948**			
GI	0.972	0.872	0.462	0.973	0.548 ***	0.609 ***	**0.934**		
KN	0.970	0.891	0.600	0.972	0.551 ***	0.614 ***	0.532 ***	**0.944**	
AIC	0.837	0.632	0.619	0.847	0.733 ***	0.787 ***	0.680 ***	0.775 ***	**0.795**

Model Fit Measures: X^2/df = 2.122, GFI = 0.866, AGFI = 0.844, CFI = 0.976, TLI = 0.973, IFI = 0.976, NFI = 0.954, RMSEA = 0.051, PClose = 0.352. Note: Bold diagonal values are the square root of AVE value. Significance of Correlations: † $p < 0.100$; * $p < 0.050$; ** $p < 0.010$; *** $p < 0.001$.

4.4. Structural Model Analysis

To evaluate the proposed routes, we carried out SEM (Figure 4) based on the fitness of the first- and higher-order measurement models. According to Table 5, the SEM model demonstrates a satisfactory fit to the data ($X^2/df = 1.352$, GFI = 0.877, AGFI = 0.856, CFI = 0.978, TLI = 0.976, IFI = 0.978, NFI = 0.959, RMSEA = 0.052, PClose = 0.275). According to the data, the model was able to explain (e.g., R^2 value) 48%, 55% and 64% of the variance in GI, OC and SP, respectively. All three hypotheses (direct effects) are statistically validated at a significance level of $p < 0.01$. Firstly, Hypothesis 1 posits AIC has a positive and significant impact on in OC that (β = 0.969, $p < 0.01$); thus, H1 is accepted. Secondly, Hypothesis H2 posits that AIC has a noteworthy and positive impact on GI (β = 0.735, $p < 0.01$) thus the H2 is accepted. Thirdly, Hypothesis 3 posits integration of AIC has a significant and positive impact on SP (β = 0.815, $p < 0.01$); thus, the H3 is accepted.

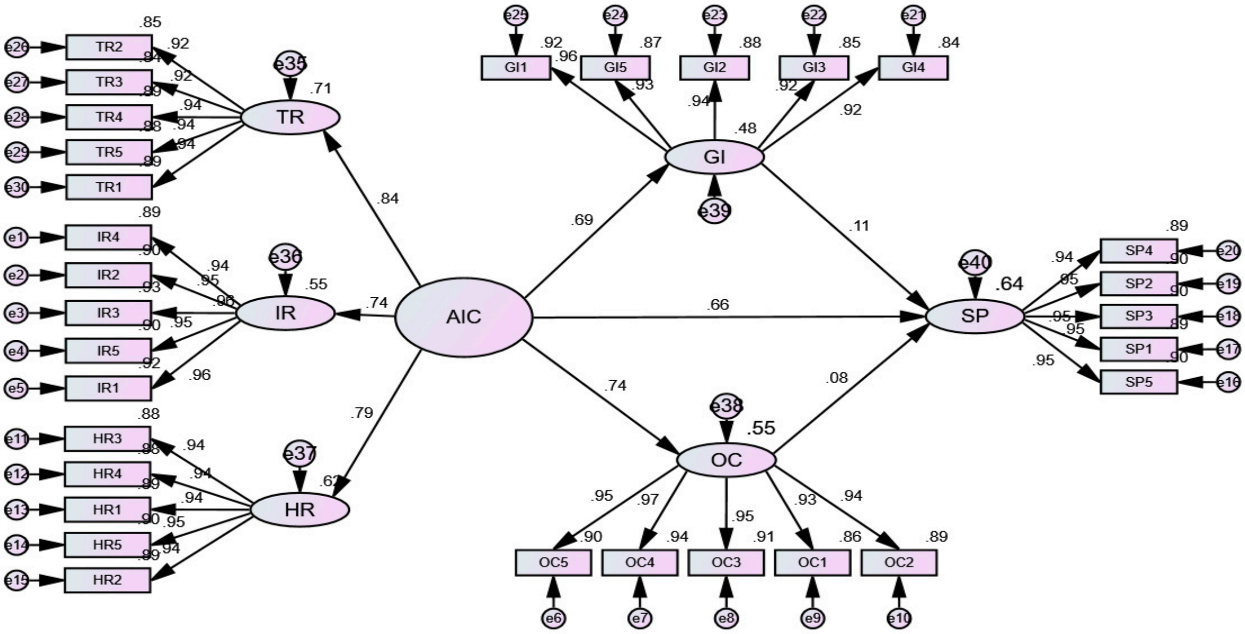

Figure 4. Structural equation model.

Table 5. Hypotheses results.

