Scientific Research Publishing

Open Journal of Business and Management, 2026, 14(4), 2178-2195
https://www.scirp.org/journal/ojbm
ISSN Online: 2329-3292
ISSN Print: 2329-3284

Creating Value in Micro, Small, and Medium-Sized Enterprises: The Role of Artificial Intelligence

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How to cite this paper: Kwuyah, E., & Pitti, H. (2026). Creating Value in Micro, Small, and Medium-Sized Enterprises: The Role of Artificial Intelligence. *Open Journal of Business and Management, 14,* 2178-2195.
https://doi.org/10.4236/ojbm.2026.144114

Received: May 26, 2026
Accepted: July 17, 2026
Published: July 20, 2026

Abstract

This research investigates the effect of artificial intelligence on value creation in MSMEs, considering the mediating roles of database use, task automation, and transaction digitization. Data were collected via questionnaires from 514 respondents from the same number of companies. They were subjected to exploratory factor analysis, confirmatory factor analysis, and structural equation modeling. The results reveal a direct positive effect of artificial intelligence on value creation and indirect positive effects via task automation and database use on value creation. A positive effect on transaction digitization is also observed, but digitization itself has no positive effect on value creation. The use of these three mediating variables constitutes the originality of the work, even though task digitization does not play this role.

Keywords

Task Automation, Value Creation, Artificial Intelligence, Transaction Digitization, Databases

1. Introduction

The issue of value creation is attracting growing interest both professionally and academically. On the professional side, it remains a credo for business leaders (Lefaix-Durand et al., 2006). Academically, research covers strategic management, corporate finance, accounting, marketing, etc. (Beulque et al., 2023). This growing interest from researchers has led to multiple publications (Zouhri, 2019; Charlin, 2017; Mazzucchi, 2018; Beulque et al., 2023). Two types of value are distinguished: financial value (for shareholders) and perceived value (for the customer). Jobin and Friel (2000) specify that this implicitly refers to value creation for shareholders and explicitly for other stakeholders.

Value creation for the customer translates into a set of qualities that the company possesses in the customer's eyes (Babei & Paché, 2015). To this end, the company must develop strategies to ensure maximum value for the customer to guarantee remuneration for all stakeholders through repeat purchases. According to Ndemo & Mkalala (2023), work organization is increasingly influenced by artificial intelligence (AI). It facilitates customer data collection, a fundamental aspect of the decision-making process. With the internet, the development of smartphones, and connected devices, the mass of collected data is becoming increasingly large, consequently making traditional statistical analysis tools unsuitable (Ndemo & Mkalama, 2023). AI solves this problem by offering companies real opportunities (finer customer segmentation, more advanced cost optimization, technological monitoring, etc.) and creating disruptive innovation (Zouhri, 2019). With the development of AI, future bankruptcies will no longer necessarily be linked to management problems, but to companies' reluctance to embrace disruptive innovations (Véry & Cailluet, 2019). The authors specify that these innovations will provide companies that adopt them with competitive advantages through better predictive capacity and value creation.

Debates on the substitutability and complementarity of AI with human work remain current. Some consider AI the cause of the elimination of human work within companies in favor of robots (Susskind & Susskind, 2015; Su & Togay, 2019). Others, however, recognize many virtues in AI (Morikawa, 2016; Sinapin, 2020). It offers humans the possibility of shedding tasks that can be automated and focusing on those with high added value. With AI, humans are responsible for integrating complexity, intuition, emotional and relational dimensions, as well as making intelligent decisions adapted to the culture, context, and DNA of the organization (Véry & Cailluet, 2019). Proponents of this thesis consider AI as a resource for value creation.

Our research falls within this perspective and aims to show, first, that AI can be considered a powerful lever for value creation in MSMEs because it allows a better understanding of resource theory (Penrose, 1959; Barney, 1991) and the combination of resources and competencies (Prahalad & Hamel, 1990). Next, we support the idea that value creation via AI in these entities depends on the perception of AI by key actors (opportunistic/risk-averse) (Espinasse, 1990; Chen et al., 2009). In this article, our main objective is to study the effect of AI on value creation in MSMEs by considering the specific mediating effects of task automation, database use, and transaction digitization. To our knowledge, very little research has focused on the effect of AI on these variables, nor on the simultaneous effects of these variables on value creation.

