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A Multi-Criteria and Empirical Study for Determining the Influencing Factors of Generative Artificial Intelligence Adoption in Companies

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ABSTRACT

Generative artificial intelligence (GenAI) has emerged as a transformative force across business and society due to its ability to generate new content. This potential to reshape businesses introduces challenges and opportunities, necessitating a deeper understanding of GenAI's impact. Despite its promise, the factors that enable effective GenAI adoption within companies remain underexplored. Based on systems thinking principles, this study proposes a comprehensive approach to determine the most critical and influential factors for effective GenAI adoption in companies. Thirteen factors are identified and validated by experts and then aggregated within a technological, business, organizational and environmental framework. After that, a multicriteria approach is applied to identify critical and influential factors, considering their interrelationships and the judgements of chiefs on technology and information from Spanish companies representing several sectors and sizes. Findings indicate that organizational factors are critical in most cases. This study guides companies and individuals in navigating effective GenAI adoption and supports future research.

1 | Introduction

Generative artificial intelligence (GenAI) has recently emerged as a powerful and unstoppable technology in many applications, from education (Qadir 2023) to several industrial sectors (AL-khatib 2023; Deveau et al. 2023; Kiangala and Wang 2024; Liu et al. 2024). In particular, after the ChatGPT launch in November 2022, GenAI has increasingly received attention due to its ability to change lives and business. GenAI is an artificial intelligence (AI) model that can produce new content, such as texts, images, music, videos and codes, based on patterns learned from large amounts of data. Previous automation waves mainly impacted routine tasks that could be programmed in a machine or a computer, such as assembly-line manufacturing tasks (Noy and Zhang 2023), but, with GenAI, creative and personalized content can be generated, and this has the potential to affect and transform society and organizations.

For example, in the creative sector, such as marketing, professionals can apply GenAI to support creativity and accelerate creative processes (Amankwah-Amoah et al. 2024). In finance, GenAI can improve customer experience, perform fraud detection, generate financial reports and predict economic outcomes (Khan and Umer 2024). In healthcare, GenAI can be used for fault diagnosis and prognostics for equipment and health management (Liu et al. 2024). ChatGPT can offer customized learning experiences in education by providing students and educators with customized content, feedback and explanations (Qadir 2023). In many industrial sectors, GenAI chatbots can obtain factory equipment conditions to minimize factory troubleshooting downtime and do predictive maintenance analysis, which are tasks dependent on operators (Kiangala and Wang 2024).

Thus, it is essential to understand the transformative impacts of GenAI on workforce dynamics, marketplace, production processes and the overall business landscape. However, the main determinants that enable and promote GenAI adoption in companies are still unclear, and there is no framework or guide to help decision-makers with GenAI adoption. Most studies examine the key factors for traditional AI adoption in organizations (Horani et al. 2023; Neumann et al. 2024; Pumplun et al. 2019) or GenAI adoption in specific industrial sectors (AL-khatib 2023), and they do not investigate the influences or interrelationships between factors for GenAI adoption (Agrawal 2024). Thus, additional studies are needed to explore the main factors and their influences on the GenAI adoption process across several industrial sectors, considering the transformative characteristics of GenAI. Most works are mainly based on the TOE framework that analyses technology adoption regarding technological, organizational and environmental contexts (Borgman et al. 2013).

For example, Pumplun et al. (2019) propose a well-known framework based on TOE and AI experts, with the key factors influencing the decision and the ability to adopt AI in organizations. It enables companies to identify areas of improvement for effective AI adoption in their processes and services. However, it does not consider the new requirements arising from GenAI, and additional studies are needed to focus on or compare specific industries (e.g., healthcare and finance) and their associated requirements and key factors. AL-khatib (2023) investigates the drivers for GenAI adoption in the retailing industry using TOE and reveals that complexity negatively impacts GenAI adoption, and exploratory and exploitative innovation positively impacts it. Gupta et al. (2024) discuss theories and theoretical frameworks, such as TOE and the technology acceptance model (TAM), to help GenAI adoption. Proposed by Davis in 1989, TAM analyses the adoption of new technology regarding perceived usefulness and ease of use.

Although TOE and TAM models enable the examination of technology adoption, due to the particularities and disruptive characteristics of GenAI, new factors for GenAI adoption should be considered in the business scenario. For example, companies may be reluctant to adopt GenAI because of the return on investment and the involved risks, such as privacy, data security, intellectual property, ethical considerations and economic disruption (Tredinnick and Laybats 2023). Another critical element is governance, which is a structure that involves roles, responsibilities and decision-making processes that ensure the correct GenAI use regarding privacy and security (Golda et al. 2024) and prevent a company from failing in compliance with ethical guidelines, reputational standards and risk aversion. Finally, another factor is talent, that is, the availability in the labour market of talented people with the ability, skills and training for developing and working on GenAI technologies. Therefore, it is important to clarify and determine the key enablers for GenAI adoption in companies and identify whether the importance of each key enabler varies in specific company sectors.

Considering the previous discussion and gaps, the following research questions were formulated for this work: (RQ1) What factors influence the effective GenAI adoption in companies? (RQ2) Which factors are most influential and critical for the effective GenAI adoption in companies? (RQ3) How does the importance of these factors vary across different company sectors? To answer these, this study incorporates a comprehensive approach and the well-known TAM theory and extends the widely accepted TOE framework to include a business context for analysing the effective GenAI adoption in Spanish companies. Specifically, this work presents a TBOE framework, which considers technological, business, organizational and environmental contexts, as well as adoption risks and governance issues, to offer a holistic, comprehensive and systems thinking approach with 13 factors influencing GenAI adoption. These factors are obtained considering the literature and the particularities of GenAI, and they are validated by AI and business experts.

Then, an analytic network process (ANP) method is employed to determine the most critical and influential factors for effective GenAI adoption in companies. ANP identifies and prioritizes critical factors and their influences on adopting GenAI by considering their interrelationships and the judgements of chiefs on technology and information from companies in several sectors (e.g., energy and services) and sizes. The results reveal that the importance of each factor varies according to each expert from a company sector; but, in general, factors such as culture, governance, organizational structure, organizational size and business processes have an essential role in most cases.

This work makes distinct contributions to the existing literature in several ways. First, a TBOE framework with 13 factors has been presented to explore the effective GenAI adoption in Spanish companies, considering not only technological, organizational and environmental contexts addressed by TOE but also a business context to offer a holistic perspective on adoption intention in companies. Second, most previous studies have focused either on general AI adoption or GenAI adoption in specific company sectors, and they do not investigate the influences between factors for GenAI adoption. This study offers a holistic perspective on GenAI adoption regarding factors' importance and interrelationships while revealing the relative prioritization of factors in each company sector. Third, the proposed work can be applied to future studies for determining the critical and influential factors considering different countries and business experts with other roles (e.g., CEOs). Thus, this study furnishes a methodology for facilitating GenAI adoption in companies, understanding and comparing general and specific company challenges and supporting future research.

This work is organized as follows. Section 2 furnishes a literature review on systems thinking, multicriteria decision-making (MCDM) methods, and theoretical frameworks for technology adoption. Section 3 presents the employed methods for GenAI adoption in companies. Sections 4 and 5 show the results and discussion of this research, respectively. Finally, Section 6 summarizes the concluding remarks.

2 | Literature Review

First, this section discusses systems thinking. Then, it presents relevant works that employ MCDM methods for analysing technology adoption. Finally, it discusses theoretical frameworks and key factors for analysing technology adoption.

2.1 | Generative Artificial Intelligence

In AI, a GenAI model refers to generative modelling that incorporates a machine learning architecture (e.g., a deep neural network) and thus can produce new data based on learned patterns (Feuerriegel et al. 2024). The new content includes text, image, video, code, audio, molecules and 3D renderings (Banh and Strobel 2023). In GenAI, *prompting* allows an interface and a GenAI property that enables users to interact with GenAI applications using natural language to create the desired outputs. In particular, the advent of GenAI tools like ChatGPT is transforming society and businesses.

The use of GenAI in businesses is increasing over time. Taiwo et al. (2025) identify opportunities and challenges of GenAI in the construction industry and propose a framework enabling companies to design customized GenAI solutions (e.g., for querying contract documents). Wasilewski (2025) proposes a GenAI framework to offer customized e-commerce product descriptions. The personalized content has the potential to produce more relevant and engaging product descriptions and improve customer satisfaction and loyalty. Wang et al. (2025) use a GenAI model called SPPformer to predict ship prices to enhance economic efficiency in shipping enterprises and manage risks in financial firms. The proposed solution aims to increase accuracy, interpretability and efficiency for the involved companies.