		Estimate	S.E.	t-Value	*p*	Decision
H1	OC <--- AIC	0.969	0.065	14.971	***	Supported
H2	GI <--- AIC	0.735	0.054	13.642	***	Supported
H3	SP <--- AIC	0.815	0.104	7.805	***	Supported

Model Fit Measures: $X^2/df = 1.352$, GFI = 0.877, AGFI = 0.856, CFI = 0.978, TLI = 0.976, IFI = 0.978, NFI = 0.959, RMSEA = 0.052, and PClose = 0.275. Notes: *** $p < 0.001$; ** $p < 0.01$.

4.5. Mediation Analysis

This study examines how OC and GI mediate the relationship between AIC and SP. Baron and Kenny's [72] definition of partial mediation—a situation in which a mediator has a substantial link with both the dependent and independent variables—is applied in this study. Bootstrapping was used with a sample size of 421 and a confidence interval of 95%, repeated 5000 times, to evaluate the mediating effects. Table 6 displays the findings, which indicate that the relationship between AIC and SP is significantly mediated by the OC and GI. At a probability threshold of <0.001, every pathway was found to be significant, showing significant partial mediation effects and supporting Hypotheses H4 and H5.

Table 6. Mediation results.

Variables		Bootstrapping Bias-Corrected 95% CI		
Indirect Effect	**Estimate**	**Lower**	**Upper**	***p*-Value**
AIC--->OC--->SP	0.987	0.893	1.102	0.000
AIC--->GI--->SP	0.840	0.700	0.988	0.000

4.6. Moderation Results

Table 7 shows how AIC affects OC, GI, and SP depending on a KNC. When moderated by KNC, the path from AIC to OC exhibits an estimate of 0.301, a t-value of 14.428, and a standard error (S.E.) of 0.021. The connection between AI capabilities and a knowledge sharing culture greatly boosts organizational creativity, leading to a moderate effect, according to this highly significant relationship ($p < 0.001$). The path from AIC to GI is similarly moderated by KNC, which estimates it to be 0.349, with a 0.038 standard error and a 9.291 t-value. Additionally, a highly significant association ($p < 0.001$) is shown, indicating that a strong knowledge sharing culture in conjunction with AI capabilities considerably fosters green innovation, leading to a moderate benefit. Finally, a t-value of 13.438 and an estimate of 0.438 with a standard error of 0.033 are revealed by the KNC-moderated path from AIC to SP. This significant link ($p < 0.001$) shows that a culture of information sharing combined with AI capabilities significantly improves sustainable performance, indicating a moderate benefit.

Table 7. Moderation results.

Hypothesized Path	Estimate	S.E.	t-Value	p	Comment
AIC × KNC→OC	0.301	0.021	14.428	***	Moderate
AIC × KNC→GI	0.349	0.038	9.291	***	Moderate
AIC × KNC→SP	0.438	0.033	13.438	***	Moderate

Notes: *** $p < 0.001$; ** $p < 0.01$.

5. Discussion

This study attempted to answer three research questions. The results of the first three hypotheses provide the first answer to the initial research question. H1: AIC positively influences OC. This indicates that an organization with AI capability will be more creative. According to our results, we found this hypothesis to be significant. This finding is consistent with Mikalef and Gupta [1], who found that AIC positively enhances OC. Similarly, Almheiri et al. [5] found that AI capabilities positively affect dynamic capabilities, creativity, and performance. This supports our finding that advanced AI capabilities boost organizational creativity, which is essential for innovation and maintaining a competitive edge. H2: AIC can positively enhance GI. This aligns with the findings of Chun and Hwang [63] and Ying and Jin [73]. H3: Organizations' AIC positively influences SP. Results indicate this hypothesis is statistically significant. These findings are consistent with earlier research [1,5,14]. This finding demonstrates how AI-capable companies can foster GI, boost OC, and enhance SP by using data-driven insights to predict environmental impacts, optimize resource use, and simplify procedures to increase productivity.

The results of Hypotheses H4 and H5 offer an answer to the second research question. H4 proposes that OC mediates the relationship between AIC and sustainable performance. Similarly, H5 anticipated that GI mediates the relationship between AIC and SP. According to the results, both hypotheses are significant. These results align with the prior studies [1,9,14,74]. For instance, Mikalef and Gupta [1] demonstrated that AI capabilities enhance organizational creativity, which in turn contributes to better performance outcomes. This implies that green innovation and organizational creativity help to balance AIC with SP. Particularly, AIC promotes OC, which increases the standards for long-term success. In a similar line, the ability of AI to foster GI results in more SP.

As the last research question, we wanted to explore the moderating role of KNC, proposing Hypotheses H6–H8. H7 suggested that KNC moderates the relationship between AI capability and GI. H8 suggested that KNC moderates the relationship between AIC and SP. Results suggest that KCN strengthens this relationship. This means that when there is a knowledge sharing culture, the influence of AI capability on OC, GI, and SP is stronger. This new concept aligns with the findings of previous studies [2,54,56,57]. It follows that companies with an information-sharing culture and the ability to apply AI will be better able to employ AI to boost organizational creativity, efficiency, and sustainability in innovation.

