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ORIGINAL

Adoption of generative artificial intelligence to improve business management innovation in Ecuador

Adopción del uso de la Inteligencia Artificial generativa en la mejora de la innovación de la administración de las empresas en Ecuador

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ABSTRACT

Generative artificial intelligence (GAI) has emerged as a disruptive technology with the potential to transform administrative processes in organisations. However, its adoption in business contexts in emerging economies, such as Ecuador, requires an understanding of the factors that influence organisational readiness for its implementation. The objective of the research was to analyse the intention to adopt the use of generative artificial intelligence to improve innovation in the administration of Ecuadorian companies, which has been empirically validated by a theoretical model based on technological and organisational dimensions. A quantitative, cross-sectional, non-experimental research design was developed. The population consisted of small and medium-sized enterprises (SMEs) in the province of Tungurahua in Ecuador, selected by random convenience sampling. A structured questionnaire with 20 items distributed across six dimensions was applied. A correlational and exploratory factor analysis (EFA) was performed to validate the structure of the instrument and examine the relationships between variables. The EFA confirmed a one-dimensional model that explained 79,24 % of the total variance, with factor loadings above 0,83. The adoption of IAG showed a high correlation with expected innovation r= 0,944, technological complexity and compatibility. The participating companies show a consistent perception of IAG adoption, based on technological, organisational and strategic factors.

Keywords: Generative Artificial Intelligence; Innovation; Technology Adoption; Exploratory Factor Analysis; SMEs.

RESUMEN

La inteligencia artificial generativa (IAG) ha emergido como una tecnología disruptiva con el potencial de transformar los procesos administrativos en las organizaciones. No obstante, su adopción en contextos empresariales de economías emergentes, como Ecuador, requiere comprender los factores que inciden en la disposición organizacional hacia su implementación. El objetivo de la investigación fue analizar la intención de adopción del uso de la inteligencia artificial generativa en la mejora de la innovación en la administración de las empresas ecuatorianas, que ha sido validado de forma empírica por un modelo teórico sustentado en dimensiones tecnológicas y organizacionales. Se desarrolló una investigación de enfoque cuantitativo, de tipo transversal y diseño no experimental. La población estuvo compuesta por pequeñas y medianas empresas (Pymes) de la provincia de Tungurahua en el Eccuador, seleccionadas por muestreo aleatorio por conveniencia. Se aplicó un cuestionario estructurado con 20 ítems distribuidos en seis dimensiones. Se realizó un análisis correlacional y factorial exploratorio (AFE) y correlacional para validar la estructura

del instrumento y examinar las relaciones entre variables. El AFE confirmó un modelo unidimensional que explicó el 79,24 % de la varianza total, con cargas factoriales superiores a 0,83. La adopción de IAG mostró alta correlación con innovación esperada (r = 0,944), complejidad tecnológica y compatibilidad. Se evidencia que las empresas participantes presentan una estructura coherente de percepción hacia la adopción de IAG, fundamentada en factores tecnológicos, organizacionales y estratégicos.

Palabras clave: Inteligencia Artificial Generativa; Innovación; Adopción Tecnológica; Análisis Factorial Exploratorio; Pymes.

INTRODUCTION

Artificial intelligence (AI) is currently transforming the way organisations conceive, develop and implement innovation. However, this disruptive process has brought with it not only benefits, but also structural, ethical and technological challenges.[1,2] In particular, the rise of generative models such as ChatGPT [3] or Gemini[4] has radically reformulated the processes of ideation, digital prototyping, and content generation, even in organisational contexts not specialised in programming or technical development.[5]

However, amid the enthusiasm for the adoption of generative artificial intelligence (GAI), significant concerns have arisen around authenticity, reproducibility, and the risk of generating inaccurate or inauthentic content, both in scientific and business environments.[6] This tension between the innovative potential of IAG and the risks associated with its unregulated use constitutes an emerging challenge for organisations seeking to integrate these technologies in an ethical, strategic, and effective manner.[7,8]