First, the theoretical framework is presented, research hypotheses are established, and a conceptual model is generated. Subsequently, we detail the research methodology and present the results arising from testing the formulated hypotheses. Finally, a study of theoretical and managerial impacts is carried out, while highlighting constraints and perspectives for future research

2. Theoretical and Conceptual Framework

2.1. Theoretical Framework

In management, a company can be perceived as a series of product-market pairs (Ansoff, 1965; cite by Mintzberg, 1991), a set of linked activities within a value chain (Porter, 1985). According to the resource-based view, a company is defined "by what it is capable of doing" (Grant, 1991: p. 116). MSMEs are a kind of articulation of the supply system and a set of services that depend on the use of the resources they have. "By resource, we mean anything that can be conceived as a strength or weakness of a given firm. More formally, a firm's resources at time can be defined as assets (tangible or intangible) semi-permanently associated with the firm" (Wernerfelt, 1984). To create value, MSMEs use resources such as AI, which constitutes a strength or a weakness. Indeed, a better use of AI makes it an asset for value creation. This value creation can only be ensured by building general competencies (coordination and decision-making processes, incentives, etc.) and operational competencies (specialized, individual knowledge) (Grant, 1996) that will enable the construction and use of databases, task automation, and transaction digitization.

Core competencies are the collective learning of the company, particularly concerning the coordination of productive know-how (specialized and individual) and the integration of multiple technology streams (Prahalad & Hamel, 1990). This is necessary for optimal use of AI. Know-how and competencies must coagulate around individuals with widely diversified efforts to recognize opportunities to merge their experiences with those of others in a relevant and profitable manner (Prahalad & Hamel, 1990). AI as a resource must produce the expected results when learning occupies an important place. Indeed, learning is a source of competence for the actors and the organization itself and ensures good use of databases, task digitization, etc. Thus, value creation via AI involves building competencies that enable the design and use of databases, task automation, and transaction digitization.

2.2. Conceptual Framework

Artificial intelligence: A concept used since the 1990s, AI intervenes in many fields. In the healthcare field, AI deployment disrupts individuals, organizations, and systems, notably through major ethical challenges (Choukhi & Habib, 2025). It can identify tumors, predict cancer progression, and help decipher different genome mutations (Leung et al., 2014). No universally accepted definition of AI has yet been found. According to Véry & Cailluet (2019), AI is defined as all machines and/or algorithms that learn from their own experience and have the ability to execute tasks performed by human beings by imitating cognitive processes specific to humans. This definition has a major flaw. It does not consider the various schools of thought on this subject. Some researchers believe that AI will one day make it possible to develop autonomous conscious machines, with emotions, even humanoids (Leduc, 2017). Others remain pragmatic and believe that we should just standardize and reproduce routine tasks generally performed by humans (Véry & Cailluet, 2019). It is important to specify that the rise of AI is accepted by all. Facts such as the manufacture of computers capable of processing large databases or performing facial recognition sometimes better than humans attest to this. Véry & Cailluet (2019) summarize AI into four main tasks: "machine learning", "reinforcement learning", "deep learning", and "natural language processing". Ultimately, we can say that AI constitutes a set of methods and technologies that enable task automation to reduce costs, save time, and create value.

Value creation: A concept with multiple meanings, it is the evaluation by the market and potential customers regarding the usefulness of the services offered by the company to meet specific requirements (Lorino, 1995). Value creation within a company can occur at different levels. Internally, the combination of resources can generate value; while externally in the market, the positioning strategy can also generate value (Porter, 1985). Value generation involves optimizing the efficiency of value-added tasks; they directly participate in customer well-being and contribute to the distinction of the offer, thus forming the core activity of the company (Porter, 1985). Thus, value creation involves a transformation of the perceived value of the company's products and a reduction in expenses. To succeed, it is essential to effectively manage several types of activities: primary, support, value-added, and non-value-added activities (Porter, 1985). According to Iselin (2009), value creation is understood by: 1) Value only exists relative to a competing offer. 2) Value is constantly perceived and relative. According to Mack (2003), this value is generated by the company establishing a mechanism that encourages and incites the customer to seek, recognize, and appreciate the company's offer. Value creation can also be based on 4 axes: economic value, socio-environmental value (Mack, 2003), and innovation (Grama-Vigouroux & Royer, 2020). This method seems more appropriate to us.

