Impact of Big Data and Artificial Intelligence in the management of information systems: A Statistical Study of Key Factors for Improving the Productivity of Industries, Enterprises and Organisations in Cameroon

Patrick Dany Bavoua Kenfack[1], Ludovic Zeh Zeh[2]
[1,2]National Advanced School of Engineering of Yaounde,
The University of Yaounde[1,2]
8390 Yaounde, Cameroon

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Abstract

Big Data and artificial intelligence (AI) are two technologies that, in the Cameroonian context, are struggling to assert themselves due to various factors. However, in the era of Industry 4.0, these technologies appear essential, particularly in the management of information systems and business processes. The main objective of this study was to explore the opportunities offered by Big Data and artificial intelligence to improve business processes and decision-making, while identifying the technical and organizational challenges related to the adoption of these technologies. To achieve this objective, we used, on the one hand, a hypothetico-deductive approach coupled with an exploration of the available literature, and on the other hand, the Partial Least Squares (PLS) regression to test the validity, robustness and predictive nature of the designed model and the formulated hypotheses. The results were obtained based on a sample of 30 companies classified by sector of activity, having respectively the status of SARL, SA, LTD and PLC, revealing that Big Data and AI, although not widespread in Cameroonian companies, have a significant impact on the optimization of decision-making, thus contributing to improving the personnel management, customers and prospects, while fostering the spirit of innovation. Furthermore, the adoption of these technologies is hampered by a large number of factors, including the lack of adequate infrastructure, insufficient good cybersecurity practices, the lack of employee skills and the high cost of training in Big Data and AI, not to mention the lack of real support from the public authorities towards companies; which contributes to accentuating Cameroon's technological backwardness. Based on these results, we have formulated some recommendations for companies and the Cameroonian State.

Keywords: Information system, Big Data, AI, business process, PLS regression, Smart PLS.

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1. Introduction

Despite the implementation of various strategies aimed at stimulating its economic and social development through digital technologies (GEFONA, 2020), Cameroon's technological lag remains very high, particularly in the areas of Big Data and Artificial Intelligence. However, these technologies are becoming almost irreversibly essential to the daily operations of businesses today because they have the unique ability to improve the lives of the individuals and organizations that adopt them (Nguefack P.J and al., 2021). They can thus foster the development and improved management of information systems and resources while facilitating data-driven decision-making. In this context, Cameroonian companies are (in a certain way) compelled to adapt if they wish to play a significant role in the global marketplace, because "the digital revolution [...] invites companies to reorganize in order to fully leverage the business model, the ability to automate processes, while focusing on customer satisfaction. This is one of the reasons why digital transformation must be a major priority for our companies (Tawamba C., 2021).

Given this, the question arises: how can Cameroonian companies leverage Big Data and Artificial Intelligence to improve the management of their information systems and make data-driven decisions? Similarly, what difficulties (internal and/or external) do Cameroonian companies face in adopting these technologies for managing their information systems?

This work will therefore aim to demonstrate, firstly, how adopting Big Data and AI in Cameroonian companies can benefit them, particularly through: optimizing decision-making, developing innovative solutions, services, and products, and improving the management of internal and external resources (personnel, processes, customers, prospects, etc.). Recognizing that such a transformation process cannot occur without obstacles, the second part will highlight all the factors that can hinder the adoption of Big Data and AI technologies in Cameroonian companies, such as: a lack of adequate infrastructure, weak cybersecurity mechanisms, a lack of skills in Big Data and AI, resistance to change, the high cost of implementing these technologies, the absence of clearly defined digital strategies by business leaders, and a lack of genuine support from public authorities.

For better organization of our work, we will subdivide it into 3 main parts: the presentation of the different key concepts allowing us to understand the subject, the working methodology used, and finally the results obtained.

1.1 Definition of Concepts

Understanding the subject of this study requires a grasp of several concepts, including: information systems, data, information, Big Data, and artificial intelligence.

1.1.1 Data

It is difficult to provide a clear and precise definition of the term "data", because data in its broadest sense has neither value nor real importance until it is processed; data is therefore "neither a truth nor a reality" (Borgman, L. C., 2020).
According to Peter Fox and Ray Harris (Peter Fox and Ray Harris, 2013), "Data is generally considered a resource for research"; it is thus becoming an increasingly valued and sought-after resource (AU Data Strategic Framework, February 2022).

1.1.2 Information

Just like data, the term information is difficult to define (Leleu-Merviel S. and al., 2008), (Tchouassi G., 2017). The complexity lies in the fact that information and data are very often confused, and vice versa. Indeed, data is any element at the basis of the creation of information, which means that information only acquires its name when it has definitively moved from the state of raw data (state zero) to the state of a genuine element of communication and decision-making.

Information only acquires its full meaning when it is included in a communication process; because information constitutes the basis of communication within a company (internally and/or externally). Therefore, before being used in a company, information must meet a number of criteria; we also speak of the qualities of good information. through, in particular, the three pillars of "reliability (accuracy and timeliness) – availability (purpose/end users) – relevance (suitability to a specific need)."

1.1.3 The concept of an information system in company

An information system is defined as an organized and structured set of resources (hardware, human resources, data, software, etc.) pooled together to manage (i.e., acquire, store, process, and communicate) information in various forms within a company or organization.

More simply, an information system refers to a set of elements that, when combined, actively contribute to the management and dissemination of information within an organization.

An information system can therefore be seen as a kind of "primary nervous system of the organization", because, in effect, the nervous system allows the rapid circulation of quality information between the different organs of the body, ensuring that this information reaches each organ (at the right time) according to the expressed needs and the objectives to be achieved. Every information system would thus play the same role in a company, contributing to its smooth operation and development.

Talking about information systems means focusing on three interacting subsystems: the decision-making system (which is the head of the company, meaning it sets the objectives to be achieved while controlling the execution of tasks assigned to the operational system), the operational system (responsible for the production of the company's goods and services), and the information system (responsible for processing the information necessary for the company's smooth operation). These subsystems are in constant communication with each other through a process of transmitting and receiving information. This interaction is best illustrated in Figure 1.1.

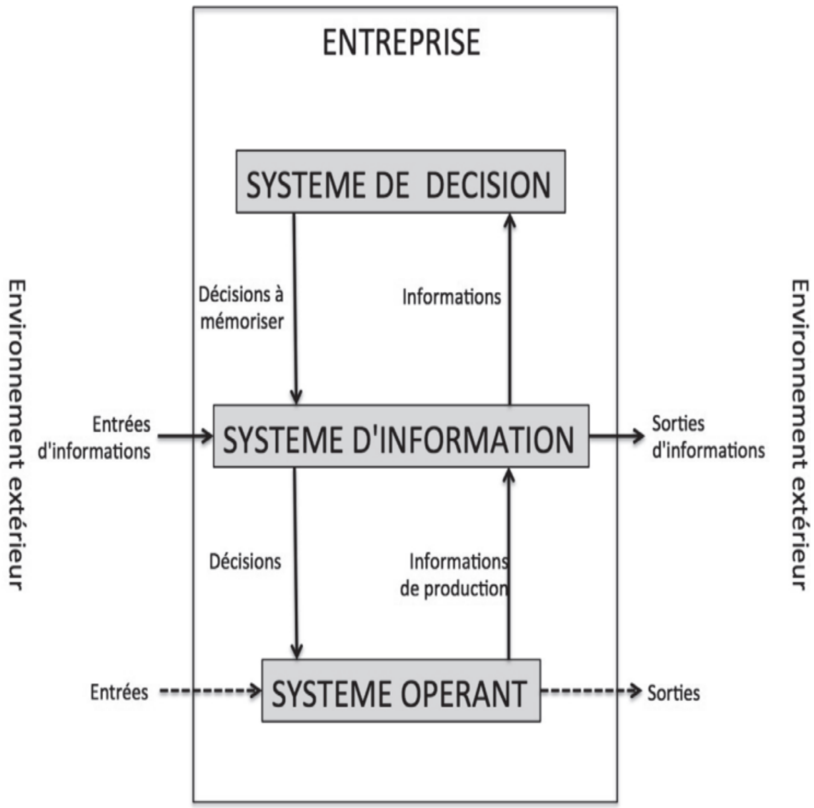

Figure 1.1: Detailed representation of an information system

1.1.4 Big Data

The term Big Data, which appeared around 1997 (Pêcheux, F., 2025), refers to a set of heterogeneous data that cannot be managed and processed by conventional systems (traditional DBMS) because this data is characterized by its very large volume, rapid influx, and extreme variety. Hence the "3V" model: Volume, Velocity, Variety, introduced in 2001 by Doug Laney, which helps to better understand this type of data. (Espinasse, B.and al., 2017), (Bourany, T., 2018).