The background shows a growing interest in the role of technology in organisational innovation, especially from a perspective based on fit theory.[9] Recent research has argued that innovation does not depend solely on technological incorporation per se, but rather on the strategic alignment between technological capabilities, organisational conditions and the socio-economic environment.[10]

In this regard, concepts such as Harmonious IT Affordance (HITA) and organisational courage represent substantial theoretical advances, as they explain how organisational courage and consistency in the use of technologies enable digital potential to be transformed into concrete innovation. On the other hand, applied studies in emerging economies, such as SMEs in Kenya and Jordan, confirm that factors such as staff technological knowledge, digital infrastructure and management commitment are key to the successful adoption of AI.[11,12]

At a theoretical level, the TOE (Technology–Organisation–Environment) framework is one of the most robust structures for analysing technology adoption in organisations. In particular, its application in recent studies on AI demonstrates its usefulness in explaining how internal conditions (technology strategy, training, management support) determine the willingness to adopt technology in SMEs.[11,13]

Similarly, the affordances and institutional human capital approach suggests that a positive attitude towards AI can act as a key mediator in the successful implementation of these systems. In this context, generative AI represents a paradigmatic innovation: it democratises access to complex design and innovation processes, but requires a methodological approach that guarantees traceability, ethics and effectiveness in its application.[14]

The Upper Echelon Theory (UET), developed by Hambrick and Mason (1984) and mentioned by Awa et al.[15], argues that strategic decisions within an organisation are strongly influenced by the demographic and cognitive characteristics of the members of the management team, such as age, experience, gender and educational level.[16,17,18] In the context of technology adoption by small and medium-sized enterprises (SMEs)[19]; This theory takes on particular significance, as investment decisions in innovation often depend on leaders with limited resources but a high degree of strategic agency. Through the above, Al-Kfairy et al.[1] explains that organisations can strengthen the reliability of their artificial intelligence applications and promote a culture based on ethics and integrity.

On the other hand, the emergence of technologies such as ChatGPT has introduced a new theoretical context for organisational management, in which the generative capabilities of AI are reshaping traditional concepts such as bounded rationality[20], organisational learning and knowledge management. Korzynski et al.[21] argue that generative AI can act as a theoretical agent of change by reconfiguring decision-making processes, knowledge management, labour relations, and customer services. In the field of knowledge, for example, tools such as ChatGPT not only allow information to be stored and retrieved, but also generate, adapt, and contextualise knowledge dynamically, integrating with models such as that of Nonaka and Takeuchi (1995).

Despite enthusiasm for the use of generative AI in businesses and institutions, Twaissi et al.[22] and Chege and Wang[23], there are still gaps in our understanding of how these models actually fit into organisations' innovation systems, especially in the early stages such as needs exploration, ideation, or no-code prototyping. Furthermore, literature lacks empirical studies that combine the technology approach with the context of potential investments and innovation.[24]

Over time, Kshefri[25] effective regulation in industries, particularly in the technology sector, has largely depended on cooperation with the business community, and this principle also applies to the development of artificial intelligence.[6] This gap limits the ability to generate practical recommendations on how organisations can strategically align their internal capabilities to take advantage of AI opportunities without compromising quality, authenticity, or ethical responsibility in innovation.[26]

In this context, the present study aims to analyse the perception of Ecuadorian small and medium-sized enterprises (SMEs) on the adoption of generative artificial intelligence (AI) as a driver of innovation in administrative management. It is intended as a theoretical and applied contribution to the debate on the strategic use of transformative technologies in business and academic contexts. It aims to fill a critical gap in the current literature and provide empirical research for the development of possible technology policies in rapidly changing environments.

METHOD

Approach

The study was based on a quantitative, cross-sectional, non-experimental approach, with the aim of analysing the perceptions of small and medium-sized enterprises (SMEs). For Creswell[27] 'In quantitative research, researchers identify a research problem based on trends in the field or the need to explain why something happens. The problem leads to the formulation of hypotheses and research questions, and data are collected using instruments that produce numerical data'.