Task automation: The evolution of digital technology leads to a change in the content of professions (Le Ru, 2016). Efficiency and productivity are increased through the automation of manual tasks (Ndemo & Mkalama, 2023). Besides saving time, the reproducibility of the implementation process ensures a result when automating tasks. Task automation leads to a portion of the work being done by machines (Le Ru, 2016). Thus, employees focus on activities where they have a comparative advantage over machines, which induces a kind of complementarity between humans and machines. When a company undertakes to automate its production chain or its various tasks, its main objective is to improve its productivity. These productivity improvements can lead to cost reductions, wage increases, increased profits, a fraction of which will be reinvested (Le Ru, 2016). Automation reduces the worker's cognitive load while guaranteeing increased productivity.

Databases: Also called data warehouses, these are structured files cataloged according to chronology, logic, etc., for the purpose of managing or making decisions of varying importance (Ndemo & Mkalama, 2023). This definition does not consider the importance of consistency and integration between fundamental data. Furthermore, databases can be based on primary or secondary documents (Bourdon et al., 1994). A database can be defined as a set of organized, integrated, and shared information necessary for the operation of a company, stored on a permanent medium and managed by software. According to Espinasse & Mantha (1986), building a database takes place in three phases: examining the real system to be modeled, structuring the model for its incorporation into a management system, and the actual implementation of the structures intended to host the data in that system. These relational databases are generally used to ensure effective customer follow-up and pave the way for promising possibilities for developing new relational instruments (Espinasse & Mantha, 1986).

Transaction digitization: A practice that allows for an improved experience within organizations (Ndemo & Mkalama, 2023), it is the act of converting information from an analog to a digital format. This definition presents digitization as a lever for agility and value creation. It involves empowering certain practices through a collaborative digital culture. It offers convenience, efficiency, and security (Ndemo & Mkalama, 2023), discourages corruption in some cases while facilitating inclusion (Jafri, 2021). The integration of digital technologies into companies reduces costs, facilitates transactions, and reduces working time. For this work, transaction digitization is the action of converting transactions (information exchanges) from analog to digital format.

MSMEs: Proposing a unified definition for these entities is complex. Each country has its own particularities. In Cameroon, Law No. 2010/001 of April 13, 2010, identifies two distinct parameters that define them: number of employees and annual turnover excluding taxes (see **Table 1**). Various influences on the functioning of MSMEs in Cameroon are observed. This characteristic could be explained by the establishment of humanist ideals (the "Ubuntu" philosophy) in these structures (Biwolé-Fouda & Causse, 2022). This class of companies operates with limited resources. It is flexible both in human resource and marketing management (Biwolé-Fouda & Causse, 2022) and in information and communication technology management (Moungou & Niyonsaba, 2015), not to mention AI. These characteristics correspond to the effectual logics specific to this type of company (Biwolé-Fouda & Causse, 2022).

Table 1. Characteristics of MS, MEs in Cameroon.

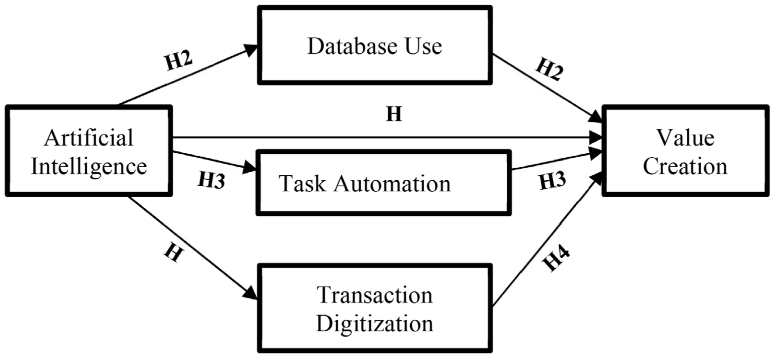
Classification	Number of Permanent Employees	Annual Turnover Excluding Taxes in millions of FCFA
Very Small Enterprise (VSE)	[1 - 5]	≤15 millions
Small Enterprise (SE)	[6 - 20]	>15 million and ≤100 million
Medium Enterprise (ME)	[21 - 100]	>100 million and ≤1 milliard

Source: Moungou & Niyonsaba (2015).

3. Research Model and Hypotheses

3.1. Research Model

The model (Figure 1) will highlight the various relationships.



Notes: Mediation effect of task automation and information (H2+) = H2a+ × H2b+; Mediation effect of large-scale database use (H3+) = H3a+ × H3b+; Mediation effect of transaction digitization (H4+) = H4a+ × H4b+.

Figure 1. Research model.