GenAI technologies like ChatGPT could furnish societal and ethical benefits, but they also introduce ethical concerns such as safety, bias, accountability and responsibility. To manage this, it is needed to have diverse stakeholder engagement, taking into account benefits and risks holistically when designing GenAI applications, and multilevel policy interventions to foster positive results Stahl and Eke (2024). Therefore, a holistic approach considering technical and non-technical enablers is essential to overcome barriers and leverage the full potential and benefits of GenAI in industry Taiwo et al. (2025). This study is expected to enrich the literature about factors influencing GenAI adoption in companies.

2.2 | Systems Thinking

Systems thinking is an approach for *thinking about systems* (Arnold and Wade 2015), and a discipline for seeing wholes, understanding interrelationships rather than things and checking patterns of changes (Bui and Galanou 2022). It consists of *elements* (i.e., characteristics), *interconnections* (i.e., how the elements relate to and/or feedback into each other) and a *function* or *purpose* (i.e., the purpose of systems thinking in a way that can be clearly understood) (Arnold and Wade 2015). Systems thinking helps organizations and people to handle complexity and uncertainty and supports managers in understanding problems that the organizations face as it inspects all the factors that may cause these problems and their interrelationships (Bui and Galanou 2022).

Due to its flexibility and efficiency, systems thinking has been employed in several research projects. For example, Hoyer et al. (2023) employ systems thinking by developing a causal loop diagram to map the relationship between Industry 4.0 implementation factors based on experts' backgrounds. (Raj et al. 2020) combines systems thinking and an MCDM technique to analyse cause-and-effect relationships between barriers to adopting autonomous vehicles. Hu et al. (2023) examine multistakeholder and multicriteria scenarios for determining key corporate social responsibility factors in build–operate–transfer companies considering a systems thinking approach. The authors demonstrate that employing systems thinking alongside an MCDM technique provides a structured and holistic framework for handling complex decision-making scenarios. This integration facilitates a comprehensive understanding of the factors and their relationship, leading to more effective decisions.

Thus, systems thinking is employed to design the research methodology of this work. The principles furnished by systems thinking were followed, and an MCDM approach and a theoretical framework were applied to determine the interrelationships between factors for GenAI adoption in companies. Therefore, an analysis based on an MCDM approach is used to determine the dependence relationships between factors and the key factors related to the problem. In particular, ANP is the key method for the MCDM analysis, integrated with the TOE framework, which allows the analysis of three dimensions that impact the decision process.

2.3 | MCDM Analysis for Technology Adoption

A decision-maker should be able to analyse a set of potential and feasible alternatives and select the optimal one. This procedure is easier when a decision-maker handles single-criterion problems like cost minimization. However, this process becomes complex when evaluating multiple criteria with conflicting natures and weights, such as cost minimization and profit maximization. This requires the use of approaches that can deal with tradeoffs among criteria and alternatives. MCDM involves evaluating multiple criteria and alternatives. MCDM approaches help decision-makers deal with a problem holistically by analysing several environmental and external factors usually neglected by traditional operations research approaches (Thakkar 2021).

In the literature, several works have employed MCDM approaches to analyse AI adoption in many sectors and objectives. Badi et al. (2022) propose the analytic hierarchy process (AHP) to prioritize the main challenges for AI adoption in the healthcare sector of the United Arab Emirates. The study was conducted by interviewing public and private healthcare organization managers. Dora et al. (2022) apply the rough-SWARA technique to rank and prioritize the critical success factors for AI adoption in the food supply chains. Wang et al. (2023) investigate the impact of AI technologies in the construction industry by employing an MCDM approach based on the Delphi method, ANP and a technique for order of preference by similarity to ideal solution (TOPSIS) under a fuzzy environment. Most MCDM approaches assume independence between criteria. However, this assumption is usually unrealistic and can lead to non-optimal evaluations (García-Melón et al. 2010).

ANP is an MCDM approach that performs pairwise comparisons between elements to determine the weight and priority of each element in the decision-making process (Saaty 1999). In particular, ANP helps decision-makers perform decisions by breaking down the problem into smaller parts and then discovering how they all connect and influence each other. Using human expertise, a network is developed to handle dependence and feedback within a group of criteria or among clusters. The final network furnishes a solution accurately and flexibly considering the mutual relationship between criteria (Thakkar 2021).

Gonzalez-Urango et al. (2024) highlight the importance of ANP in improving the efficiency and effectiveness of decision-making in business evaluation frameworks in economics, finance and management. In particular, several ANP applications for analysing technology adoption can be found. For example, Aparisi-Cerdá et al. (2024) employ ANP to identify and rank critical elements for adopting decentralized renewable energy technologies using experts' knowledge and furnish an individual influence index of each element. Chen et al. (2020) investigate the main organizational barriers to big data adoption in the healthcare industry using ANP. The proposed work can help decision-makers evaluate the interrelationships among all the factors. Rajak et al. (2024) apply an ANP model to identify the differences in the drivers of Internet-of-Thing adoption in road, rail and maritime freight transport so that specific challenges in the transportation industry are determined. Hu et al. (2023) adopt ANP to determine key factors for corporate social responsibility in build–operate–transfer companies.

Thus, considering the advantages and relevance of ANP and its ability to incorporate expert knowledge, this paper employs ANP to identify the importance and influence of factors in GenAI adoption across companies.

2.4 | Theoretical Frameworks and Key Factors for Technology Adoption

The TOE framework furnishes a multiple-dimensional analysis of new technology adoption in organizations regarding *technological context*, which is all the relevant technologies for a company; *organizational context*, which are the characteristics and resources of a company; and *environmental context*, which involves external factors/pressures and government regulations influencing technology adoption. Its popularity over other frameworks may rely on the explicit importance of the organizational and environmental contexts, alongside the technological context that tends to dominate in most other frameworks, and its priority on organizational rather than individual technology adoption (Neumann et al. 2024).

The main factors of the general TOE are *relative advantage* (i.e., the degree to which an organization recognizes a technology better than previous solutions), *compatibility* (i.e., the degree to which a technology matches the actual needs of an organization), *top management support* (i.e., the degree to which top management understands and accepts a technology), *organizational size* (i.e., the degree to which an organization's size impacts a technology adoption), *resources* (i.e., the available resources to allow a technology adoption), *competitive pressure* (i.e., pressures arising from the needs and expectations of customers and the market) and *government regulation* (i.e., regulations influencing the technology adoption) (Pumplun et al. 2019).

Studies have used slightly different factors for each TOE context according to their technologies' characteristics since different types of innovations may have different factors that impact their adoption (Baker 2012). Pumplun et al. (2019) adapted TOE for analysing AI adoption in organizations, and other works have used it according to their applications, such as in public organizations (Neumann et al. 2024) and the exhibition sector (Hradecky et al. 2022). Its main differences between the general TOE framework are the inclusion of *organizational structure* as an organizational factor, and *industry requirements* and *customer readiness* as environmental factors; *compatibility* is analysed regarding business processes and cases; *resources* are analysed regarding budget, employees, and data; and *top management support* is replaced by *culture*, which considers top management support, change management and innovative culture. Neumann et al. (2024) added AI strategy alignment and collaboration factors in their framework since it is common for organizations to work together with external partners.

In the context of GenAI technologies such as ChatGPT, TOE provides a structured approach for analysing how several factors influence the integration and adoption of such technologies into businesses (Gupta et al. 2024). In particular, TOE facilitates a systematic analysis of the technological factors of GenAI, the internal readiness and capabilities of the organization and the environment that may help or impede its adoption. AL-khatib (2023) proposes a TOE framework for GenAI adoption. The study analyses GenAI adoption regarding *exploratory* and *exploitative* innovation impacts, and it affirms that complexity impacts negatively on GenAI adoption, while exploratory and exploitative innovation impacts positively. However, it focuses only on the retailing industry. Agrawal (2024) presents a TOE approach for GenAI adoption in organizations. The work introduces new factors, such as absorptive capacity and environmental uncertainty, and takes data from organizations in India to define the priority of each factor. However, the study does not explore the interrelationships between factors and their effects on GenAI adoption. Table 1 summarizes the main described works that apply TOE for technology adoption.

Another framework for analysing the adoption of new technology is TAM. It allows the analysis of a technology adoption regarding perceived usefulness, ease of use and subsequent behavioural intentions and actual usage (Masrom 2007). These factors can also be used in the GenAI context to examine potential user behaviour drivers and the efficacy of AI technologies. Namely, users are likelier to use GenAI if they believe it is a valuable and easy tool. Paper (Gupta et al. 2024)

TABLE 1 | Works based on the TOE framework for analysing technology adoption.