6. Conclusions

This study sought to address several research gaps by demonstrating the impact of AI capabilities on GI, OC, and long-term success, particularly in Bangladesh. The research highlights that the incorporation of AI can significantly enhance green innovation and creative processes within businesses. Furthermore, it emphasizes the importance of cultivating a culture that encourages knowledge exchange in order to achieve these outcomes. The study employs a second-order framework to offer a novel and comprehensive analysis, thereby improving our theoretical understanding. In essence, these findings provide practical advice for managers to effectively deploy artificial intelligence and for legislators to create favorable conditions that encourage AI adoption and information sharing. This research contributes to the existing information and offers crucial guidance for both implementing in organizations and formulating policies.

6.1. Theoretical Contribution

This work significantly contributes to the theory by filling in several research gaps. By looking at the impact of artificial intelligence abilities on environmentally friendly innovation in a specific context, such as Bangladesh, a developing country, this paper increases the present body of knowledge. Previous research has paid little attention to this specific topic. The paper also looks at the effects of AIC on OC and SP, which has received little scholarly attention. We gain a deeper understanding of these interactions by examining the intermediate roles of GI and OC. Furthermore, the study highlights the moderating effect of a KNC, a topic that has received less attention in previous studies. Investigating these relationships through a second-order paradigm offers a fresh analytical viewpoint and a more comprehensive understanding. The study aims to provide a comprehensive understanding of how AIC impacts organizational outcomes. This theoretical contribution clarifies the complex interplay among proposed variables and lays a foundation for the next studies in these fields.

6.2. Practical Implications

From a practical perspective, the findings of this study offer several actionable insights for Bangladesh to enhance sustainable performance through AI capabilities. AI technology and resources can improve operational efficiency and organizational creativity and innovation; thus, enterprises should prioritize them. Managers can gain valuable insights from this study, providing them with practical guidance on effectively utilizing AI to drive innovation and improve performance. Managers can use the findings to implement AI solutions that promote environmentally friendly innovation and foster creativity among their workforce. Furthermore, cultivating a climate of knowledge sharing can enhance collaboration and strengthen these goals, leading to a more innovative and sustainable organization.

The study emphasizes the importance of policymakers endorsing AI adoption and promoting policies that encourage environmentally friendly innovation and creativity. Implementing measures that promote AI technology accessibility and knowledge sharing can improve a company's long-term viability and competitive advantage. Directing attention towards these specific sectors can help policymakers achieve greater economic and environmental gains. By implementing these strategies, Bangladesh can leverage AI capabilities to enhance creativity, drive green innovation, and achieve improved sustainable performance.

6.3. Limitations and Future Research Directions

One potential limitation of this study is the sample size and its representativeness. This sample may not fully capture the diversity across different industries and regions, potentially limiting the generalizability of the findings. Additionally, the adoption of AI tools in Bangladesh remains limited, with few organizations currently utilizing these technologies and employees having minimal experience. This uneven distribution may impact the findings and their applicability across organizations with different levels of AI integration. To improve generalizability, future research should involve a larger, more diverse sample across various sectors and regions and account for differing degrees of AI adoption. Moreover, the cross-sectional nature of the study provides a snapshot in time but does not account for the evolution of AIC, OC, GI, and SP over time. Longitudinal studies could offer valuable insights into how these variables interact and change over time.

Another limitation is related to cultural and contextual factors specific to Bangladesh, which may not be applicable to other developing countries. Comparative studies involving multiple developing nations could help identify context-specific factors and allow for broader generalizations. The reliance on self-reported data also introduces potential biases, such as social desirability or inaccurate self-assessment. Future research could incorporate objective measures or secondary data to validate self-reported findings and provide a more comprehensive perspective.

Moreover, while this study focuses on OC and GI as mediators and KNC as a moderator, it may overlook other relevant factors that could influence the relationships between AIC, OC, GI, and SP. Exploring additional mediators or moderators, such as organizational structure or leadership styles, could yield a more nuanced understanding of these dynamics.

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Abbreviations

AIC	Artificial intelligence capability
OC	Organizational creativity
GI	Green innovation

SP	Sustainable performance
KNC	Knowledge sharing culture
RBV	Resource-based view
SEM	Structural equation modeling
EFA	Exploratory factor analysis
CFA	Confirmatory factor analysis
CMV	Common method variance
CR	Composite reliability
AVE	Average variance extracted
VIF	Variance inflation Factor
X^2/df	Chi-square divided by degrees of freedom
GFI	Goodness of fit index
AGFI	Adjusted goodness of fit index
CFI	Comparative fit index
TLI	Tucker–Lewis index
IFI	Incremental fit index
NFI	Normed fit index
RMSEA	Root mean square error of approximation
PClose	*p*-value for RMSEA

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