It should be noted that Big Data, unlike data that can be managed by traditional systems such as DBMS and relational databases (using SQL as the query language), tends to use a different paradigm called NoSQL due to its complexity. Thus, several DBMSs (Database Management Systems) have emerged with the sole purpose of making Big Data processing possible and easy.

As such, there are several types of NoSQL databases, grouped into four main categories; the choice of one or another of these four types of NoSQL databases is made according to the use case:
- Key/Value-oriented DBMSs. Examples: SimpleDB (Amazon), Voldemort (LinkedIn);
Column-oriented DBMSs. Examples: Cassandra (Facebook), Elasticsearch (Elastic);
- Document-oriented DBMSs. Examples: MongoDB (MongoDB), CouchDB (Apache);
- Graph-oriented DBMSs. Examples: FlockDB (X (formerly Twitter)), OrientDB (Apache).

1.1.5 Artificial Intelligence

Artificial intelligence refers to a set of advanced technologies that enable machines (computers, robots, etc.) to simulate the cognitive systems of the human brain, such as perception, analysis, planning, and creativity, with the aim of optimizing business performance.

We can thus distinguish two main types of AI: narrow AI, which encompasses all the forms of AI we use today (generative, predictive, and decision-making), and strong AI (or General AI), whose mission is to develop systems capable of perfectly copying and reproducing the abilities of the human brain; a concept that, at present, remains purely theoretical (Vangrunderbeeck P. and al., 2024), until the advent of the very first systems with such a high level of technology.

Speaking of forms of AI, they are generally grouped into three main categories: generative AI (capable of generating or creating content on demand, autonomously and interactively, such as ChatGPT (Berger R., 2023), predictive AI (capable of forecasting future events based on available data, e.g., IBM Watson Analytics), and decision-making AI (which, far from replacing humans, provides them with a much more informed and detailed perspective on decisions to be made, with record-breaking accuracy, e.g., ChartAI, Findly AI, ClicUp, etc.).

1.1.6 Artificial Intelligence and Big Data: What is the relationship?

While Big Data refers to the storage and processing of large quantities of data, artificial intelligence focuses more on the design of machines with automatic and autonomous learning capabilities, and continuous improvement, with the sole purpose of effectively assisting humans in performing tasks. complex and tedious.

These are therefore two distinct but complementary technologies because massive datasets (Big Data) can now be processed more effectively thanks to intelligent algorithms and programs (i.e., AI). Artificial intelligence, for its part, cannot deliver incredible and satisfying results if it is not fed with data, generally from Big Data: data is therefore at the heart of artificial intelligence.

2. Method

In this section, we will begin by highlighting the existing literature review relevant to our study. We will then identify the factors that contribute to a better understanding of the subject of study, and the other sections will follow progressively.

2.1 Formulation of the Research Question

For this study, we formulated the following research question: What factors allow us to measure the opportunities and challenges related to the adoption of Big Data and AI technologies by Cameroonian companies within the framework of effective information systems management?

2.2 Literature Review

We present the results in a multi-column table (see Table 2.1 below).

Table 2.1: Critical review of literature

Author(s) and year of publication	Objective of the study	Independent variables	Dependent variables	Research Approach	Search results	Limitations of the study
Fosso Wamba, S., Akter and al. (2015)	Examine how big data impacts organizational performance	Data quality, analytical capabilities, IT infrastructure	Chain performance, decision-making, agility	Systematic review + longitudinal case study	Big Data improves agility and performance through analytical capabilities.	Focus on a single case; difficulty in generalizing
Nguefack P.J and al. (2021)	Measuring the effect of new technologies on corporate governance in Cameroon	Use of robotics, security camera, use of video conferencing, networked computers and employees, communication platform, control software, website	Corporate Governance	Quantitative approach (questionnaires administered to 90 companies (PLC and LTD))	New technologies have positive and statistically significant effects not only on the frequency of board meetings but also on the attendance of institutional investors. However, their influence is rather negative and statistically significant on the duration of external audit engagements.	The study focuses primarily on videoconferencing and computer networking, which, to some extent, may exclude other relevant technologies that could influence corporate governance. Similarly, it does not explicitly establish a link between Big Data and AI and the strategic or operational management of information systems.
Belhadi, Kamble, Wamba, Fosso Wamba, Queiroz (2021)	Developing an AI-based framework to strengthen supply chain resilience	Factors in the AI framework (e.g., decision-making quality)	Chain resilience (robustness, adaptability)	Framework design + analytical validation	The AI framework improves resilience under uncertainty	Validation limited to available data; future empirical study needed
Vassileva, J. (2020)	Examine how AI can optimize business decision-making	Data availability and quality, AI methods used, organizational maturity, skills.	Effective decision-making, operational gains.	A mix of theoretical arguments and a review of use cases.	**Opportunities**: AI facilitates optimized decision-making in businesses (e.g., more reliable predictive scores). **Challenges**: Insufficient governance, need to adapt business processes. **Recommendations**: Strengthen data governance, provide training, and implement strategic management.	The study lacks systematic empirical analysis based on a large sample of companies, and provides very little quantitative data to measure the actual impact of AI on decision-making. Furthermore, the study has no connection to Cameroonian companies.
Jean-Sébastien Vayre	Analyse how Big Data helps transform customer relationship management	The "3Vs": Volume, Variety and Speed, mastery of Big Data technologies in business, organizational culture and data-oriented marketing, consumer trust.	Effective customer relations, quality and speed of decision-making, and the company's external reputation.	Theoretical and critical analysis, based on a review of marketing practices and socio-technical developments.	Big Data represents a strategic opportunity to improve decision-making and customer relationship management, anticipate consumer needs and personalize offers based on the data studied, etc.	This study focuses solely on customer relationship management, deliberately ignoring other functions. The study's findings cannot be generalized as it does not consider African companies.

2.3 Identification of Research Factors

In addition to the literature we identified (which proved insufficient), we also started from a general observation: Big Data and Artificial Intelligence in the era of Industry 4.0 are essential technologies that find their place perfectly in so-called modern companies, such as those in Cameroon. By combining these two approaches, we offer a new perspective based on six factors: decision-making factor, human resource and customer relationship management factor, innovation factor, technical factor, organizational factor, and national policy factor. These factors will be used as independent variables, useful and essential for explaining and, above all, understanding the challenges and opportunities arising from the adoption of Big Data and AI in information systems management; this last element (which appears to have a dual nature) will be used as the dependent variable.

2.4 Hypothesis Formulation

Based on the literature review and our personal observations on issues related to the adoption of Big Data/AI in Cameroon, we formulated six hypotheses, numbered H1 to H6.
H1: The adoption of Big Data and Artificial Intelligence in Cameroonian companies can greatly improve decision-making for better management of information systems.
H2: Better management of Human Resources and/or customer relations in companies now requires the combined use of Big Data and Artificial Intelligence.
H3: By adopting Big Data and AI, Cameroonian companies can create innovative products (in all sectors) and better position themselves against the competition.
H4: Technical difficulties, coupled with data protection problems faced by almost all Cameroonian companies, are a major obstacle to the actual implementation of Big Data and AI solutions.
H5: The lack of Big Data/AI skills, resistance to organizational change, the cost of implementing Big Data/AI, and the lack of a clearly defined digital strategy in the Big Data/AI field not only lead to a considerable labor shortage for companies wishing to implement these technologies, but also hinder the adoption of new working methods and/or new technologies.
H6: Cameroonian companies are left to fend for themselves in the face of these new technologies.