3.2. Direct Effect of AI on Value Creation

According to the work of Morikawa (2016), conducted with 3000 Japanese companies, AI is perceived more favorably and positively influences performance. It contributes positively to improving productivity, expanding the potential of these organizations, and spreading innovations. The author highlights a complementarity between artificial intelligence and the skill level of employees. This indicates that the acceleration of technological progress and its AI-based propagation require an updating of human skills. According to Su & Togay (2019), the emergence of AI could considerably reduce human tasks in skilled professions. This circumstance can lead to a decrease in job qualifications and the replacement of competent staff with less qualified employees to perform certain tasks that remain unplanned due to their elementary nature (Su & Togay, 2019). Thus, low-skilled or unskilled individuals may fill these positions. Professional definitions could gradually evolve due to a constant overlap of tasks between different existing qualification levels (Su & Togay, 2019). For example, in the medical image analysis sector, AI facilitates diagnosis by less qualified individuals, thus reducing the need for specialists.

The combinations of human actions and AI capabilities can only be enriching (Frimousse & Peretti, 2019), and the potential AI offers companies in value creation is undeniable. Indeed, it facilitates learning and organization for actors, is a resource for creating value, and accelerates processes through routines. Hence, adaptation to a crisis-prone and turbulent environment (Zouinar, 2020; Cameroon Association of Economists and Managers, 2025). AI gives companies the keys to better understand and manage customer expectations; today, many companies use it in customer support services (Frimousse & Peretti, 2019). According to these same authors, the use of AI allows the deployment of skills on high-value-added projects or processes, improvement in the quality of services rendered to customers, optimization of the most structured and routine actions, and processing of the most basic questions. We can thus formulate the following hypothesis 1: Hypothesis 1: AI has a positive influence on value creation.

3.3. Indirect Effect of AI on Value Creation

AI is of great importance in the pharmaceutical sector, used as a means of innovation, and more than 200 companies are conducting studies to discover new therapeutic compounds (Isaac, 2020). Molecule discovery generates added value. The study by Susskind & Susskind (2015) highlights the potential emergence of a new employment system ("paraprofessional"), where all specialists could gradually be substituted by less qualified individuals, armed with intelligent systems to perform high-value-added tasks. The impact of AI on the labor market is still little discussed today (Susskind & Susskind, 2015). Indeed, its advancement could lead to job insecurity for skilled workers. Professions requiring highly skilled workers can be subdivided into simple tasks executed by AI. According to Espinasse (1990), AI presents promising opportunities in various fields such as: assistance in problem-solving, deduction of models to solve them, creation and development of databases, etc. Results from highly formalized systems are based on databases (Espinasse, 1990) produced by AIs. Robust databases are the foundation on which solid mathematical models rest. The larger the database, the more stable the model and the lower the probability of errors during analysis compared to "traditional arguments and analyses". Indeed, a notable difference exists between Boolean logic and natural reasoning (Borel et al., 1983). Consequently, hypothesis 2 can be formulated as follows:

Hypothesis 2: AI influences database use (H2a), which in turn positively influences value creation (H2b).

Sinapin (2020) examines various AI applications and their benefits. The conclusions of this study demonstrate that AI represents knowledge engineering, a sophisticated process that allows solving multiple problems, thus offering a change of perspective for managers on their environment, helping to better understand sometimes more complex situations for human intelligence and simplifying decision-making. According to the latter, AI promotes optimization of experience, company flexibility, resource sharing, and generates efficiency. From a financial perspective, the possibilities linked to AI are numerous; it promotes the improvement of certain activities such as process and data automation, optimizing financial analysis, credit approval process management, information systems, anti-money laundering, as well as various operational and customer interaction processes and systems (Carpinella et al., 2017). Thus, AI influences various factors of the financial system and promotes indirect value generation by optimizing all the previously mentioned elements; AI creates value through automation. Thus, we can posit the following hypothesis 3:

Hypothesis 3: AI has a positive influence on task automation (H3a), which in turn positively influences value creation (H3b).

Chen et al. (2009) suggest that AI could have much smaller effects on value creation. The overall economic impact of AI from 2016 to 2026 should be between 1.5 and 3 trillion dollars, or about 0.15% to 0.3% of global GDP. According to the author, such a result is facilitated by the digitization of transactions, which allows service companies to acquire significant time savings. AI can contribute to value creation through transaction digitization, but it can also encounter problems such as: data loss caused by infectious viruses, data degradation, etc. (Zouhri, 2019). This requires ongoing training for AI users. The latter are primarily confronted with risks of data loss and viral infections. We can therefore state hypothesis 4 as follows:

Hypothesis 4: AI influences transaction digitization (H4a), which in turn positively influences value creation (H4b).