Group/work	General TOE for technology adoption	TOE for AI adoption (Pumplun et al. 2019)	TOE for GenAI adoption in retailing (AL-khatib 2023)	TOE for GenAI adoption in organizations (Agrawal 2024)
Tech.	Relative advantage	Relative advantage	Relative advantage	Relative advantage
	Compatibility	Compatibility[a]	Compatibility	Compatibility
	—	—	Complexity	Complexity
Organizational	Top management support	Culture[b]	Top management support	—
	Organizational size	Organizational size	—	Organizational size
	Resources	Resources[c]	—	Technological resource proficiency
	—	Organizational structure	—	—
	—	—	Organizational readiness	—
	—	—	—	Absorptive capacity
Environment.	Competitive pressure	Competitive pressure	Competitive pressure	Competition intensity
	Government regulation	Government regulation[d]	—	Regulatory support
	—	Industry requirements	—	—
	—	Customer readiness	Customer pressures	—
	—	—	—	Environmental uncertainty

[a]Subfactors: business processes and business cases.
[b]Subfactors: top management support, change management and innovative culture.
[c]Subfactors: budget, employees and data.
[d]Subfactors: GDPR and employees council.

is recommended for other adoption theories and their relevance in ChatGPT.

3 | Methods

Since ANP is employed to assess the importance and influence of factors for GenAI adoption, this section first outlines the ANP steps. Then, it presents the proposed methodology.

3.1 | The ANP Steps

ANP performs pairwise comparisons between elements to determine the priority of each element in the decision-making process. Its steps can be summarized as (Aparisi-Cerdá et al. 2024; García-Melón et al. 2010; Saaty 1999):

- **Step 1: Define the problem and Build an ANP model with a network structure.** The problem is transformed into a network structure of decision clusters and elements (factors) connected through network links. Links denote the interdependencies between elements and clusters. Thus, a network should be built considering all interdependencies between them. Figure 1 furnishes an ANP structure with influences and interdependencies between clusters and elements (Bottero et al. 2020). The interdependencies among elements can be called: *outer dependence* when elements in a cluster have a dependency on elements in another cluster (e.g., the arrow from Cluster 1 to Cluster 3 shows an outer dependence of the elements in Cluster 3 on the elements in Cluster 1); and *inner dependence* when elements in the same cluster influence each other (e.g., the loop in the Cluster 2 reveals an inner dependence between their elements).
- **Step 2: Perform pairwise comparisons between clusters and elements and determine priority weight vectors.** Pairwise comparisons on a pair of elements within the clusters are performed according to their relative importance on each element in another cluster they are connected to (Saaty 1999). Similarly, pairwise comparisons between clusters are also made based on their influences and impact on achieving goals. During this phase, decision-makers (experts) judge the relative importance between a pair of elements and clusters using Saaty's fundamental scale (Saaty and Vargas 2006). Table 2 shows this scale, where an element or a cluster is an item. The ANP computations are performed based on a matrix framework. Thus, after making all the items' comparisons, a priority weight vector (**w**) is determined as the unique solution as follows:

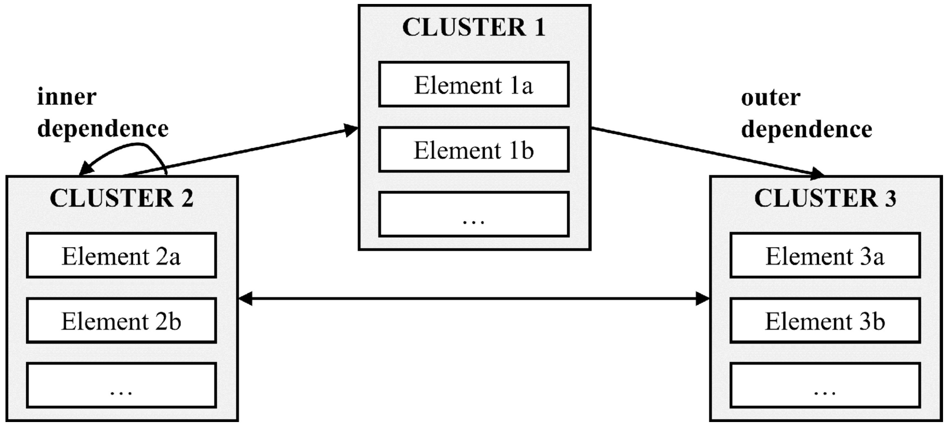

FIGURE 1 | An example of connections in an ANP structure.

TABLE 2 | Saaty's fundamental scale (Saaty and Vargas 2006).

Intensity of importance	Definition	Explanation
1	**Equal importance**	Two items **contribute equally** to the objective
2	Weak	—
3	**Moderate importance**	Experience and judgement **slightly favour** one item over another
4	Moderate plus	—
5	**Strong importance**	Experience and judgement **strongly favour** one item over another
6	Strong plus	—
7	**Very strong importance**	An item is **favoured very strongly** over another
8	Very, very strong	—
9	**Extreme importance**	Experience and judgement **extremely favour** one item over another

$$\mathbf{A} \times \mathbf{w} = \lambda_{max} \cdot \mathbf{w} \quad (1)$$

and

$$\mathbf{A} = \begin{bmatrix} w_1/w_1 & w_1/w_2 & \cdots & w_1/w_n \\ w_2/w_1 & w_2/w_2 & \cdots & w_2/w_n \\ \cdots & \cdots & \cdots & \cdots \\ w_n/w_1 & w_n/w_2 & \cdots & w_n/w_n \end{bmatrix} = \begin{bmatrix} 1 & a_{12} & \cdots & a_{1n} \\ a_{21} & 1 & \cdots & a_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ a_{n1} & a_{n2} & \cdots & 1 \end{bmatrix}, \quad (2)$$

where a_{ij} is the relative importance of an item in row i over an item in column j, $a_{ij} = w_i / w_j$, w_i is the weight of item i, w_j is the weight of item j, n is the number of items to be compared, λ_{max} is the largest eigenvalue of matrix $\mathbf{A}$, and $\mathbf{w}$ is its eigenvector. Comparisons are done on two levels: element level and cluster level.

The consistency of a matrix $\mathbf{A}$ can be determined. In particular, a matrix is consistent if the consistency ratio (CR) is less than or equal to 0.10. The CR value can be calculated as $CR = CI / RI$, where CI is a consistency index and obtained as $CI = \frac{(\lambda_{max} - n)}{(n-1)}$, and RI is a random index and depends on the n value (e.g., $RI = 1.56$ for $n = 13$) (Giannakis et al. 2020; Saaty and Sodenkamp 2010).

- **Step 3: Supermatrices forming and solving.** The supermatrix represents the influence of elements on other elements in the network. Firstly, an *unweighted supermatrix* is obtained, which results in the relative importance of weights (eigenvectors) in the pairwise comparisons. It illustrates the interconnectedness among all the elements in the decision process (Aparisi-Cerdá et al. 2024; Saaty 1999). Then, a *weighted supermatrix* is built, which is calculated by weighting the blocks of the unweighted supermatrix by the corresponding clusters' priorities (also called cluster matrix) to be column stochastic or simply a stochastic matrix. Finally, a *limit supermatrix* is obtained by raising the weighted supermatrix to limit powers to converge until the supermatrix elements are identical and a stable set of weights is obtained.
- **Step 4: Select the best option.** In the limit supermatrix, the final weight of each element in the decision process is accessible from the element's column. The element with the highest weight should be preferred over the others; namely, it has the highest priority.

Mu et al. (2020) propose a guide with the best practices in ANP studies. The authors affirm the importance of literature review and expert opinions to identify factors during the ANP development, select a theoretical framework to contextualize factors, provide clear definitions and sources/references for factors and report all the generated matrices, among other practices. This work applies this guide to design the proposed methodology and report results.

3.2 | Proposed Methodology Description

As described, systems thinking was employed to design the research methodology of this paper, considering an analytic approach (ANP) and a theoretical framework (TBOE). In particular, the proposed factors and clusters can be seen as *elements*; connections and interdependences between factors and clusters can be seen as *interconnections*; and the analysis of GenAI adoption in companies can be seen as a *purpose* considering a systems thinking approach. This study involves three phases, as shown in Figure 2. The following subsections detail each phase and its steps.