2.5 Data Collection

Data was collected through a field survey of 30 companies with the legal status of SA, SARL, LTD, and PLC. The survey consisted of a questionnaire that we designed beforehand using a 5-point Likert scale. This data collection method was justified by the lack of an (online) database highlighting Cameroonian companies using Big Data/AI technologies.

2.6 Data Analysis Methods

Here, we primarily used mathematical data analysis techniques, including PLS regression for designing the structural model, and specific methods to test the effectiveness of this model and the hypotheses made, notably: Cronbach's alpha coefficient, Rho_A, composite reliability, extracted mean variance, the Fornell-Larcker criterion, R^2, adjusted R^2, and blindfolding.

The choice of PLS regression is justified here by the fact that the goal of our study is to measure the effects of the challenges and opportunities related to the adoption of Big Data and AI on information systems management. This is a predictive and exploratory analysis; a type of analysis perfectly suited to the PLS method. Furthermore, this study is based on a small sample size (n=30); PLS regression being very well suited to small samples. In addition, there are latent variables.

2.7 Design of the PLS Model for the Study

For the design of the PLS regression model, we will use the items (indicators) defined in our survey questionnaire. Each indicator will be associated with its corresponding latent variable; an indicator can only be linked to one and only one latent variable. Based on our questionnaire and the research factors identified previously, we formed the following latent blocks: OPD consisting of 3 items (OPD1, OPD2, OPD3), OGRH_OGRC consisting of 4 items (OGRH_OGRC1… OGRH_OGRC4), INN consisting of 3 items (INN1…INN3), DT consisting of 3 items (DT1…DT3), DO consisting of 4 items (DO1…DO4), PN consisting of 2 items (PN1, PN2), and ABI consisting of 3 items (ABI1…ABI3). This led us to the structural model represented in the following Figure 3.1:

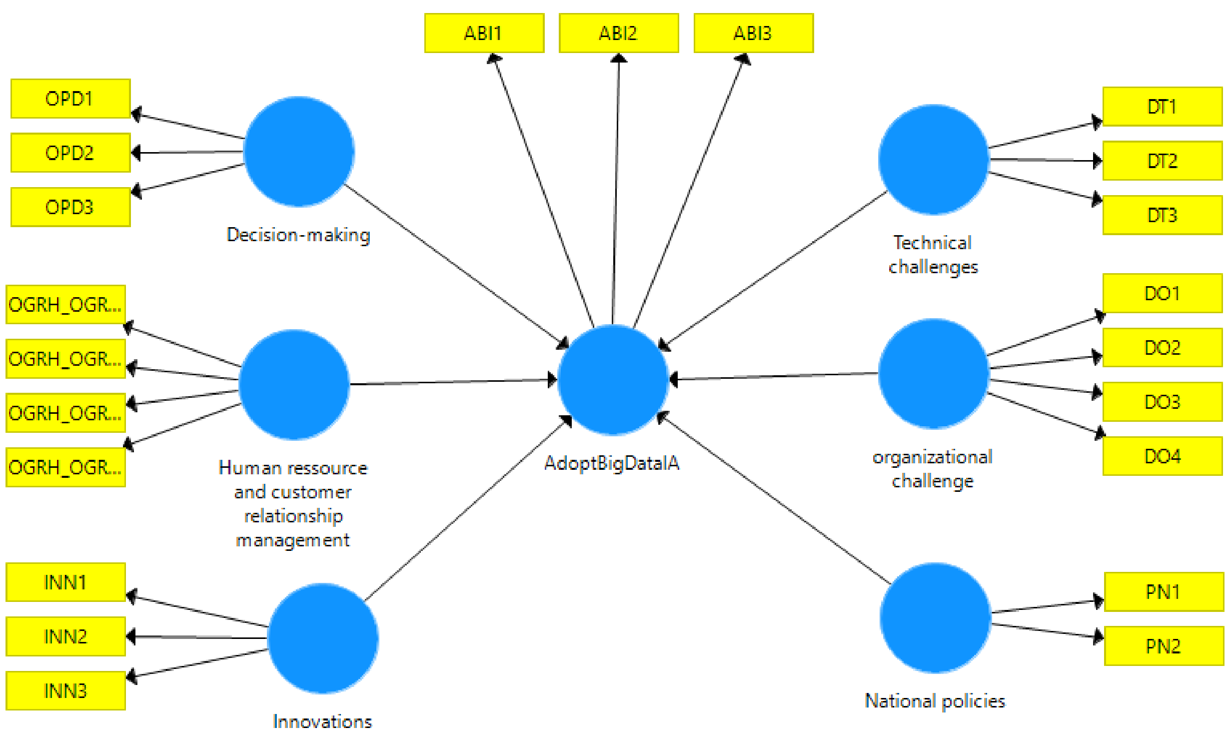

Figure 2. 1: PLS structural model of the study

2.8 Calculation of Cronbach's Alpha coefficient

The calculation of Cronbach's Alpha coefficient can be done using the following formula:

$$\alpha = \frac{N}{N-1}\left(1 - \frac{\sum_{i=1}^{N}\sigma_{Y_i}^2}{\sigma_X^2}\right) \text{ where} \quad (1)$$

- N = Number of items
- σ_X^2 = Variance of total score
- $\sigma_{Y_i}^2$ = Variance of item i.

In our study, we will calculate this coefficient for each item we measured (e.g., OPD1, OPD2, OPD3) for each defined latent variable (e.g., Decision-Making). We thus obtain the following equations:

Example of application to the latent variable OPD

Step 1: Determine the variance of each item: $Var(OPD1), Var(OPD2), Var(OPD3)$

Step 2: Calculate the variance of the total score $Var(OPD1), Var(OPD2), Var(OPD3)$

Step 3: Apply the coefficient formula:

$$\alpha = \frac{3}{3-1}\left(1 - \frac{Var(OPD1) + Var(OPD2) + Var(OPD3)}{Var(OPD1 + OPD2 + OPD3)}\right) \quad (2)$$

The same principle will thus be applied to all other latent variables of the PLS model.

2.9 Calculation of Dijkstra-Henseler Reliability (Rho_A)

Rho_A is a method used in PLS regression to confirm or inform the results returned by the Alpha coefficient. It is obtained using the following formula:

$$\rho A = \frac{\left(\sum_{i=1}^{k}\lambda_i\right)^2}{\left(\sum_{i=1}^{k}\lambda_i\right)^2 + \sum_{i=1}^{k}\sigma_i^2} \quad (3)$$

The Dijkstra-Henseler reliability calculation will therefore be performed in four main steps:

- Calculating of the sum of loadings: $\sum \lambda_i$
- Determination of the square of the sun of loadings: $(\sum \lambda_i)^2$
- Calculation of residual errors: $\sum \sigma_i^2$
- Actual calculation of Rho_A by direct application of the formula stated above.