The design was descriptive-correlational, focusing on identifying the technological factors associated with the intention to adopt generative AI and the expected impact on organisational innovation.

Participants

The target population initially consisted of 258 SMEs located in the province of Tungurahua, Ecuador, characterised by an active business ecosystem in the manufacturing, commerce and services sectors. Non-probabilistic convenience sampling was applied, due to logistical constraints and the specific objective of accessing companies that meet particular criteria. This technique, although useful for exploratory studies, may introduce selection bias, as it does not guarantee that the sample is representative of the total universe of Ecuadorian SMEs.

These criteria were: (a) companies that had not previously implemented generative artificial intelligence, and (b) that had at least one department or member of staff responsible for information and communication technologies (ICTs).

Before the instrument was applied, each participating company received detailed information about the purpose, scope, and procedures of the research. Informed consent was obtained, explicitly guaranteeing data confidentiality and voluntary participation, in accordance with ethical standards for research applied in organisational contexts. A response rate of 45,7 % was achieved, obtaining 118 valid questionnaires. This level of response, although moderate, is adequate for exploratory studies in business contexts, and allows us to establish general patterns with acceptable internal validity.

Instrument

For data collection, a structured questionnaire was designed based on and adapted to the study context within the Technology-Organisation-Environment (TOE) framework developed by Twaissi et al.[22], to assess Ecuadorian SMEs' perceptions of the adoption of generative artificial intelligence (AI) for innovation in SME management. The adaptation included a linguistic and cultural review process to ensure semantic clarity and contextual relevance of the items. In addition, a validation by expert judgement and a pilot test with 12 local companies was carried out, which allowed the wording to be adjusted to the organisational reality of the country.

The instrument consisted of 20 items distributed across six dimensions: relative advantage (which assesses perceived benefits, such as efficiency and improved decision-making), technological complexity (which assesses the perceived difficulty of understanding and implementing generative AI)[8], organisational compatibility (which examines the alignment of the company's infrastructure and culture with the adoption of new technologies) Awa et al.[15], testability (which measures openness to experimenting with AI before full adoption), intention to adopt generative AI (which reflects future willingness to integrate these technologies), and expected innovation in administrative management (which captures anticipated improvements in internal processes and strategic capabilities).[24]

Each item was measured using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The questionnaire underwent content validation by expert reviewers to ensure conceptual clarity and relevance to the study context. In addition, a pilot test was conducted with a small group of SMEs to refine the language and consistency of the items. The internal consistency of the instrument was verified using Cronbach's

alpha, which yielded a value greater than 0,85 in all dimensions, confirming the reliability of the instrument for use in organisational studies related to technology adoption.

Data analysis

For the processing and analysis of the data, SPSS v.26 software was used, which allowed the application of descriptive statistics (means, standard deviations, frequencies and percentages) to characterise the sample and the main variables. In addition, Cronbach's alpha coefficient was applied to confirm the reliability of the instrument.

Despite having a predefined theoretical model, an Exploratory Factor Analysis (EFA) was chosen instead of a Confirmatory Factor Analysis (CFA), because the scale was adapted and contextualised for a different national reality, which justified exploring the emerging latent structure and empirically validating the internal consistency of the construct in the new context.

The AFE allowed identifying a robust factorial solution, revealing the convergence of items within consistent theoretical dimensions. Finally, Pearson correlation coefficients were calculated to examine the relationships between variables, revealing significant associations that support the TOE model as a valid analytical framework for the analysis of the adoption of emerging technologies in Ecuadorian SMEs.

RESULTS

The results obtained made it possible to characterise the profile of the participating companies and the managers who responded to the questionnaire, as shown in Table 1. In terms of the age of the companies, it can be seen that most are in a consolidation phase: 47,5 % has been operating for between 6 and 15 years, followed by 30,5 % with less than 5 years, which shows a young business fabric that is in the process of maturing. Only 7,6 % report more than 26 years of existence, which is indicative of a lower relative weight of traditional or long-standing companies within the study.