3.2.1 | Phase 1: Problem Defining and ANP Model Preparation

Due to the ability of TOE to examine several aspects of an organization regarding technology adoption, this work presents a new framework for GenAI adoption in companies. It considers *organizational* and *environmental* contexts, as well as a new context called *technological and business*, which covers the relevant technology (e.g., technological acceptance) and business (e.g., risks) aspects that impact GenAI adoption. Due to this modification, the framework will be referred to as TBOE (i.e., technological, business, organizational and environmental contexts). TAM theory is also incorporated into the proposed framework as a factor: technology acceptance. Thus, this work merges theoretical frameworks to develop an ANP model, as recommended by the best practices in ANP (Mu et al. 2020).

A panel with three AI/business experts and the authors was arranged to obtain and validate a set of factors. This small group of experts allowed for a more profound, precise and efficient discussion about the importance of each factor for GenAI adoption in companies. The experts have strong experience with AI and GenAI in the business context, as presented in Table 3. Based on the literature (reported in Section 2.4) and the authors' and experts' experiences, 13 factors for GenAI adoption in companies were identified, as shown in Figure 3.

In the *technological and business context*, *relative advantage* was replaced by *technology acceptance*; that is, the perceived usefulness and ease of use of a GenAI solution that affects the organizational and customers' acceptance, as proposed by TAM. Complexity, which can be described as the difficulty in understanding a technology by users (AL-khatib 2023), was omitted since it is implicitly addressed in *technology acceptance*. *Adoption risk* was added since GenAI adoption may involve several risks. On the other hand, as affirmed by an expert, not adopting GenAI may lead to a loss of competitive advantage and innovation of a company, so *nonadoption risk* was included. The

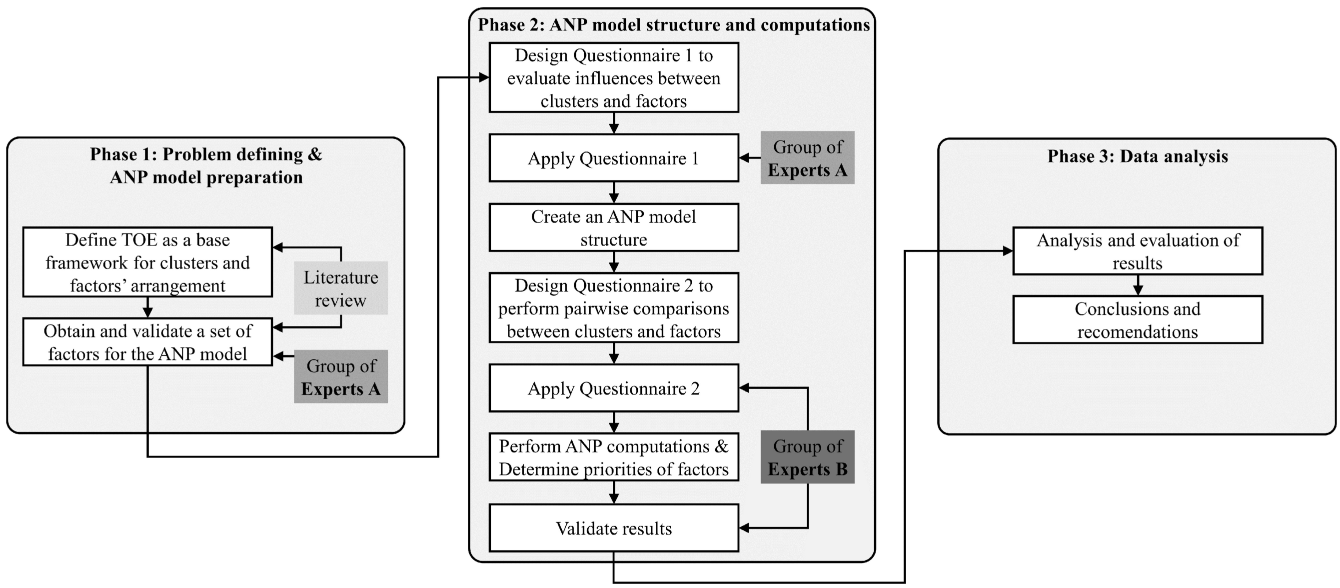

FIGURE 2 | Proposed methodology for GenAI adoption in companies.

TABLE 3 | Profiles of the AI and business experts (Group of Experts A).

Expert	Education level	AI experience	Job role
Expert A1	Doctor's degree	30 years	University professor and board member
Expert A2	Master's degree	25 years	CEO and former CTO
Expert A3	Doctor's degree	10 years	University professor and researcher on Industry 4.0

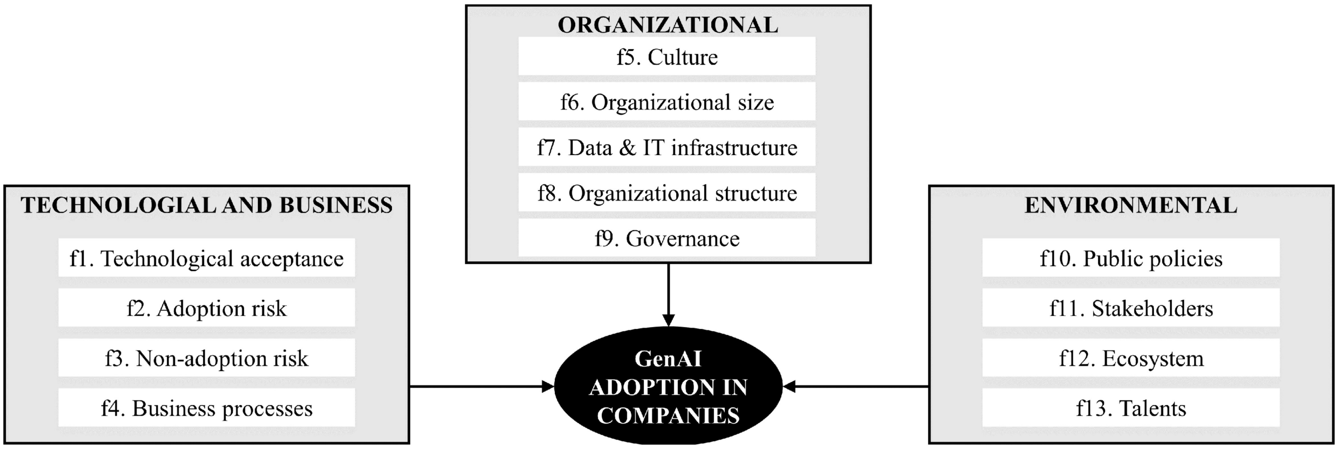

FIGURE 3 | TBOE framework with important factors for GenAI adoption in companies.

compatibility and adaptation abilities of the business processes to the new requirements arising from GenAI adoption are considered with the *business processes* factor. *Competitive pressure* and *customer pressure* were not included since they are implicitly addressed in *nonadoption risk*, and *customer pressure* is also handled by *stakeholders*.

In the *organization context*, *organizational size* and *organizational structure* were added as proposed by Pumplun et al. (2019), and *culture* was included to analyse top management support, change management and innovative culture, and also, AI strategic alignment and collaborative culture, as considered by Neumann et al. (2024). Data and IT infrastructure resources were grouped. The objectives are to analyse the impact of the availability of high-quality data and the importance of hardware and software components within an IT infrastructure (European Commission 2020; Horani et al. 2023; Jöhnk et al. 2021) for supporting GenAI applications. In addition, *governance* was included because it enhances alignment, clarity, thoughtfulness, accountability, trust and public perception of a company (Gill et al. 2022) through compliance and ethics guides, among other guidelines. *Organizational readiness*, which is the tangible and intangible resources that enable technology adoption (AL-khatib 2023), was omitted since it is addressed in a transversal way by several other factors, such as *culture*, *data and IT infrastructure*, *organizational structure* and *business processes*. That is, if these factors are well-accomplished and well-co-ordinated, *organizational readiness* for GenAI adoption will also be achieved.

In the *environmental context*, *government regulations* were changed to *public policies*. In this case, beyond evaluating the influence of regulations, public investment support is considered to measure its impact on GenAI adoption. *Stakeholders* address the impact of individuals or groups who affect or are affected by the companies' activities. *Ecosystem* was included to address the impact of an interconnected and collaborative network of actors on the cooperation in implementing GenAI solutions. *Talents* consider the availability in the labour market of professionals with GenAI ability for developing and working on GenAI technologies. *Customer readiness* was not added since it is addressed in *technology acceptance* and *stakeholders*, and *industry requirements* are omitted since this study already identifies the specific requirements (factors) that impact GenAI adoption in each company sector.