2.10 Calculation of Composite Reliability

Unlike Cronbach's alpha coefficient, which assumes that all items have the same importance (and therefore equal element loadings), composite reliability takes into account the actual factor loadings of the elements; this is undoubtedly what makes it more precise than the alpha coefficient (fr.statisticseasily.com).
The calculation of composite reliability is possible using the following mathematical formula:

$$CR = \frac{(\Sigma\lambda)^2}{[(\sum\lambda)^2 + \sum(1-\lambda)^2]}$$ Or the following formula: $$CR = \frac{(\sum\lambda_i)^2}{(\sum\lambda_i)^2 + \sum\left(1-\lambda_i^2\right)} \quad (4)$$

Example of application on the latent variable OPD

$$CR = \frac{(OPD_1 + OPD_2 + OPD_3)^2}{(OPD_1 + OPD_2 + OPD_3)^2 + \left[(1-OPD_1{}^2) + (1-OPD_2{}^2) + (1-OPD_3{}^2)\right]} \quad (5)$$

The same principle will be applied to the calculation of all other latent variables.

2.11 Calculation of Convergent Validity (AVE)

This method verifies whether items belonging to the same block actually measure the same latent concept. Indeed, "the evaluation of convergent validity consists of an analysis of the links between the statement-questions and the latent variables, [analysis] based on loadings [...]" (Amora J.T., 2021, pp.1-2). Its formula is defined as follows:

$$AVE = \frac{\sum_{i=1}^{k} \lambda_i^2}{k} \quad (6)$$

λ_i = The factor load of indicator i

k = Total number of indicators in a block

Example of application on the latent variable OPD

$$AVE_{OPD} = \frac{OPD\,1^2 + OPD\,2^2 + OPD\,3^2}{3} \quad (7)$$

2.12 Calculating Discriminant Validity

To determine discriminant validity using the Fornell-Larcker criterion, it is necessary to verify that the square root of the AVE (Average Value of a Latent Variable) of a latent variable is greater than all correlations between that variable and the other variables. The first step is simply to determine the AVE for each latent variable. Next, the square root of each latent variable must be calculated. Finally, the results obtained are compared to determine whether or not there are correlations between the different latent variables in the model. Thus, $\forall\ \xi_i \in \{latent\ variable\}$, and $\forall\ \xi_i \neq \xi_j$ the discriminant validity will be:

$$\sqrt{AVE_{(\xi_i)}} > \left|Corr\left(\xi_i, \xi_j\right)\right| \tag{8}$$

2.13 Calculation of the coefficient of determination (R Square)

The R^2 indicates the extent to which a dependent variable is explained by variations in other variables, known as explanatory or independent variables. It is calculated using the following formula:

$$R^2 = 1 - \frac{\sigma_r^2}{\sigma^2} = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{9}$$

Within the framework of PLS regression, the latent score of the dependent variable Y will be modeled as follows: $\boldsymbol{Y} = \beta_1 \mathrm{X}_1 + \beta_2 \mathrm{X}_2 + \cdots + \beta_k \mathrm{X}_k + \varepsilon$ thus, for our dependent variable

ABI (Adopt Big Data/AI), we will have:

$$\hat{y}_i = \beta_1 \mathrm{OPD1}_i + \beta_2 \mathrm{OPD2}_i + \beta_3 \mathrm{OPD3}_i + \beta_4 OGRH\_OGRC1_i + \cdots + \beta_{18} \mathrm{PN1}_i + \beta_{19} \mathrm{PN2}_i$$

2.14 Calculating the adjusted coefficient of determination (R Square adjusted)

The adjusted R^2 corrects the R^2 by penalizing unnecessary variables; thus, the adjusted R^2 value only increases if the added variable actually improves the model. It is calculated using the following formula:

$$\boldsymbol{R^2_{ajusted}} = 1 - \left(\frac{(1 - R^2)(n-1)}{n-k-1}\right) \tag{10}$$

For our dependent variable ABI, the adjusted R2 will be calculated as follows, directly applying the formula provided above:

$$R^2_{ajusted\ (ABI)} = 1 - \left(\frac{\left(1 - R^2_{ABI}\right)(30-1)}{30-6-1}\right) = 1 - \left(\frac{\left(1 - R^2_{ABI}\right)(29)}{23}\right) \tag{11}$$

2.15 Blindfolding (Stone-Geisser's Q2 estimation)

Blindfolding is a technique specific to PLS regression and used when evaluating the internal predictive capabilities of a PLS model, particularly for dependent or endogenous variables (Stone, 1974; Geisser, 1974). The Q2 can be calculated using the following formula:

$$Q^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2} \tag{12}$$

2.16 The PLS Algorithm

To better observe the results of our study, it is essential to first construct the PLS algorithm. Why?

Note that, generally speaking, "PLS regression allows us to link a set of dependent variables Y={Y_1,…,Y_P} to a set of independent variables X={X_1,…,X_M} when the number of independent and/or dependent variables is high." (Tenenhaus, M., Gauchi, J., Ménardo, C., 1995, p.7). This method is therefore based on the principle of calculating "the weights associated with all the links in the model using an iterative algorithm based on successive estimations of the scores of the latent variables using the observed variables" (Jakobowicz, E., 2019).

In effect, it is impossible to work with PLS regression without the accompanying algorithm, as PLS regression is a statistical method that intrinsically relies on the PLS algorithm to function.

The construction of this regression algorithm is structured in three steps, well explained by (Tenenhaus and al. 2020) in the paper "PLS Regression and Applications" as follows:

- The first step (preparatory step) consists of defining two tables: E_0 and F_0
- The second step consists of constructing a linear combination u_1of the columns of E_0 Maximizing cov(u_(1,) t_1)=cor(u_(1,) t_1)·√(var(u_1)·var(t_1)), allows us to obtain the two variables from the previous equation u_(1)and t_1. These two variables exhibit a strong correlation and thus summarize the tables E_0 et 〖 F〗_0; this allows us to construct the following regressions:

$$\begin{aligned} \boldsymbol{E_0} &= t_1 p'_1 + \boldsymbol{E_1} \\ \boldsymbol{F_0} &= t_1 r'_1 + \boldsymbol{F_1} \end{aligned} \tag{13}$$

- In the third step, we repeat step 1, replacing the previous tables E_0 and F_0 by E_1 and F_1. This operation allows us to obtain two new components: u_2, which is the linear combination of the columns of F_1, and t_2, which is the linear combination of the columns of E_1; from this, we obtain the following regression decompositions:

$$\begin{aligned} \boldsymbol{E_0} &= t_1 p'_1 + t_2 p'_2 + \boldsymbol{E_2} \\ \boldsymbol{F_0} &= t_1 r'_1 + t_2 r'_2 + \boldsymbol{F_2} \end{aligned} \tag{14}$$

The final task of this step is to iterate (repeat) the procedure until the components $t_1, \dots, t_A$ sufficiently explain$\boldsymbol{F_0}$. The components $t_h$are linear combinations of the columns of$\boldsymbol{E_0}$, and are uncorrelated with each other. From the decomposition$\boldsymbol{F_0} = t_1 r'_1 + \cdots + t_h r'_h + \boldsymbol{F_h}$, the deduction of the PLS regression equations therefore leads us to$Y_k = \beta_{kO} + \beta_{k1}X_1 + \cdots \beta_{kM} + X_M F_{hk}$

Using Smart PLS v. 3.2.9 software, the PLS algorithm of the study illustrated in Figure 2.2 will be generated, based on the data (collected in the field during the survey) that we will have provided as inputs into the software (starting from the basic PLS model built previously).