In terms of location, there is a marked urban concentration, with 90,7 % of companies located in urban areas, compared to 9,3 % in rural areas. This distribution highlights the centralisation of business activity with technological adoption capacity in areas with better infrastructure and connectivity, conditions that are generally more conducive to implementing artificial intelligence-based solutions.

In terms of the positions of those responsible for responding to the survey, the commercial area stands out with 48,3 %, reflecting this segment's growing interest in integrating digital solutions into customer relations, sales and market strategies. This is followed by managerial positions with 31,4 % and administrative positions with 20,3 %, indicating a diversity of approaches in terms of adoption intentions, although those most closely linked to strategic processes and direct interaction with the competitive environment predominate.

Finally, in terms of academic qualifications, the profile is highly skilled: 44,9 % have a university degree and 40,7 % have postgraduate qualifications, suggesting a favourable environment for understanding, valuing and eventually adopting emerging technologies such as generative artificial intelligence. In contrast, only 6,8 % and 7,6 % reported basic and secondary education levels, respectively. This high level of academic training is positively linked to innovative leadership skills and a willingness to integrate new digital tools into organisational management.

Table 1. Characteristics of demographic variables of companies

		Frequency	Percentage
Years in operation	Between 16 and 25 years old	17	14,4 %
	Between 6 and 15 years old	56	47,5 %
	Over 26 years old	9	7,6 %
	Under 5 years old	36	30,5 %
Location	Rural	11	9,3 %
	Urban	107	90,7 %
Position of the person in charge	Administration	24	20,3 %
	Commercial	57	48,3 %
	Management	37	31,4 %
Level of academic training	Basic	8	6,8 %
	Postgraduate	48	40,7 %
	Secondary	9	7,6 %
	University	53	44,9 %

The Pearson correlation matrix is shown in table 2 with the significant and positive associations between the variable Adoption of Generative Artificial Intelligence (ADOPTION IAG) and all the dimensions analysed

in the adapted TOE model. In particular, the highest correlation is observed with the INNOVA dimension (r = 0,944), indicating that the greater the expectation of administrative innovation in the company, the greater the intention to adopt generative artificial intelligence technologies. This result suggests that Ecuadorian organisations that view AI as a tool for transforming administrative processes show a significantly greater predisposition towards its implementation.

In addition, there is a strong correlation between ADOPTION IAG and COMPLEX (r = 0,895; p < 0,001), which in this case should be interpreted with caution: although technological complexity often acts as a barrier, this result suggests that companies that recognise the advanced nature of generative AI do not necessarily reject it, but rather understand its technical nature and are willing to adopt it based on an informed perception. Similarly, high correlations are evident with the COMP (r = 0,892) and TRIAL (r = 0,891) dimensions, supporting the idea that compatibility with existing systems and the possibility of prior testing are key factors that directly influence business readiness for the implementation of generative AI.

The Relative Advantage (RA) dimension also shows a strong positive correlation with ADOPTION IAG (r = 0,829; p < 0,001), reinforcing the principle that the perception of concrete benefits—such as efficiency, process improvement or competitive differentiation—is an important determinant of adoption intention.

Table 2. Correlation matrix for the adoption of generative artificial intelligence

		ADOPTION IAG	RA	COMPLEX	COMP	TRIAL	ADOPTION	INNOVA
ADOPTION IAG	Correlation	1						
	p-value							
RA	Correlation	,829**	1					
	p-value	,000						
COMPLEX	Correlation	,895**	,843**	1				
	p-value	,000	,000					
COMP	Correlation	,892**	,719**	,732**	1			
	p-value	,000	,000	,000				
TRIAL	Correlation	,891**	,587**	,755**	,761**	1		
	p-value	,000	,000	,000	,000			
ADOPTION	Correlation	,877**	,616**	,764**	,734**	,805**	1	
	p-value	,000	,000	,000	,000	,000		
INNOVA	Correlation	,944**	,731**	,779**	,788**	,835**	,802**	1
	p-value	,000	,000	,000	,000	,000	,000	

In order to validate the internal structure of the instrument designed to measure the intention to adopt generative artificial intelligence (GAI) in companies, an Exploratory Factor Analysis (EFA) was applied using the principal component extraction method. To verify the suitability of the analysis, the Kaiser-Meyer-Olkin (KMO) and Bartlett's sphericity tests were applied. The results obtained were satisfactory, with a KMO value of 0,849, indicating a commendable level of sample adequacy, while Bartlett's test was statistically significant (x^2 = 709,802; gl = 15; p < 0,001), confirming the existence of sufficient correlations between the items to justify factor analysis. These results are presented in table 3.