Therefore, the factors' selection was guided by two approaches: (*i*) a literature review on technology adoption frameworks (including TOE and TAM); and (*ii*) an expert validation process involving professionals with domain-specific knowledge in AI and industry. These approaches ensure that the selected factors reflect theoretical robustness and practical relevance. While many of the identified factors are well-established in the literature on technology adoption, the inclusion of new factors such as technology acceptance, adoption risk, nonadoption risk, governance, stakeholders and ecosystem extends the actual literature to consider the distinctive and disruptive characteristics of GenAI. Furthermore, categorizing these factors into technological/business, organizational and environmental dimensions facilitates and ensures a holistic assessment of GenAI adoption readiness. This grouping enables organizations to address internal capabilities and external (environment) influences, while it is considered comprehensive for the present technological context. Appendix A furnishes a detailed description and reference of the factors.

The distinction between technological/business and environmental clusters should be carefully considered to avoid potential overlap between clusters. Environmental factors are defined as external influences on GenAI adoption (e.g., public policies and stakeholders). In contrast, technological and business factors refer to internal technological aspects in an organization related to the adoption and perceived acceptance of GenAI, along with its integration into business processes. This separation ensures that the external technological environment does not overlap with the organization's internal technological context. Furthermore, while technological and economic capabilities of organizations are critical determinants for GenAI adoption, they are implicitly represented within the proposed framework. For example, data and IT infrastructure reflect the organization's technological capability, whereas organizational size captures economic and resource-related capabilities. These inclusions ensure that technological and economic aspects are adequately represented without expanding the number of factors.

This study contributes to the literature by advancing the traditional TOE model into a TBOE framework adapted for GenAI adoption.

Conceptually, including the business dimension and integrating adoption risk, nonadoption risk, and governance as essential factors provides a more comprehensive analysis of GenAI adoption behaviour in organizations. Methodologically, the research introduces originality by combining systems thinking with the ANP, enabling the examination of complex interdependencies among factors across all dimensions. This approach offers a dynamic and empirically grounded model that enhances theoretical insight and practical guidance for companies adopting GenAI.

3.2.2 | Phase 2: ANP Model Structure and Computations

The first step of Phase 2 defines how clusters and factors are connected (i.e., their influence) by designing Questionnaire 1. As shown in Figure 3, three clusters and 13 factors are proposed. For the cluster evaluation, three questions (one for each cluster) were designed. Table 4 shows an example of a question for cluster evaluation, where an expert should select the clusters that influence cluster C1 (technological and business). For the factor evaluation, 13 questions (one for each factor) were proposed. Table 5 presents an example of a question for factor evaluation, where an expert should mark factors influencing factor f1 (technology acceptance). All the questions were arranged in a file to compose Questionnaire 1 (see Supporting Information).

For the second step, a Group of Experts A was asked to answer Questionnaire 1. With the answers, it was defined that an influence of a cluster/factor on another cluster/factor occurs if the majority of the experts (i.e., two experts) agree on it, similar to the work (Giannakis et al. 2020). Tables 6 and 7 reveal the influences between clusters and factors, respectively. The results show five influences between clusters and 74 influences between factors. It is observed that the technological and business cluster (C1) does not influence the environmental cluster (C3).

To create the ANP model structure and computations, the SuperDecisions V3.2 software was selected (Creative Decisions Foundation 2019). It is a well-known decision-making software that implements ANP. Initially, the clusters and factors' objects were created, and then the influence data (Tables 6 and 7) were inputted into the software. Figure 4 represents the obtained ANP structure.

To design Questionnaire 2, the needed pairwise comparisons between clusters and factors were extracted from the software. The objectives of this questionnaire are to answer: considering cluster C_a, which cluster, C_b or C_c, most influences cluster C_a and to what degree (1 – 9 using the Saaty's scale); and, considering factor f_d, which factor, f_e or f_f, most influences factor f_d and to what degree (1 – 9). Tables 8 and 9 present an example for each pairwise comparison type. The Saaty's scale was reduced (i.e., 2,4,6,8 values were omitted) to simplify Questionnaire 2. Then, seven pairwise cluster comparisons and 64 pairwise factor comparisons were needed. In ANP, for factors, pairwise comparisons are made only between factors from the same cluster. All the questions were arranged in a file to compose Questionnaire 2 (see Supporting Information).

A panel was arranged with senior experts on technologies/information and business (Group of Experts B) to apply Questionnaire 2. Unlike other survey methods based on large sample sizes, for ANP, the quality and qualification of the experts are significantly more important than the number of them (Bastida-Molina et al. 2022). There is no clear guideline on the number of experts. However, the best practices in ANP studies are recommended to justify the expert qualification (Mu et al. 2020). During the literature review, it was observed that this number usually varies between 8 and 30 (Aparisi-Cerdá et al. 2024; Bastida-Molina et al. 2022; García-Melón et al. 2010; Gonzalez-Urango et al. 2024; Wang et al. 2023).

TABLE 4 | Example of a question from Questionnaire 1—Influences between clusters.

Select the clusters that influence C1. Technological and business.	
C2. Organizational	☐
C3. Environmental	☐

TABLE 5 | Example of a question from Questionnaire 1—Influences between factors.

Select the factors that influence f1. Technology acceptance.							
f2. Adoption risk	☐	f5. Culture	☐	f8. Organizational structure	☐	f11. Stakeholders	☐
f3. Nonadoption risk	☐	f6. Organizational size	☐	f9. Governance	☐	f12. Ecosystem	☐
f4. Business processes	☐	f7. Data and IT infrastructure	☐	f10. Public policies	☐	f13. Talents	☐

TABLE 6 | Influences between clusters.

	C1. Technological and business	C2. Organizational	C3. environmental
C1. Technological and business		✓	
C2. Organizational	✓		✓
C3. Environmental	✓	✓	

TABLE 7 | Influences between factors.

		C1. Tech. and Bus.				C2. Organizational					C3. Environmental			
		f1	f2	f3	f4	f5	f6	f7	f8	f9	f10	f11	f12	f13
C1. Technological and business	f1. Technology acceptance		✓	✓	✓			✓						
	f2. Adoption risk			✓	✓					✓				
	f3. Nonadoption risk		✓											
	f4. Business processes	✓	✓			✓		✓	✓					
C2. Organizational	f5. Culture	✓	✓	✓	✓		✓		✓	✓				✓
	f6. Organizational size		✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓
	f7. Data and IT infrastructure				✓									
	f8. Organizational structure		✓		✓	✓	✓	✓		✓		✓		✓
	f9. Governance	✓	✓	✓		✓	✓	✓	✓			✓	✓	✓
C3. Environmental	f10. Public policies		✓	✓			✓			✓		✓		
	f11. Stakeholders		✓	✓		✓	✓		✓	✓	✓		✓	
	f12. Ecosystem					✓	✓							✓
	f13. Talents	✓	✓	✓	✓	✓	✓						✓	

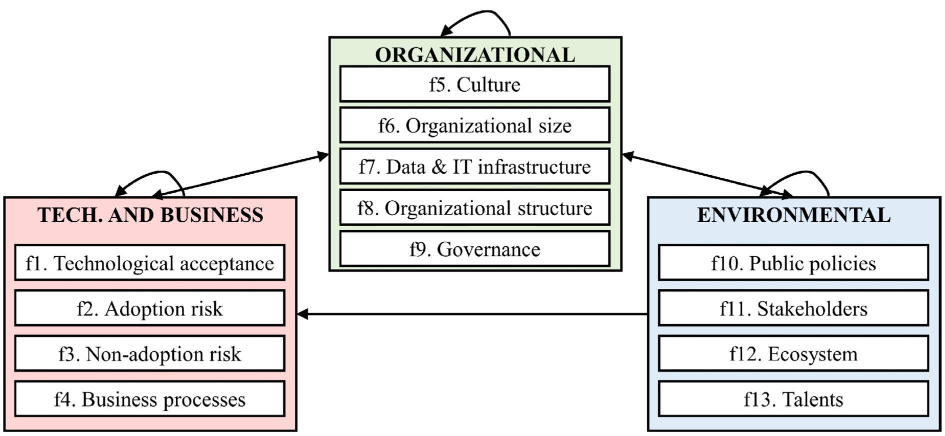

FIGURE 4 | ANP structure for GenAI adoption in companies. [Colour figure can be viewed at wileyonlinelibrary.com]

For this study, 12 chief IT officers from companies in Spain were selected to answer Questionnaire 2. Their profiles are presented in Table 10. As observed, this group mainly comprises chief information and/or technology officers. Thus, the experts are highly qualified and specialized in analysing the key factors for GenAI in companies. In addition, different company sectors and sizes were selected to offer a holistic view of GenAI adoption in companies. For instance, an enterprise is classified as SME (i.e., micro-, small- or medium-sized) or large according to the EU recommendation 2003/361/EC (European Commission 2003). Using Questionnaire 2, the experts were asked to provide their opinions on the degree of influence between clusters and factors considering their company sectors.