4. Research Methodology

4.1. Data Collection and Sampling

Once the model and hypotheses were established, we proceeded to data collection, analysis, and presentation of results. 700 questionnaires were distributed to Cameroonian micro, small, and medium-sized enterprises (MSMEs). Of this number, 566 were returned, of which 403 were usable after checking for completeness and consistency of responses. At the same time, 111 questionnaires were collected online via an electronic form. The final sample thus consists of 514 distinct companies, each response corresponding to a unique entity. The final sample comprises 514 companies, varied by size, sector of activity, turnover, etc., as well as their characteristics (see **Table 2** and **Table 3**). We retained only one respondent per company in order to ensure the consistency of the collected data and to avoid duplicates. Although the majority of respondents belong to the management team, some non-managerial employees also participated. Their inclusion is justified by their operational knowledge of the company's daily practices, particularly regarding the use of artificial intelligence. These employees were directly involved in digital processes (databases, automation, dematerialized transactions) and therefore had better knowledge to respond to the questionnaire. Data collection was carried out in several urban areas (Douala, Yaoundé, and Bafoussam) and the rest took place online in various regions where MSEs are active.

Table 2. Sectoral distribution of the study sample by validated questionnaires.

Branch of Activity	Absolute Frequency %	Relative Frequency %
Agrifood Industries	38	7.39
Commerce	147	28.60
Accommodation	26	5.05
Manufacturing Industries	51	9.92

Continued

Financial Institutions (savings and credit cooperatives, insurance)	77	14.99
Training	18	3.50
Other services (transport, IT, freight forwarding, money transfer boxes, etc.)	157	30.54
Total	**514**	**100**

Source: Authors.

Table 3. Characteristics of respondents.

Variables	Categories	Frequency	Percentage (%)
Gender	Male	284	55.25
	Female	230	44.75
Age	≤25 years	86	16.73
	26 - 34 years	98	19.06
	35 - 49 years	237	46.10
	≥49 years	93	18.09
Position held in the MS/ME	Member of management team	396	77.04
	Other employees	118	22.95
Nationality	Cameroonian	476	92.60
	Non-Cameroonian	38	07.39
Education Level	≤High school	40	7.78
	GCE	131	25.48
	Bachelor's	133	25.87
	Master's	123	23.92
	≥Master's degree	87	16.92

4.2. Measurement of Variables

The work of Véry and Cailluet (2019) and Ndong Ntah (2004) produced the 7 items related to AI. The scale used for task automation was developed from research by Carpinella et al. (2017), incorporating some elements from the work of Ndong Ntah (2004). These elements are more appropriate as they were carried out in the Cameroonian context. Database implementation and transaction digitization were based on research by Mateu & Pluchart (2019). It comprises 5 items, as does transaction recording, which also has 5. To capture value creation, we modified and adjusted the scale developed by Mack (2003). It integrates three components (economic, socio-environmental, and innovation). In total, 8 items were selected (see **Table 4**).

Table 4. List of items used.

Code	Concepts_Measurement Items_Source
	Artificial Intelligence: [Scale adapted from Véry & Cailluet (2019)].
INTAR 1	I automate certain tasks within the company using artificial intelligence.
INTAR 2	I automatically send personalized messages on a large scale to various clients.
INTAR 3	An electronic time clock is used to validate employees' arrival and departure times.
INTAR 4	Customer relationship management is automated in your company.
INTAR 5	I automate responses to customer calls.
INTAR 6	We allow clients to access the company's product via phone or computer.
INTAR 7	Employees use instant messaging to improve the quality of their work..
	Task Automation: [Scale adapted from Ndong Ntah (2004) & Carpinella et al. (2017)].
AUTOT 1	I have automated my cash register operation.
AUTOT 2	Supplier payments are automated and processed via connected devices.
AUTOT 3	Incoming and outgoing merchandise control is automated (using barcodes).
AUTOT 4	Staff arrival and departure times are monitored by an automated system (an application).
AUTOT 5	My company's security is ensured by a computer system.
AUTOT 6	Our data is protected by specialized software**.**
	Database usage: [Scale adapted from Mateu & Pluchart (2019)].
UBADO 1	Software (Excel, for example) is used to manage company data.
UBADO 2	I have customer data on one or more devices (phone or computer).
UBADO 3	I update my customer and prospect lists.
UBADO 4	I use my prospect database for field and telephone follow-ups.
UBADO 5	The company's products, their various prices, and margins are listed in a file.
	Transaction digitization: [Scale derived from the recommendations of Mateu & Pluchart (2019)].
NUTAC 1	Electronic payments (e.g., MOMO) are accepted in our company.
NUTAC 2	Our interactions with customers and suppliers are increasingly conducted via connected devices.
NUTAC 3	Business documents are digitized and stored on a platform accessible to all.
NUTAC 4	My company's production units are connected to computers and can be programmed.
NUTAC 5	Word processing, design, and sales territory allocation software are used.