Table 3. Bartlett's sample adequacy and sphericity test

Statistical	Value
KMO (Kaiser-Meyer-Olkin)	0,849
Bartlett's chi-square (approximate)	709,802
Degrees of freedom	15
Significance (Sig.)	0,000

Also, based on the analysis of commonalities, it was observed that all variables had values above 0,70, indicating that the factorial model adequately explains the variance of each dimension included in the questionnaire. The highest communalities extracted corresponded to the dimensions of Expected Innovation (0,857), Technological Complexity (0,832) and Probability of Trial (0,792), followed by Adoption Intention (0,784), Organisational Compatibility (0,785) and Relative Advantage (0,705). These results show that the items are well represented within the common factor and support the convergent validity of the instrument.

Additionally, the total variance analysis explained a single component with an eigenvalue of 4,755, representing 79,24 % of the cumulative variance. This percentage is considered excellent in social studies

and suggests the existence of a strong underlying unidimensional construct that coherently groups the six dimensions proposed in the theoretical model.

As for the component matrix, all factor loadings were above 0,83, indicating a strong association between each dimension and the extracted factor. The highest loadings corresponded to Expected Innovation (0,926) and Technological Complexity (0,912), followed by Probability of Testing (0,890), Organisational Compatibility (0,886), Intention to Adopt (0,885) and Relative Advantage (0,839). This pattern of factorial loading confirms that the dimensions of the instrument converge into a single latent factor, providing empirical support for the internal consistency of the model and its applicability in the study of organisational behaviour towards the adoption of emerging technologies. Table 4 presents the corresponding results.

Table 4. Factor loadings of the extracted component

Dimension	Factorial loading
Expected Innovation (INNOVA)	0,926
Technological Complexity (COMPLEX)	0,912
Probability of Trial (TRIAL)	0,890
Organisational Compatibility (COMP)	0,886
Intention to Adopt (ADOPTION)	0,885
Relative Advantage (RA)	0,839

DISCUSSION

The results obtained allow for a consistent interpretation of the degree of preparedness of Ecuadorian small and medium-sized enterprises for the adoption of generative artificial intelligence (GAI) technologies, as well as the conceptual structure underlying this readiness.[28] Exploratory factor analysis (EFA) empirically validated the structure of the proposed instrument, revealing remarkable internal consistency among the six theoretical dimensions considered.[29]

Analysis of the profile of participating companies showed that more than 87 % of those responsible for adoption have university or postgraduate training, which suggests a high level of technological understanding and appropriation. In addition, more than 77 % of companies have been in existence for less than 15 years, suggesting a young business structure that is potentially more flexible and receptive to change. These factors, combined with high urban concentration 90,7 %, create an ecosystem conducive to the adoption of advanced technologies, provided that support policies, training and strategic guidance are put in place. This finding is in line with Venkatraman's proposal[9] and Chatterjee et al.[10], those who argue that the innovative value of emerging technologies does not lie exclusively in their technical availability, but in the degree of strategic alignment that organisations manage to build between their digital vision, internal capabilities and competitive environment.[30]

In addition, the high factor loadings (all above 0,83) and the communalities extracted (all above 0,70) corroborate a high consistency in the perception of business actors regarding the value of generative AI in administrative processes.[31] In particular, the Expected Innovation (INNOVA) dimension showed the highest score (0,926), suggesting that business leaders understand the transformative potential of these tools in areas such as planning, automation, organisational design and efficiency improvement. This perception is in line with the findings of Korzynski et al.[21], Those who argue that generative AI reconfigures the paradigm of organisational knowledge management, moving from a model of collection and storage to one of contextual knowledge generation, supported by algorithmic capabilities.