Their answers were employed to create ANP models and define the importance of clusters and factors. In particular, an

TABLE 8 | Example of a question from Questionnaire 2—Clusters' pairwise comparisons.

Comparisons regarding C1. Technological and business:
Which cluster most influences and to what degree the technological and business cluster in the GenAI adoption in your company sector?

	EX	**VS**	**S**	**M**	**EQ**	**M**	**S**	**VS**	**EX**	
	9	7	5	3	1	3	5	7	9	
C3. Environmental	☐	☐	☐	☐	☐	☐	☐	☐	☐	C2. Organizational
C3. Environmental	☐	☐	☐	☐	☐	☐	☐	☐	☐	C1. Technological and business
C2. Organizational	☐	☐	☐	☐	☐	☐	☐	☐	☐	C1. Technological and business

Abbreviations: EQ, equally important; EX, extremely more important; M, moderately more important; S, strongly more important; VS, very strongly more important.

TABLE 9 | Example of a question from Questionnaire 2—Factors' pairwise comparisons.

Comparisons regarding f12. Ecosystem:
Which factor most influences and to what degree the ecosystem factor in the GenAI adoption in your company sector?

	EX	VS	S	M	EQ	M	S	VS	EX	
	9	7	5	3	1	3	5	7	9	
f6. Organizational size	☐	☐	☐	☐	☐	☐	☐	☐	☐	f9. Governance
f11. Stakeholders	☐	☐	☐	☐	☐	☐	☐	☐	☐	f13. Talents

Abbreviations: EQ, equally important; EX, extremely more important; M, moderately more important; S, strongly more important; VS, very strongly more important.

TABLE 10 | Profiles of the technology and business experts (Group of Experts B).

Expert	Experience	Role in the company	Company state level	Company size	Company sector
Expert B1	20 years	Chief digital officer	International	Large	Energy
Expert B2	25 years	Chief information and technology officer	International	SME	Services/technology
Expert B3	20 years	Chief Industry 4.0 officer	International	Large	Services/IT consultancy
Expert B4	25 years	Chief information officer	National	Large	Education
Expert B5	20 years	Chief information officer	International	Large	Manufacturing/metal
Expert B6	15 years	Chief technology officer	International	Large	Manufacturing/automotive
Expert B7	15 years	Chief digital transformation officer	National	SME	Services/insurance
Expert B8	22 years	Executive, business and technology responsible	International	Large	Technology
Expert B9	25 years	Chief technology officer	International	SME	Agriculture/wine
Expert B10	30 years	IT director	International	SME	Manufacturing/building
Expert B11	20 years	Head of innovation strategy and growth	International	Large	Transportation/infrastructure
Expert B12	25 years	***IT director***	International	SME	Transportation

ANP model for each expert was generated. In this case, the created ANP model structure, developed on SuperDecisions, was used as a base for each model. Then, the comparisons of each expert were inputted into each model. The pairwise comparison matrices' consistencies were checked. If the inconsistency of a matrix was larger than 0.1, the comparisons

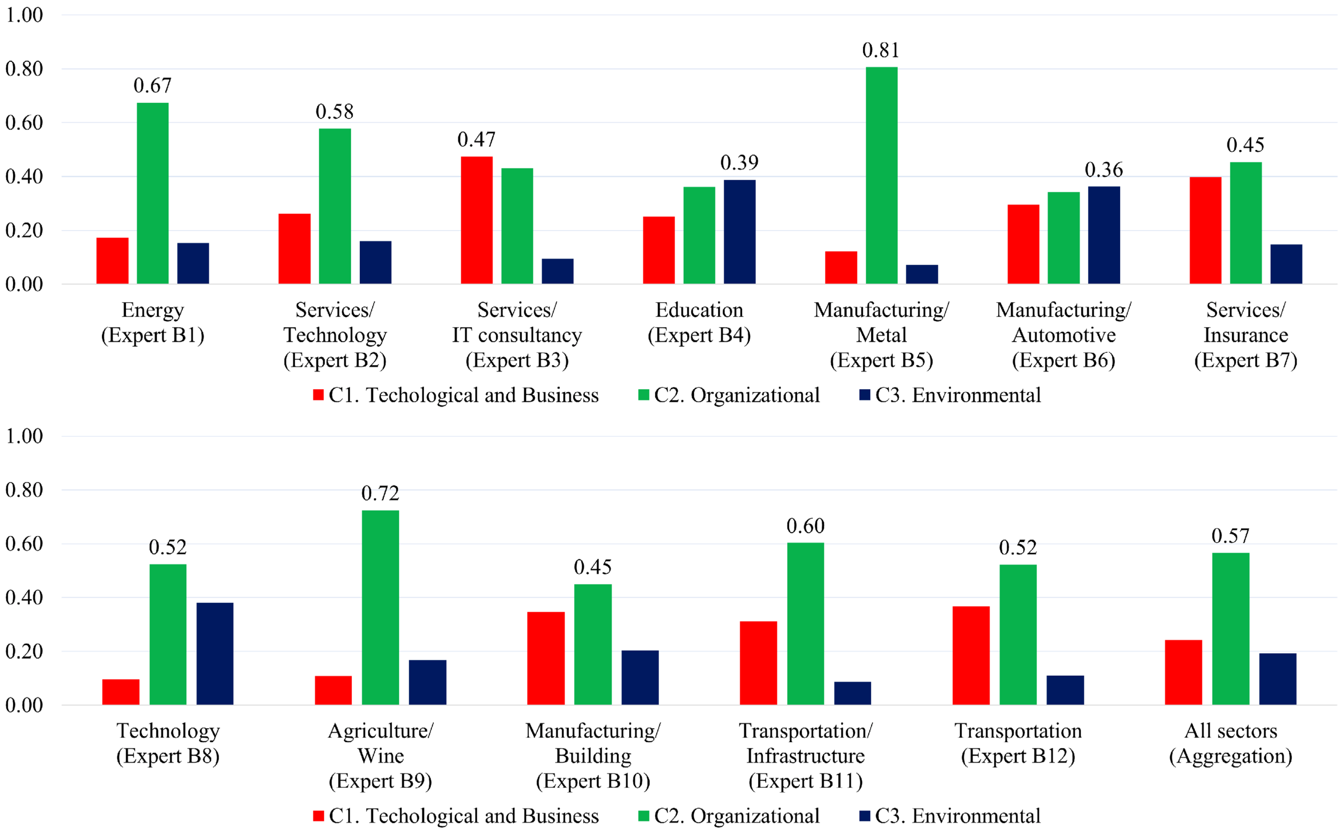

FIGURE 5 | Individual and global clusters' weights. [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 11 | Cluster matrix from the aggregation approach (global results).

	C1. Technological and business	C2. Organizational	C3. Environmental	Weight
C1. Technological and business	0.458	0.268	0	0.242
C2. Organizational	0.416	0.614	0.667	0.566
C3. Environmental	0.126	0.117	0.333	0.192

were reviewed with the expert (Bastida-Molina et al. 2022). Then, ANP computations were performed to obtain relevant ANP matrices. Finally, the individual results of each ANP model were shown to each expert to check if they were meaningful and represented their preferences and knowledge. In all cases, the experts agreed that the results reveal what they know about key factors for GenAI adoption in their company sectors.

An aggregation approach of all the expert comparisons was performed to obtain a global view of influencing factors in all the company sectors. The aggregation was done using the geometric mean of all the experts' pairwise comparisons (Saaty and Vargas 2006). The geometric mean performs better than the arithmetic mean and avoids extreme values (Elshaboury et al. 2020). For this reason, it is widely employed to aggregate experts' judgements (Aparisi-Cerdá et al. 2024; Bastida-Molina et al. 2022; García-Melón et al. 2010; Giannakis et al. 2020). This paper uses aggregation to create a new ANP model with the global prioritization of the factors for GenAI adoption in all the company sectors.