Continued

	Value Creation: [Scale adapted from Grama-Vigouroux & Royer (2020)]
CREVA 1	I believe my company creates value when profits are high.
CREVA 2	When the number of employees and the volume of goods produced by the company increases, this constitutes value creation.
CREVA 3	My company's increased contribution to youth education creates value.
CREVA 4	When the amount of donations offered to communities increases, the company creates value.
CREVA 5	My company creates value when it contributes to environmental protection.
CREVA 6	I create value when my products contribute to the well-being of my community.
CREVA 7	Improving my company's competitiveness creates value.
CREVA 8	Regular innovation within my company is a sign of value creation.

Some items of the "AI" construct describe automated or digitized practices. However, the distinction lies in the level of generality: items related to AI measure the overall integration of intelligent tools within the company (e.g., automated CRM, instant messaging to improve work), whereas the mediators (task automation, transaction digitization) capture specific and operational dimensions of this integration. In other words, AI constitutes the overall resource mobilized, while automation and digitization represent particular mechanisms through which AI influences value creation.

5. Research Results

5.1. Results of Exploratory Factor Analysis

A sample of 514 companies was subjected to Principal Component Analysis (PCA) to control the validity and reliability of the measurement tools. This allowed streamlining the initial items. The scale purification was carried out using Principal Component Analysis with Varimax rotation. Items with factor loadings below 0.5 or cross-loadings were removed (INTAR 4, INTAR 5, AUTOT 1, AUTOT 6, NUTAC 5, CREVA 6). We selected those that are strongly correlated with their factor and display conforming characteristics ($R > 0.5$). The explained variance is also adequate (>60%), allowing the obtaining of structures based on appropriate factors. Cronbach's alpha values ($\alpha > 0.7$) suggest superior internal consistency of the scales. EFA and CFA were conducted on the same sample of 514 companies, whose size ensures sectoral representativeness and the robustness of the results.

5.2. Results of Confirmatory Factor Analysis

We examined the measurement models and estimated the overall model. Good fit with the data is noted according to the following indices: Chi-square = 338.62; df = 95; p-value < 0.00; RMSEA = 0.072; CFI = 0.91; TLI = 0.92; and $\chi^2/df = 3.56$. Internal consistency is satisfactory (Jöreskog's Rho > 0.7). Convergent validity is assessed by examining the robustness and relevance of the factor loadings compared to the Rho value (>0.5). We proved discriminant validity by analyzing the Rho v value and the squared correlations between various constructs (see Table 5).

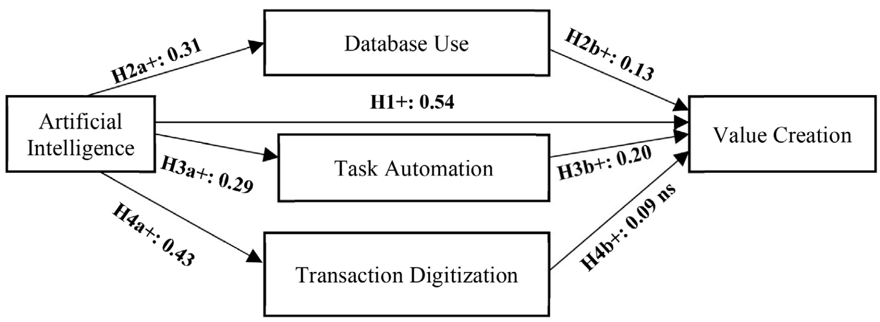
Table 5. Validity of measurement instruments and various fit indices.