The behaviour of the correlations reinforces this argument: the relationship between IAG Adoption and INNOVA reached a Pearson coefficient of 0,944, which constitutes solid empirical evidence that the expectation of change and innovation acts as a determining factor in business readiness towards generative AI. This result has direct implications, as Bilgram & Laarmann argue[14] in theory, as it suggests a reinterpretation of the TOE model not only from the structural logic of adjustment, but also from an organisational affordance approach, in which technology is significant in terms of perceived opportunities for action.

One of the most striking findings that require further analysis is the high correlation between the Technological Complexity dimension and Adoption Intention (r = 0,895). At first glance, this result may seem paradoxical, as higher technical complexity is traditionally considered to act as a barrier to adoption. However, in the context of Ecuador, this finding can be understood as a strategic view of complexity: firms not only see the technical aspect of IAG but also see it as an opportunity to stand out and create competitive advantages. Instead of avoiding complexity, SMEs, especially those with academically trained leadership and agile structures, take it on as a desirable challenge that can generate returns if accompanied by training, technical advice and controlled experimentation.

For its part, the Trial Probability dimension also showed a high correlation with adoption (r = 0,891), which reinforces the importance of experimentation environments in the phase prior to technological implementation.[32] The possibility of conducting controlled tests prior to final deployment helps reduce perceived risk and strengthens confidence in integration processes. This practice is consistent with the principles of agile prototyping and iterative validation advocated by contemporary digital innovation, as highlighted by Hamed et al.[6] in the context of applied artificial intelligence.

Overall, these results are consistent with the management theories discussed in the literature cited by Korzynski et al.[21] and the TOE framework Twaissi et al.[22], by demonstrating that technology adoption decisions in the Ecuadorian business environment respond to technological, strategic and organisational factors, all of which are highly correlated with the innovative vision of companies.

CONCLUSIONS

The findings obtained allowed us to empirically validate the structure of the instrument designed to measure business readiness for the adoption of generative artificial intelligence (GAI) in administrative innovation processes. Factor analysis revealed conceptual consistency between the dimensions proposed in the theoretical model, allowing us to identify a structured and consistent pattern in the perceptions of business leaders. The integration of the variables under a single common factor supports the existence of a solid latent construct that explains organisational behaviour towards emerging technologies.

The dimensions associated with the perception of innovation, organisational compatibility, technological complexity and the possibility of conducting pilot tests were those that showed the strongest association with willingness to adopt. This behaviour reveals that the decision to incorporate tools such as IAG is not based solely on technical criteria, but is deeply linked to strategic expectations, perceptions of added value and institutional conditions that enable their effective integration.

Also, the profile of the participating companies suggests a business base with high potential for adopting advanced technologies, characterised by qualified technical management, flexible organisational structures, and a favourable orientation towards digital transformation. The combination of these factors provides a comprehensive view of the phenomenon under investigation, allowing us to conclude that the analysis objective was achieved with empirical evidence and methodological rigour.

The results obtained empirically validate the structure of the proposed theoretical model and offer a clear view on the willingness of Ecuadorian small and medium-sized enterprises to adopt generative artificial intelligence (GII). However, the study has several limitations that should be considered when interpreting its results. Firstly, the application of the questionnaire was limited exclusively to companies located in the province of Tungurahua, so it is not possible to generalise the results to other regional contexts in the country that could present significant differences in terms of level of technological development, organisational infrastructure or competitive dynamics.

Furthermore, the cross-sectional design of the research is an important methodological limitation, as it allows for the identification of associations between variables but does not make it possible to establish causal relationships. For example, although a strong correlation was observed between innovation expectancy and the intention to adopt GPI, it is not possible to claim that one variable directly causes the other. To validate such inferences, longitudinal studies would be necessary to analyse the temporal evolution of these perceptions and their correspondence with actual technological implementation processes.

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