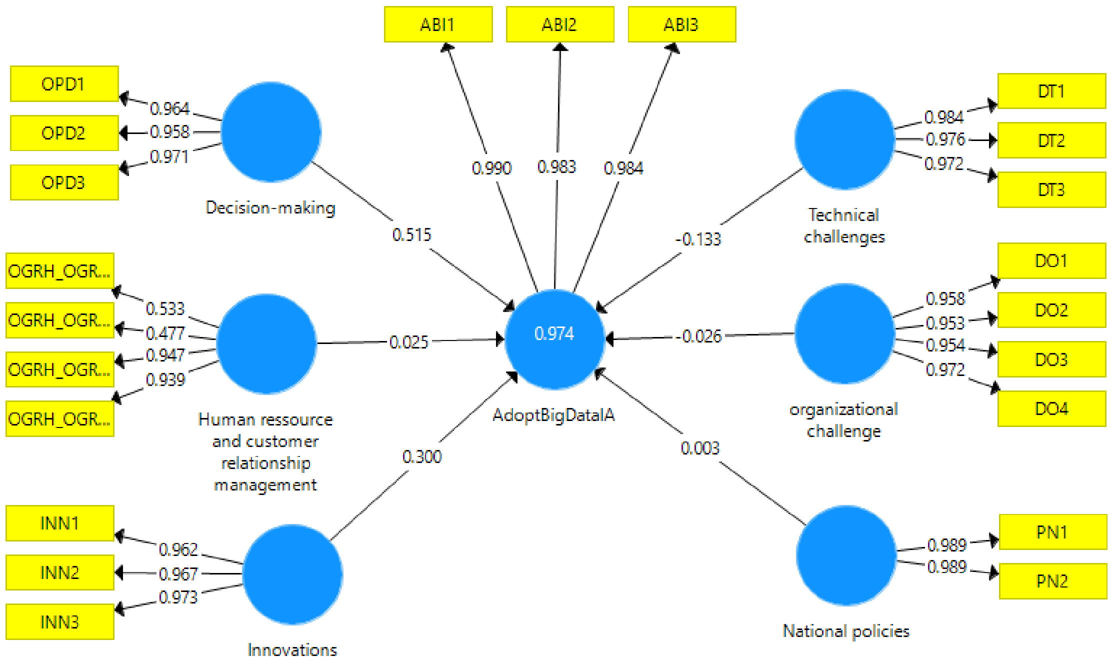

Figure 2.2: PLS algorithm of the study

Based on this, we can now present the results obtained from the calculations performed beforehand. We will present the results of the Alpha coefficient.

2.17 Tools

The tools used in this work mainly concern the software we used to implement various elements. These are primarily Microsoft Excel and Smart PLS.

2.17.1 Description of Microsoft Excel

This software belongs to the spreadsheet family. It allows users to create tables, graphs, perform calculations, etc., and is widely used in data analysis. In our study, we used it to design the questionnaire items and to record the data collected in the field, which was useful for analysis in the Smart PLS software. We primarily used the ProPlus 2021 version of this software.

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2.17.2 Description of SmartPLS Software

Smart PLS is a structural equation modeling software using the Partial Least Squares (PLS) method. Version 3.2.9, which we used in this study, includes several features, among them:
- Generation of partial least squares trajectory modeling algorithms;
- Ordinary least squares regression based on sum scores;
- Importance-performance matrix analysis (IPMA);
- Multigroup analysis (MGA);
- Generation of results reports as Excel or HTML files;
- The ability to export results to the R software, etc.

We used it for designing the PLS model, generating the PLS algorithm, and analyzing the data collected in the field.

3. Results

Here we will present the results of the construct's reliability and validity, discriminant validity, coefficients of determination, blindfolding, and conclude with some recommendations based on the results obtained.

3.1 Construct Reliability and Validity

This section will present the results of the following tests: Cronbach's alpha coefficients, composite reliability, and the AVE. We will begin by presenting the matrix that groups the numerical results of all these tests, and then present the individual graph for each test. The corresponding matrix is shown in Figure 3.1.

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
AdoptBigDataIA	0.985	0.985	0.990	0.971
Decision-making	0.962	0.963	0.975	0.930
Human ressource and ...	0.771	0.945	0.831	0.572
Innovations	0.966	0.966	0.978	0.936
National policies	0.977	0.977	0.988	0.977
Technical challenges	0.976	0.976	0.984	0.955
organizational challen...	0.971	0.971	0.979	0.921

Figure 3. 1: Matrix of reliability and construct validity results

The matrix above presents the results for Cronbach's alpha coefficient, rho_A, composite reliability, and AVE for each variable in our PLS model. We will discuss these results in more detail below.

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3.1.1 Cronbach's Alpha Coefficient

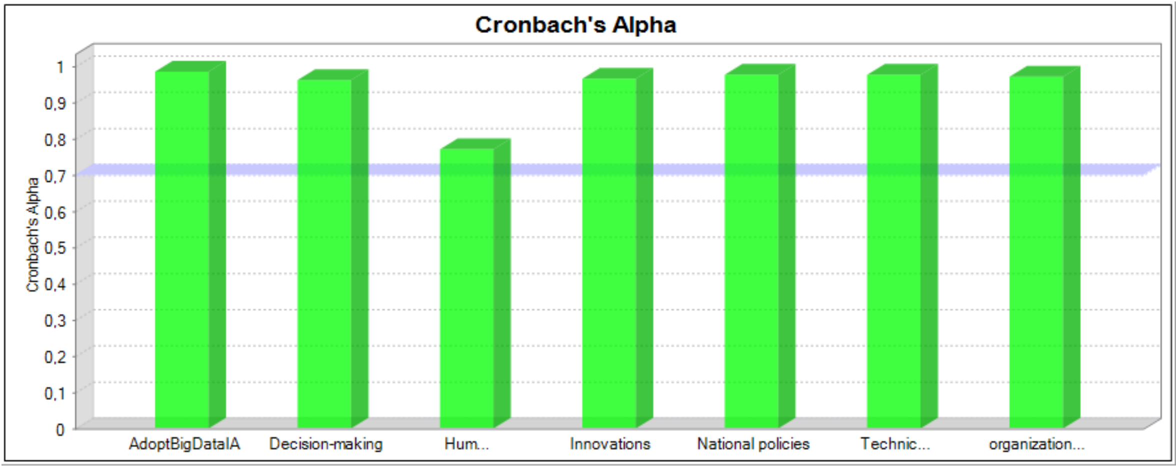

Figure 3. 2: Cronbach Alpha Coefficients Graph

The recommended threshold for validating Cronbach's alpha results is $\alpha \geq 0.70$ (Peterson R.A., 1994). Observing the results of this coefficient in Figure 3.1 and the graph presented in Figure 3.2 above, for each variable in the model, we see that they are all greater than the recommended threshold; this indicates good internal consistency between the items of each latent variable.

3.1.2 Dijkstra-Henseler Reliability (Rho_A)

Similar to the Alpha coefficient, the reference threshold for Dijkstra-Henseler reliability is set at $\rho A \geq 0.70$ for robust reliability (Dijkstra and al., 2015). In our case, the constructs exhibit a score higher than the recommended threshold, as illustrated in Figures 3.1 and 3.3.

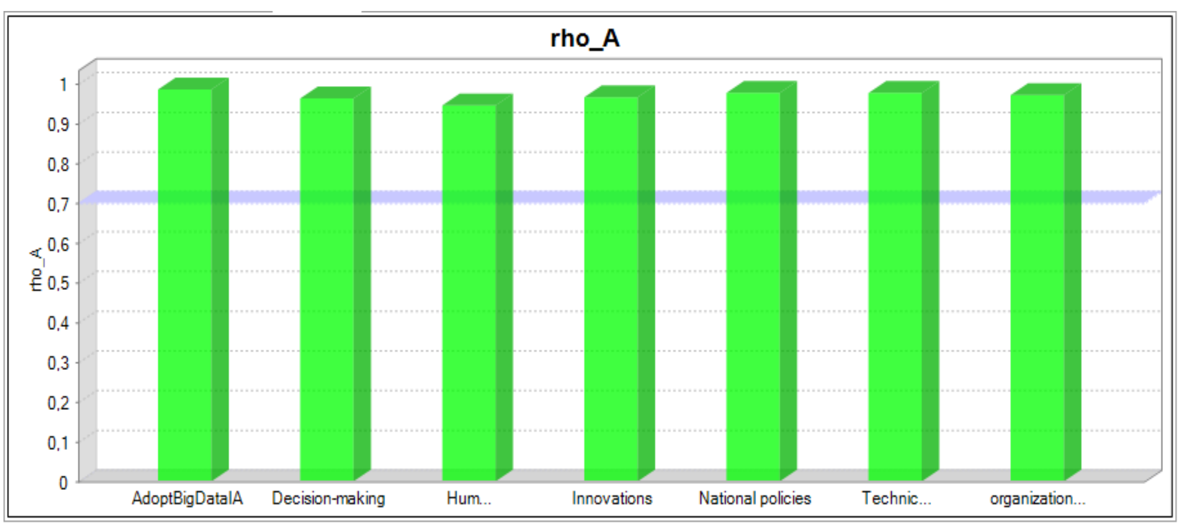

Figure 3.3: Graph of the Dijkstra-Henseler reliability results of the model variables

Indeed, since the Rho_A values are well above the recommended threshold, and given that the latter is considered more robust than Cronbach's Alpha coefficient, we conclude firstly that the values obtained from the calculation of the α coefficient are accurate, and consequently, secondly, we confirm the stability and reliability of the measurement, and the internal consistency of each latent variable, because even for the variable Human ressource and customer relationship management whose alpha coefficient was 0.771, its Rho_A reaches 0.945.