Concepts and reliability	Fit-Measurement Items [Khi-deux = 338.62; ddl = 95; $p < 0.00$; RMSEA = 0.072; CFI = 0.92; TLI = 0.91 and $\chi^2/ddl = 3.56$]	Loading stand.[1]	ρvc (AVE)	Corr[2(2)]
Artificial Intelligence (ρ = 0.85)	INTAR 1.	0.79	0.68	0.17
	INTAR 2.	0.89		
	INTAR 3.	0.76		
	INTAR 6.	0.84		
Value Creation (ρ = 0.80)	CREVA 1.	0.83	0.53	0.44
	CREVA 2.	0.80		
	CREVA 3.	0.65		
	CREVA 4.	0.59		
Database Use (ρ = 0.81)	UBADO 1.	0.72	0.55	0.09
	UBADO 2.	0.61		
	UBADO 3.	0.86		
	UBADO 4.	0.76		
	UBADO 5.	0.87		
Task Digitization (ρ = 0.84)	NUTAC 1.	0.89	0.61	0.45
	NUTAC 2.	0.70		
	NUTAC 3.	0.73		
	NUTAC 4.	0.63		

[(1)]All loadings are significant at $p < 0.001$. The overall measurement model was estimated to obtain coefficients and correlations between constructs. [(2)]Discriminant validity is compliant when ρvc is greater than the various observed coefficients.

5.3. Testing the Structural Model

A good fit of the conceptual model to the data is observed, with fit indices: Chi-square = 338.62; df = 95; $p < 0.00$; RMSEA = 0.072; CFI = 0.92; TLI = 0.91; and $\chi^2/df = 3.56$. The direct influence of AI is measured by the t-test value and p-value. According to Figure 2, it is positive and significant ($\gamma = 0.54$; $p < 0.001$). Therefore, hypothesis H1 is confirmed. The analysis of indirect effects (mediation) was carried out using AMOS software and BC bootstrap (1000 bootstraps with a 95% confidence interval), following Diallo et al. (2015). However, with AMOS, one only obtains the p-value associated with the overall indirect effects. Thus, mediation was assessed individually using the Monte Carlo method to test indirect effects. Figure 2 demonstrates that AI positively and significantly influences database use ($\gamma = 0.31$; $p < 0.001$), which in turn has a beneficial effect on value creation ($\gamma = 0.13$; $p < 0.001$). The result of these direct effects ($0.31*0.13 = 0.040$) is significant ($\gamma = 0.040$, $p < 0.001$). This suggests a mediation function by database use. Therefore, hypothesis H2 is confirmed. Furthermore, AI has a beneficial impact on task automation ($\gamma = 0.29$; $p < 0.001$). Task automation also has a positive impact on value creation ($\gamma = 0.20$; $p < 0.001$). The combination of these two factors is significant ($\gamma = 0.058$; $p < 0.001$), demonstrating the existence of a significant indirect impact of AI on value creation (hypothesis H3 confirmed). This is partial mediation, as the direct impact of artificial intelligence on value generation is notable. Figure 2 highlights that AI has a positive impact on transaction digitization ($\gamma = 0.43$; $p < 0.001$). However, this digitization does not have a positive effect on value generation ($\gamma = 0.09$; $p > 0.001$). The interaction of these two influences is not significant ($\gamma = 0.09$; $p > 0.005$). Therefore, hypothesis H4 is rejected.



Notes: ns = non-significant link; $p < 0.01$. Hypotheses tested with non-standardized bootstrap coefficients obtained with Amos: H2 = 0.249*0.169 = 0.042 [0.010; 0.079]; H3 = 0.226*0.269 = 0.060 [0.029; 0.097]; H4 = 0.395*0.073 = 0.029 [−0.09; 0.077].

Figure 2. Hypothesis test results.

6. Discussion, Implications, Limitations, and Future Research Directions

6.1. Discussion and Theorical Implications

The primary result here is highlighting the influence of AI on value creation in MSMEs. Few studies to date have focused on this relationship in this type of organization in a developing country context. Thus, this research has the merit of being among the first to establish this positive and direct link between AI and value creation in MSMEs in the African and specifically Cameroonian context. Previous authors noted the positive effect of artificial intelligence on the performance of large companies (Morikawa, 2016; Nohayla & Bamousse, 2023). This result highlights the importance of AI in value creation within MSMEs. It aligns with the work of Frimousse & Peretti (2019), which presents AI as a means to effectively respond to customer needs or even anticipate their expectations. Also, this work shows the direct effect compared to the total indirect effects leading to value creation in MSMEs. Furthermore, the positive relationship between AI and task digitization, as well as with database use and task automation, validates the importance of AI in MSMEs. One can deduce here both an operational and strategic dimension of AI, which has been very little addressed in management sciences to date (Véry & Cailluet, 2019), particularly in this type of entity. The weaker link between database use and value creation may reflect a non-optimal use of available databases in these companies with very limited resources (Yankson & Aboagye, 1992). This result can be explained by the limitation of resources and competencies in MSMEs necessary for optimal use of AI to produce the expected results (Ndong Ntah, 2004).