3.2.3 | Phase 3: Data Analysis

The final phase involves a thorough data analysis of the results to address the research questions. Assessing the interrelationships between factors will help decision-makers set priorities in promoting effective GenAI adoption. The data analysis will also allow the comparison of priorities in different company sectors and identify the importance of each TBOE context for GenAI adoption.

4 | Results

The results are systematically structured in this section to address the research questions. The obtained ANP supermatrices of the aggregation approach are available in this section and Appendix B, and the supermatrices of the individual approach are available as additionalSupporting Information.

Figure 5 shows the individual and global results of the clusters' weights using cluster matrices. The global results (Table 11) indicate that the organizational cluster (0.566) has the highest weight, followed by the technological and business cluster (0.242) and environmental cluster (0.192). The individual results reveal that the experts hold different points of view regarding the clusters' importance. Differences are also noted in the same company sector. However, most experts (B1, B2, B5, B7, B8, B9, B10, B11 and B12) agree that the organizational cluster has the highest weight. They are from company sectors of energy, services/technology, manufacturing/metal, services/insurance, technology, agriculture/wine, manufacturing/building and transportation. Experts B4 and B6 from the education and manufacturing/automotive sectors judge that the environmental cluster has the highest priority. In contrast, Expert B3 from services/IT consultancy gives more importance to the technological and business cluster. Experts from SMEs (B2, B7, B9, B10 and B12) prioritize the organizational cluster.

Figure 6 presents the global prioritization results of the factors obtained by the limit matrix (Table B2). Five factors, namely, culture (0.18), governance (0.15), organizational structure (0.14), organizational size (0.13) and business processes (0.12) emerge as the top contributing factors. They contribute a minimum of 10% of the total weight (i.e., they have weights larger than 0.1), so they are considered the primary factors (Aparisi-Cerdá et al. 2024) for effective GenAI adoption in companies. Most of them are organizational factors, and together, they account for 71% of the total prioritization weight in the decision process. Thus, organizational factors (except data and IT infrastructure) are essential in fostering GenAI in companies. Therefore, comprehensive understanding and enabling them is fundamental for promoting effective GenAI adoption in companies.

The three lowest ranked factors are nonadoption risk (0.01), data and IT infrastructure (0.02) and ecosystem (0.02). Their contribution to the total weight is 5%. However, their final weights should not lead to the interpretation that these factors are irrelevant to the decision process since the rankings only show the priorities of the proposed 13 factors. Finally, factors with a moderate contribution to the total weight (24%) are adoption risk (0.07), stakeholders (0.06), technological acceptance (0.04), talents (0.04) and public policies (0.04).

Figure 7 shows the global and individual prioritization results using radar graphs. The orange surface highlights factors that contribute less or more than 10% of the total weight. The factors with the highest priorities in the global results (Figure 6) also have the highest weights, with different combinations, for the experts B1, B2, B5, B8, B9, B10 and B11 from energy, services/technology, manufacturing/metal, technology, agriculture/wine sectors, manufacturing/building and transportation/infrastructure, respectively. On the other hand, technological and business factors, such as business processes, adoption risk and technology acceptance, have the highest priority, according to experts B3, B7 and B12 from the sectors of services/IT consultancy, services/insurance and transportation, respectively. Public policies and stakeholders from the environmental cluster have the highest weight, according to Experts B4 and B6 from the education and manufacturing/automotive sectors, respectively.

It should be pointed out that experts' differing opinions reveal that not all of them perceive factors and clusters' importance for GenAI adoption in their company sectors. However, the global importance results of factors and clusters show how differences among them compensate, and, on average, by the aggregation approach, the organizational cluster and its associated factors converge to be the most critical factors for effective GenAI adoption in companies.

Additional insights regarding influences among clusters and factors can be obtained from the ANP matrices. The cluster matrix (Table 11) also shows the influences between clusters. The results reveal that each cluster strongly influences itself, but external solid influences are also observed. For example, the organizational cluster strongly influences the technological and business (0.416) and environmental (0.667) clusters.

The weighted matrix (Table 12) indicates the influence among factors. It offers valuable information on the interactive and influencing mechanisms between factors. This table highlights values higher than a threshold, defined as the mean plus two times the standard deviation (Aparisi-Cerdá et al. 2024). From this matrix, nine strong and significant influences can be noted. For example, strong influences are observed from business processes to technology acceptance (0.458), from culture to organization size (0.420) and from organization size to public policies (0.667). For instance, moderate influences (≈0.3) can be noted from culture to technology acceptance,

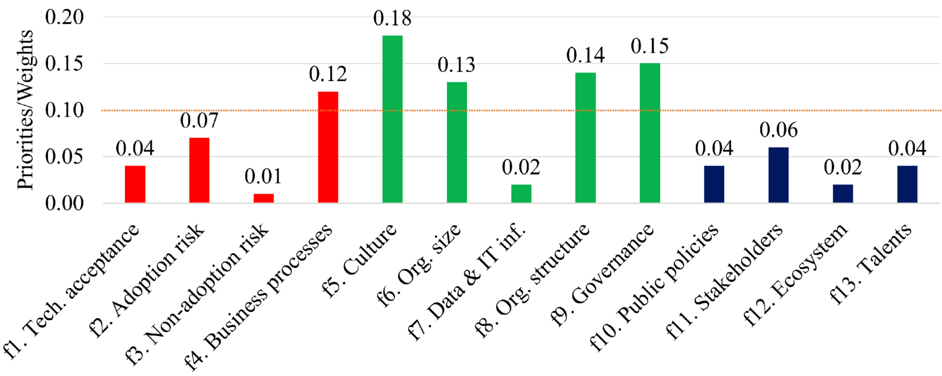

FIGURE 6 | Global prioritization results for GenAI adoption in companies. The orange dashed line ··· highlights factors with weights larger than 0.1, ■ are factors in the technological and business cluster (C1), ■ are factors in the organizational cluster (C2), and ■ are factors in the environmental cluster (C3). [Colour figure can be viewed at wileyonlinelibrary.com]