3.1.3 Composite Reliability

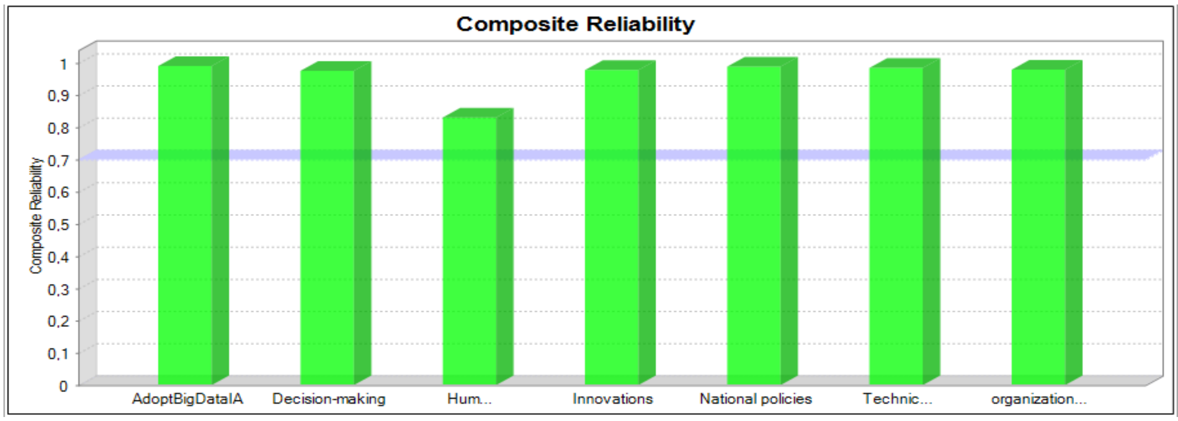

Figure 3. 4: Graph of composite reliability (CR) results for model variables

The minimum acceptable threshold for validating composite reliability is set at CR ≥ 0.70. Thus, with values greater than 0.8 for all latent variables in our basic model, and peaks reaching 0.988 (which far exceeds the recommended threshold), we can conclude that the items for each variable effectively measure said variables. These results are illustrated in Figures 3.1 and 3.4.

3.1.4 Convergent Validity (AVE)

Convergent validity is measured using the extracted mean variance, commonly referred to as AVE. The recommended threshold for an acceptable AVE is: AVE ≥ 0.50 (Hair and al., 2022). We present the results obtained in Figures 3.1 and 3.5.

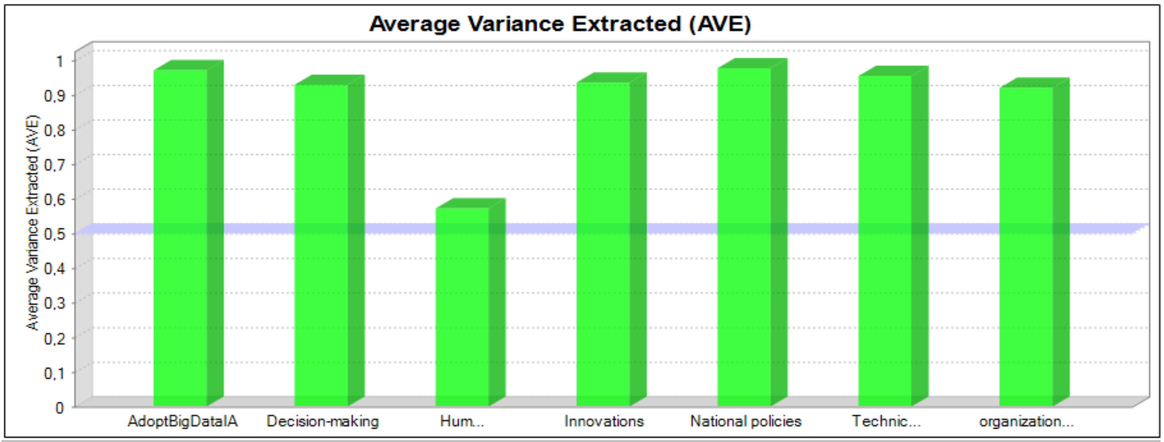

Figure 3. 5: Graphical presentation of the results of the AVE of the model variables

The verification of convergent validity through the AVE test thus leads us to the following conclusion: all AVE values are much higher than the recommended threshold of 0.50 (reaching very high peaks for some variables (Ex: AVE (National policies) = 0.977)); which means that each latent variable explains very well a substantial proportion of the variance of its indicators.

3.2 Discriminant Validity

Recall that discriminant validity, as applied to the Fornell-Larcker criterion, highlights the correlations between latent variables in a PLS model (Fornell, C., and Larcker, D. F., 1981); each value being a Pearson correlation coefficient ranging from -1 (perfectly negative correlation) to 1 (perfectly positive correlation). The value 0 represents the absence of a linear relationship.

The principle for confirming discriminant validity is as follows: the square root of the AVE (calculated along the diagonal of each row of the matrix) must be greater than all off-diagonal correlations in its row and column. Let us observe the resulting matrix in Figure 3.6 below.

	AdoptBigDataIA	Decision-maki...	Human ressou...	Innovations	National policies	Technical chall...	organizational ...
AdoptBigDataIA	0.986						
Decision-making	0.983	0.964					
Human ressour...	0.944	0.944	0.757				
Innovations	0.979	0.979	0.960	0.967			
National policies	-0.951	-0.946	-0.928	-0.959	0.989		
Technical chall...	-0.967	-0.967	-0.927	-0.968	0.985	0.977	
organizational ...	-0.965	-0.968	-0.919	-0.967	0.966	0.979	0.959

Figure 3.6: Correlation matrix between the latent variables of the basic PLS model

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Table 3.1 below gives a detailed description of the results in Figure 3.6.