It is also observed that task digitization does not influence value creation. Chen et al. (2009), on the other hand, spoke of a weak influence of task digitization on the performance of service companies. This low contribution of task digitization to value creation can be justified by viral attacks, loss of digitized data, etc.

6.2. Managerial Implications

This research highlights the crucial role of AI in value creation within Cameroonian MSMEs. These various results indicate that focus should be placed on AI-related practices that determine value creation. Thus, these companies must explicitly integrate AI as a resource into their strategies. Many studies show that this category of companies has very high mortality rates (Biwolé-Fouda & Causse, 2022). Hence the need to consider AI as a value creation lever. Previous work on value creation focused on the short term and favored operational actions (Lorino, 1995). The latter emphasizes that the use of ordinary management tools, such as accounting, marketing, and logistics, is essential. However, this study highlights that AI is another factor in value generation. We recommend a refocusing of investments on AI in MSMEs beyond old habits that advocate investing in heavy equipment and labor (Lefaix-Durand et al., 2006). Database uses, as well as task digitization and automation, can be improved. Furthermore, three indirect pathways are identified in this work as leading to value creation. However, the results specify that only methods involving database use and task automation are activatable. This implies that value creation in MSMEs primarily involves database use and task automation. Thus, to create value, these entities must rely on database use to implement, for example, a better customer relationship management policy, while automating tasks to save time, increase efficiency, and optimize processes. This is all the clearer as database uses and task automation have positive and significant effects on value creation, respectively. Indeed, to promote value creation in MSMEs, public authorities have an interest in simplifying access to various inputs related to AI use. First, entrepreneurs and managers of this category of companies need to be trained on the potential and benefits of AI for their activities. Train them in creating and using databases, automation (determinants of value creation), etc. Second, organizations responsible for supporting MSMEs must give AI an important place as a vector for value creation. Operationalization of AI practices in these entities must be ensured. Finally, public authorities must facilitate access to tools that allow AI to flourish in MSMEs. For example, reducing the costs of internet access, software acquisition (multiplying freely accessible software while guaranteeing MSME security), etc. Let us not forget that Cameroon lags in digital infrastructure, specialized training, and AI integration into key sectors of its economy (Cameroon Association of Economists and Managers, 2025). It is clear that these actors need resources and competencies for better use of AI to ensure value creation. However, the support plans proposed by public authorities seem less adapted; it would be preferable to let grassroots actors express themselves and establish an adequate environment that would encourage them to move towards a formal sector more favorable to their activities.

6.3. Limitations and Future Research Directions

This work has several limitations, some of which constitute avenues to explore. First, it is based on an empirical sample. As the data are cross-sectional and collected by self-administered questionnaires, a common method bias may exist. In addition, the mediation tested is transversal and does not allow strong causal relationships to be inferred. The results should therefore be interpreted as statistical associations, without allowing strong causal relationships to be asserted. Despite the reliability and validity of our results, it is important to replicate the study with another type of sampling. Also, it could be interesting to classify the MSMEs studied according to the manager's profile or the number of cooperations or joint ventures with other companies/research centers and study the link between the concepts retained in this work according to entrepreneur profiles. Such an approach would better understand the influence of AI on value creation in MSMEs and shed additional light on stakeholder theory and value creation in these organizations. Furthermore, even if our work aims to study the effect of AI on value creation in MSMEs, future work in this direction would benefit from choosing capital structure as a control variable. Indeed, a company created and operating on equity does not face the same realities as those that have built their capital through debt. Moreover, this research focuses essentially on MSMEs in the French-speaking zone of Cameroon. Almost all respondents are French-speaking. However, a comparison between companies from two different cultures (French-speaking versus English-speaking) would have allowed a better understanding of the organizational behaviors of these entities. Thus, the cultural element could reveal new insights. The category of companies studied has characteristics that vary by region of the world. Therefore, this study should be conducted in countries with different contexts.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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