Table 3.1: Detailed description of the discriminant validity results

Variable (construct)	**AVE**	**Value on the diagonal** $(exacte\ \sqrt{AVE}\ /rounded)$
Adopt Big Data IA	0.971	0.985 ≈ 0.986
Organizational challenges	0.921	0.959
Technical challenges	0.955	0.977
Innovations	0.936	0.967
Human resource and customer relationship management	0.572	0.756 ≈ 0.757
Decision-making	0.930	0.964
National policies	0.977	0.988 ≈ 0.989

Table 3. 2: Interpretation of the key correlations of the model

Correlations	Value	Interpretation
Adopt Big Data IA & Decision-making	0.983	Very strong correlation: This indicates that the adoption of Big Data and AI in a company significantly improves the quality of decisions made. This supports the H1 hypothesis.
Technical challenges & National policies	0.985	Existence of a very strong relationship: this implies that the inadequacy or lack of support from the public authorities is a major factor at the origin of the technical challenges experienced by Cameroonian companies, not favoring the implementation of Big Data and AI technologies in the latter. This supports hypothesis *H6* by deduction.
Human resource and customer relationship management & Decision-making	0.944	Existence of a strong relationship: Better management of human resources and customer relations is closely linked to the quality of decisions made by decision-makers; these in turn are strongly linked to the adoption of Big Data/AI. Therefore, better human resource and customer relationship management is highly dependent on the adoption of Big Data and AI, which supports the *H2* hypothesis.
Adoption Big Data et organizational challenges	-0.965	Strong negative correlations: These 2 relationships support the *H4* and *H5* hypotheses that technical and organizational challenges are unquestionably holding back the adoption of

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Adopt Big Data IA & Technical challenges	-0.967	Big Data and AI technologies in Cameroonian companies. These correlations are therefore logical and thus reinforce the theoretical coherence of the model established in the previous section.
Adopt Big Data IA & Innovations	0.979	Very strong and positive correlation: we understand here that adopting Big Data/AI in a company leads to a strong capacity for innovation. (Hypothesis *H3*)

Concluding this section requires us to provide a scientific interpretation of the key correlations provided by the previous matrix (Figure 3.6). Table 3.2 below clearly illustrates this.

3.3 Coefficients of Determination (R Square and R Square Adjusted)

Note that in PLS-SEM regression, the values considered for R^2 and adjusted R^2 are as shown in Table 3.3 below (Hair and al., 2019).

Table 3.3: R2 value ranges

Indicator	Value	Interpretation
R^2	$R^2 \geq 0.75$	**Noun** (very good explanation)
	$R^2 \approx 0.50$ to 0.74	**Moderate**
	$R^2 \approx 0.25$ to 0.49	**Low** (but acceptable)
	$R^2 < 0.25$	**Very limited** (variable is poorly explained)

The results obtained are summarized in table 3.4 below.

Table 3.4: Results of R2 and adjusted R2 calculations

Indicator	Value
R^2 (Standard Coefficient of Determination)	0.974
Adjusted R^2 (adjusted coefficient of determination)	0.967

Based on our R^2 value of 0.974, it appears that the latent variable Adopt Big Data IA is very well explained by the six independent variables. This indicates that 97.4% of the variance in Big Data and AI adoption by Cameroonian companies is explained by the model's explanatory variables. It is worth noting that this is the same value we obtained when generating the PLS algorithm for our study.

Regarding the adjusted R^2, we obtained a value of 0.967. Since this corrects for the standard R^2, its value is very close to that of R^2 (96.7%), confirming that the included predictors are relevant

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and contribute to the actual explanation of the dependent variable Adopt Big Data IA. Thus, it would not be inappropriate to state that, within the framework of PLS regression, the explanatory power observed from our results is considered excellent (Hair and al., 2017); which suggests a very strong fit of our PLS model to the reality observed in the field during the surveys carried out.

3.4 Blindfolding (Stone-Geisser's Q2)

The values generally observed for validating or invalidating a Q2 are grouped in Table 3.5 as follows:

Table 3.5: Q2 value ranges

Indicator	Value	Interpretation
Q^2	Q2 > 0.35	Very good predictive ability
	$0.15 < Q^2 \leq 0.35$	Moderate predictive ability
	$0.02 < Q^2 \leq 0.15$	Low predictive ability
	$Q2 \leq 0.00$	No predictive capability

The values obtained after the Q2 test are presented in Table 3.6 below:

Table 3.6: Blindfolding Result

Q^2	SSO	SSE	Q2 (1-SSE/BSP)
Adopt Big Data IA	90.000	7.717	**0.914**
Organizational challenges	120.000	120.000	
Technical challenges	90.000	90.000	
Innovations	90.000	90.000	
Human ressource and customer relationship management	120.000	120.000	
Decision-making	90.000	90.000	
National policies	60.000	60.000	

In PLS regression, the Q2 is used to assess the predictive power of a model. In this regard, considering the value ranges mentioned previously (see Figure 3.5) and the results we obtained, the dependent variable Adopt Big Data IA exhibits a high Q2 (0.914), indicating excellent predictive quality. These results thus confirm that the adoption of Big Data and artificial intelligence is well explained by the selected predictive constructs. It should be noted that the other variables do not need a Q2, as they are explanatory variables (used to assess the predictive power of the explained variable).

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4. Discussions and Recommendations

Based on the research model and the PLS model established previously, we obtained results that sufficiently validate the initial hypotheses and justify the robustness of the aforementioned models. In light of the results obtained in this study, it is clear that the adoption of Big Data and Artificial Intelligence in Cameroonian companies offers major opportunities but faces several structural and organizational challenges that can be grouped according to several factors.

In other words, Big Data and AI represent a unique and invaluable opportunity to increase the competitiveness of Cameroonian companies and strengthen the country's digital sovereignty (given that Cameroon has set itself the goal of being the digital leader in the Central African sub-region). Concerted action between the private sector and the State is therefore essential to transform the challenges identified into drivers of sustainable growth. This section aims to formulate some recommendations for Cameroonian businesses on the one hand, and for Cameroonian public authorities on the other. Tables 4.1 and 4.2 below highlight these recommendations and the factors associated with them.

4.1 Recommendations for Cameroonian companies

Table 4.1: Recommendations for Cameroonian companies

Recommendations	Factor(s) concerned
- Implement AI-based HR analysis platforms to optimize recruitment (profile-job matching) and anticipate training needs. - Develop CRM systems integrating Big Data to analyze customer behavior and offer personalized products/services.	Human resources and customer relationship management factor
Invest in predictive tools (modeling, predictive AI) to anticipate market trends and quickly adapt the company's strategy	Decision Making Factor
- Leverage data analytics to detect new market opportunities and design innovative products aligned with emerging trends - Encourage initiatives and personal ideas related to innovation to develop new products	Innovation and value creation
- Adopt cloud solutions to circumvent weak on-premises infrastructure and reduce the cost of implementing technologies - Strengthen internal cybersecurity through the adoption of robust security protocols and employee awareness of digital risks.	Technical factors
- Implement change management programs (training,	

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internal communication) to reduce employee resistance. - Training employees and attracting specialized talent	Organizational Factor
Develop a clear internal digital strategy plan (including Big Data and AI) to avoid dispersing technology efforts	Organizational Factor

4.2 Recommendations for the Cameroonian public authorities

Table 4.2: Recommendations for the Cameroonian public authorities

Recommendations	Factor(s) concerned
Establish a clear regulatory framework on the use of data and AI, including the protection of personal data and AI ethics.	National Political Factor
Introduce tax and financial incentives (grants, tax credits, relief) to encourage businesses to invest in digital technologies.	National Political Factor
Develop national training and certification programs in Big Data, AI and cyber security in partnership with universities and research centers	National Political Factor
Launch a national strategy for Big Data and AI, including a ten-year digital development plan and public-private partnerships.	National Political Factor

Conclusion

At the end of this study, whose main objective was to explore the opportunities offered by Big Data and Artificial Intelligence to improve business processes and decision-making, while identifying the technical and organizational challenges related to the adoption of these technologies in Cameroonian companies, we formulated several hypotheses (H1…H6) to better define the scope of our subject. These hypotheses are based on a research question formulated to capture the factors that allow us to measure the opportunities and challenges related to the adoption of Big Data and AI technologies by Cameroonian companies within the framework of effective information systems management.

Based on this, we identified various factors, some explaining the opportunities linked to the adoption of Big Data and AI, and others explaining the challenges faced by Cameroonian companies in this process. These factors include: decision-making, human resource and customer relationship management, innovation and value creation, technical and organizational factors, and national policy.

Having verified all the hypotheses, it appears that the adoption of Big Data and AI technologies in Cameroonian companies, while not yet a widespread reality, nevertheless presents numerous opportunities and advantages that companies lagging behind could leverage to better meet the ever-increasing needs of their customers and improve their competitive positioning. On the other hand, the various challenges observed represent a significant obstacle to this process, including: the lack or inadequacy of adequate infrastructure to meet the requirements of these technologies, weak cyber security mechanisms that expose user data, a lack of skills in using these technologies, and therefore a shortage of skilled labor, resistance to organizational change, the often very high cost associated with implementing these technologies in companies, not to mention the cost of training in these areas, and the absence of a clearly defined digital strategy within many Cameroonian companies. Added to this is the apathy of the Cameroonian public authorities regarding regulation and the failure to take genuine initiatives to help and encourage Cameroonian companies to adopt these technologies for the recovery of the Cameroonian economy.

It is therefore important that Cameroonian companies and public authorities make greater efforts to promote the adoption and use of these technologies, which are now essential in the era of Industry 4.0. This could help Cameroon achieve one of its major objectives: to position itself as the leader in digital technologies in the Central African sub-region.

References

African Union. (2022). *AU Data Strategic Framework. Addis-Abeba: African Union.*

Amora, J. T. (2021). *Convergent validity assessment in PLS-SEM: A loadings-driven approach*. In *Data Analysis Perspectives Journal*, *2*(3), 1–6.

Belhadi, A., Kamble, S. S., Wamba, S. F., Fosso Wamba, L., & Queiroz, M. M. (2021). *Building supply chain resilience: An AI-based technique and decision-making framework***.** In *International Journal of Production Research***,** *59*(11), 3366–3383. Available on: https://doi.org/10.1080/00207543.2020.1737680

Berger. R. (2023). L'IA générative - mythes et réalités. Roland Berger GmbH.

Borgman. L. C. (2020). « 2. Qu'est-ce qu'une donnée ? ». *Qu'est-ce que le travail scientifique des données ?*, translated by Charlotte Matoussowsky, OpenEdition Press, 2020, https://doi.org/10.4000/ books.oep.14732

Bourany, T. (2018). *Les 5 V du big data*. In *Regards croisés sur l'économie*, 23(2), 27–31. Available on: https://doi.org/10.3917/rce.023.0027

Dijkstra.T.K et Henseler.J.(2015). Consistent Partial Least Squares Path Modeling. MIS Quarterly, 39(2)

Espinasse, B. (2017). *Introduction au Big Data : stockage, analyse et fouille des mégadonnées*. In *Techniques de l'Ingénieur. Réf. : H6040 v1*

Fornell, C., et Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39-50. https://doi.org/10.2307/3151312

Fosso Wamba, S., Akter, S., Edwards, A., Chopin, G., & Gnanzou, D. (2015). *How 'Big Data' Can Make Big Impact: Findings from a Systematic Review and a Longitudinal Case Study*. *International Journal of Production Economics, 165*, 234–246. Available on the internet: https://doi.org/10.1016/j.ijpe.2014.12.031

Fox, P., & Harris, R. (2013). ICSU and the challenges of data and information management for international science. *Data Science Journal*, 12, WDS1–WDS12. Available on: https://doi.org/10.2481/dsj.WDS-001

GEFONA (2020). *State of Application Security in Enterprises*. Disponible sur : STATE of APPLICATION SECURITY in ENTERPRISES Contacts: Hello@Gefona.Org Yaoundé, Cameroon Content - DocsLib

Geisser. S. (1974). A predictive approach to the random effect model. Biometrika, 61(1)

Hair, J. F, Hult, G. T. M, Ringle, C. M, & Sarstedt, M. (2017). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)* (2nd ed.). Thousand Oaks, CA: SAGE Publications.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. Dans *European Business Review, 31*(1), 2–24. Available on: https://doi.org/10.1108/EBR-11-2018-0203

Hair. J. F., Hult.G. T. M., Ringlle. C. M., & Sarstedt. M. (2022). A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM) (3rd ed.). SAGE. https://doi.org/10.1007/978-3-030-80519-7

Leleu-Merviel. S et Useille. P.(2008). Quelques révisions du concept d'information. In *Problématiques émergentes dans les sciences de l'information* (p.25-26)

Nguefack, P. J., Tatang Atabonfack, P. L., Djatang Yawouo, T. J., & Nyasseu, E. J. (2021). *Nouvelles technologies : un levier d'amélioration de la gouvernance des entreprises en contexte camerounais*. In *International Journal of Economic Studies and Management, 1*(3), 295–311. Available on : https://doi.org/10.52502/ijesm.v1i3.204

Pêcheux. F. (2025). Big Data. *Encyclopaedia Universalis*. Available on: https://www.universalis.fr/encyclopedie/big-data/

Peterson.R.A.(1994). Méta-analyse du coefficient alpha de Cronbach. Journal of Consumer Research, 21(2), 381-391. Available on: https://doi.org/10.1086/209405

Stone. M. (1974). Cross-validatory choice and assessment of statistical predictions. Journal of the Royal Statistical Society, 36(2)

Tawamba.C.(2021). *Digitalisation des entreprises : enjeu de notre développement*. Dans *L'entreprise face au défi de la transformation digitale* (Bulletin du patronat, nº 83, p.2). GICAM.

Tenenhaus, M., Gauchi, J.-P., & Ménardo, C. (1995). Régression PLS et applications.
Revue de Statistique Appliquée, 43(1), 7–63. ffhal-01604598.

Tchouassi. G. (2017). Les besoins en informations dans les entreprises. Revue Congolaise de Gestion, 2017/2 Numero 4. Editions ICES.

Vangrunderbeeck, P., Baur, M., Deville, Y., Guisset, M., & Biot, M. (2024, october). *Intégrer l'IA générative dans les stratégies pédagogiques*. Louvain Learning Lab. On :

Vol. 11, No. 01; 2026

ISSN: 2456-3676

https://oer.uclouvain.be/jspui/bitstream/20.500.12279/1089.3/6/CahierLLL_IAG_OKOER.pdf

Vassileva, J. (2020). *L'intelligence artificielle au service de la prise de décisions plus efficace*. Version available online: https://www.researchgate.net/publication/339677215_L%27intelligence_artificielle_au_service_de_la_prise_de_decisions_plus_efficace. ResearchGate+1

Vayre, J.-S. (2013). *Les big data et la relation client*. Communication présentée au 12e Journées Normandes de Recherches sur la Consommation : Société et Consommation, Caen, France. HAL. Available on: https://hal.science/hal-00911765

https://www.republik-it.fr/definition/big-data-definition.html [Accessed on 05/24/2025 at 03:05 AM]

https://intelligence-artificielle.com/intelligence-artificielle-faible-guide-complet/ [Accessed on 05/28/2025 at 2:03 AM]

https://cameroon-eco-business.info/2025/03/25/intelligence-artificielle-le-cameroun-face-au-defi-de-lia-un-potentiel-a-concretiser/ [Accessed on 06/09/2025 at 04:12 PM]

https://www.africa-press.net/cameroun/economie/lia-en-afrique-un-potentiel-enorme-et-des-defis-a-relever [Accessed on 06/09/2025 at 04:28 PM]

https://files.apsis.com/efficy/french/Basics-Tome-5-Augmented-Customer-Relationship-FR.pdf [Accessed on 06/24/2025 at 03:50 AM]

https://statorials.org/coefficient-de-determination-r-au-carre/ [Accessed on 29/06/2025 at 6:30 PM.]

https://www.stat4decision.com/fr/regression-pls/ [Accessed on 06/15/2025 at 10:12 PM]

https://fr.wikipedia.org/wiki/Coefficient_alpha_de_Cronbach [Accessed on 06/20/2025 at 11:22 AM]

https://fr.statisticseasily.com/glossaire/Qu%27est-ce-que-la-fiabilit%C3%A9-composite-et-comprendre-son-importance/ [Accessed on 06/21/2025 at 02:05 PM]