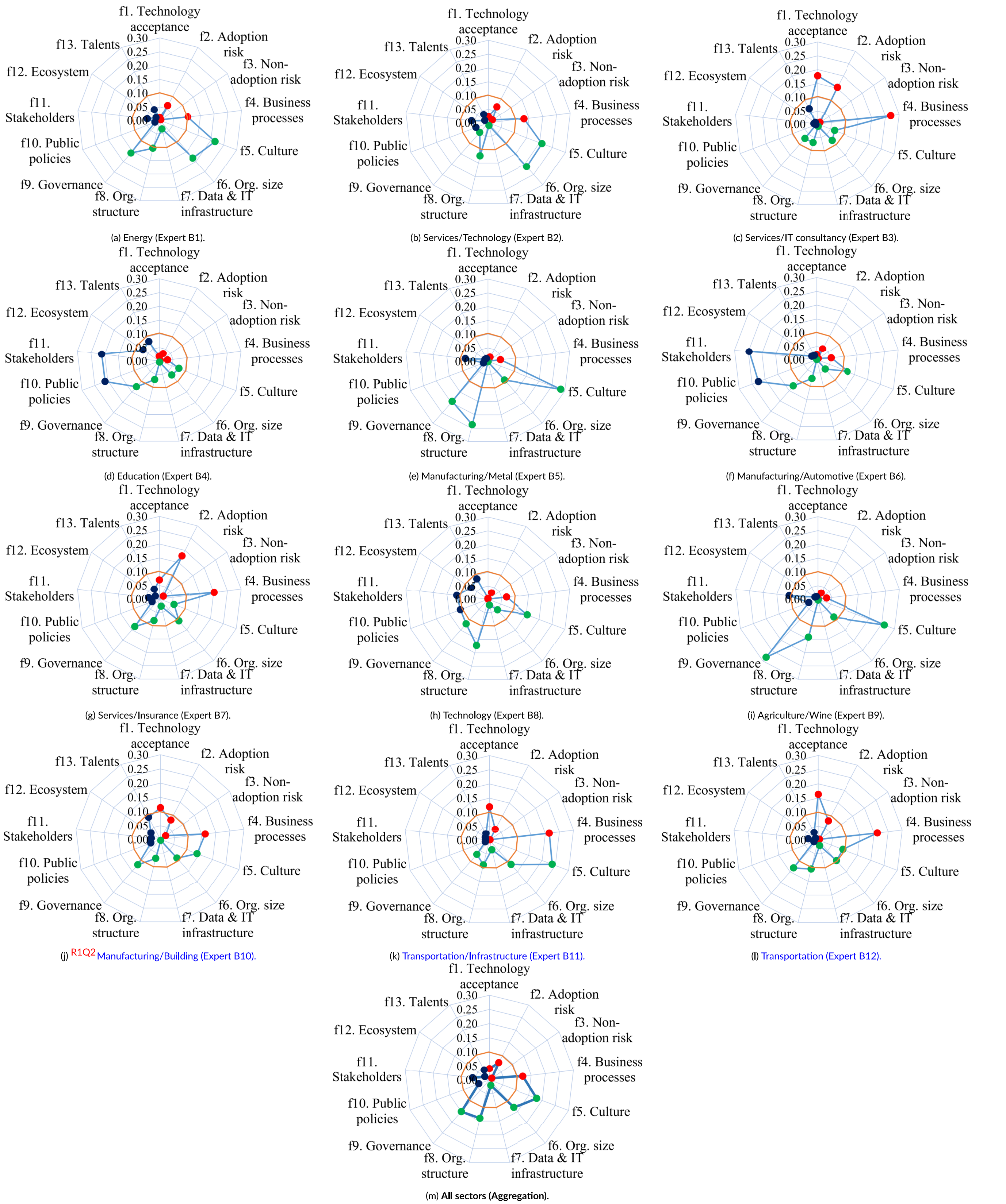

FIGURE 7 | Individual and global prioritization results for GenAI adoption in companies. The orange shape highlights factors with weights larger than 0.1, ■ are factors in the technological and business cluster (C1), ■ are factors in the organizational cluster (C2), and ■ are factors in the environmental cluster (C3). [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 12 | Weighted supermatrix from the aggregation approach (global results). Highlighted values are higher than the average plus two times the standard deviation.

		C1. Tech. and business				C2. Organizational					C3. Environmental			
		f1	**f2**	**f3**	**f4**	**f5**	**f6**	**f7**	**f8**	**f9**	**f10**	**f11**	**f12**	**f13**
C1. Technological and business	f1. Technology acceptance	0	0.150	0.229	0.229	0	0	0.101	0	0	0	0	0	0
	f2. Adoption risk	0	0	0.229	0.229	0	0	0	0	0	0.268	0	0	0
	f3. Nonadoption risk	0	0.119	0	0	0	0	0	0	0	0	0	0	0
	f4. Business processes	**0.458**	0.189	0	0	0.268	0	0.203	0.268	0	0	0	0	0
C2. Organizational	f5. Culture	**0.312**	0.141	0.225	0.148	0	**0.420**	0	0.254	0.246	0	0	0	0.213
	f6. Organizational size	0	0.058	0.068	0.052	0.160	0	0.232	0.160	0.123	**0.667**	0.173	**0.333**	0.105
	f7. Data and IT infrastructure	0	0	0	0.136	0	0	0	0	0	0	0	0	0
	f8. Organizational structure	0	0.099	0	0.081	0.201	0.210	0.232	0	0.246	0	0.218	0	0.187
	f9. Governance	0.104	0.117	0.124	0	0.254	0.210	0.232	0.201	0	0	0.275	**0.333**	0.162
C3. Environmental	**f10**. Public policies	0	0.052	0.042	0	0	0.033	0	0	0.059	0	**0.333**	0	0
	f11. Stakeholders	0	0.033	0.042	0	0.039	0.047	0	0.117	0.059	**0.333**	0	0.167	0
	f12. Ecosystem	0	0	0	0	0.039	0.033	0	0	0	0	0	0	**0.333**
	f13. Talents	0.126	0.041	0.042	0.126	0.039	0.047	0	0	0	0	0	0.167	0

from organization size and governance to ecosystem, from public policies to stakeholders (and vice versa) and from ecosystem to talents.

The highest average influences (i.e., the sum of influence values of each factor divided by the number of factors) are from organizational size (0.164), governance (0.155), culture (0.151), organizational structure (0.113) and business processes (0.107). Thus, these factors notably influence most factors, and consequently, addressing them can positively impact other factors in a cascade effect. Looking at the global prioritization results (Figure 6), these factors are also highly important for GenAI adoption in companies.

5 | Discussion

This work contributes to identifying the most critical and influential factors for effective GenAI adoption in Spanish companies considering systems thinking principles. For this purpose, three research questions were addressed. RQ1 focuses on determining the factors influencing effective GenAI adoption in companies. This is done with the proposal of the TBOE framework with the 13 factors influencing GenAI adoption in companies (Figure 3), six factors (i.e., technology acceptance, adoption risk, nonadoption risk, governance, stakeholders and ecosystem) having not been explicitly addressed by other works. This framework, validated by AI and business experts, aims to handle the disruptive characteristics of GenAI.

The research results revealed the importance of the TBOE contexts, considering the perception of senior IT experts from SMEs and large companies. Our results offer a holistic perspective of the GenAI adoption trends and show that the organizational context has the highest weight, followed by environmental and technological/business contexts. To explain this result, we compare the introduction of this new GenAI technology to the digital transformation processes performed by large industrial companies, like the ones in our study, from 2016 to 2018. In these projects, internal reluctance to change, legacy systems or governance concerns arose as the main barriers for the digital transformation processes to be successfully implemented, often leading to intense friction and even project failure. With these learned lessons, companies are apparently focusing on the organizational factors with higher predominance than technological/business or environmental.

According to the experts, four organizational factors emerge as the most critical and influential for successful GenAI adoption in companies: culture, governance, organizational structure and organizational size. This result answers RQ2 and reinforces the importance of the organizational context. Three factors (viz., culture, organizational structure and organizational size) were previously proposed by work (Pumplun et al. 2019) to deal with standard AI adoption in organizations. However, governance, which was not addressed by previous studies, significantly impacts GenAI adoption. Thus, appropriate governance is crucial to ensure the correct and ethical GenAI use since this new technology can produce new risks and unintended consequences (Nah et al. 2023). Responsibility for the bad use of GenAI technology, regardless of intentionality, is not clearly defined or delimited in current laws, which may also be a factor in explaining this clear concern on governance as a critical factor for GenAI adoption. Additionally, the factors' priorities are not totally aligned with the work by Agrawal (2024), which ranks regulatory support, complexity, compatibility and competition intensity as the most critical enablers for GenAI adoption in organizations. From this set, compatibility is correlated to the business process factors of this work, which moderately influences GenAI adoption in companies.

Therefore, in summary, this study reveals the importance of the organizational factors to allow effective GenAI adoption, namely, cultural aspects (top management support, innovative/collaborative culture and AI strategic alignment) (Neumann et al. 2024); adequate governance to ensure correct GenAI use (Nah et al. 2023); and organizational structure and company size (Pumplun et al. 2019). On the other hand, data and IT infrastructure, an organizational factor, have a low priority in the adoption process. Considering that digital technologies fully enable GenAI, this fact might be counterintuitive. However, it is consistent with the study by Agrawal (2024), which shows that technological resource proficiency does not substantially influence GenAI adoption. Then, we argue that companies that have succeeded in the process of becoming data-driven may already feel that integrating this technology into their processes is seamless. In contrast, companies less proficient in data governance might regard these services as full Cloud services and, therefore, reasonably independent from their data and computational infrastructure. We believe the full integration of this technology in the digital stack of industrial companies will require deploying small GenAI agents on-premise. Therefore, many companies will experience friction in the GenAI adoption process derived from their lack of maturity on data and IT infrastructure, even though currently, they find organizational factors more relevant.

From the environmental perspective, the stakeholders have more priority than the ecosystem. Thus, it is perceived that stakeholders such as shareholders, employees, customers and suppliers have more impact and engagement than other external partners (e.g., companies, startups and universities) for GenAI adoption. In addition, the experts recognize that public policies such as regulations and public financial support have moderate importance in the adoption process. Unexpectedly, experts perceive that the availability of GenAI talent in the labour market is a moderate priority for adoption. This may happen because industrial companies are observing the development trajectory of GenAI by external actors and, therefore, are more concerned with attracting talent with general digital expertise rather than specific GenAI abilities.

In the technological and business context, business processes have the highest priority. So, most experts recognize the importance of the compatibility and adaptability of the business processes to the new requirements and characteristics arising from GenAI adoption. Risks related to GenAI adoption have moderate importance for experts, whereas nonadoption risk and technology acceptance have low priorities. Nonadoption risks may be less critical since experts perceive that GenAI adoption cannot bring competitive advantages over their competitors. In contrast, technology acceptance is not a concern for the experts since they may note GenAI's usefulness and ease of use.

RQ3 addresses the importance of the factors between different company sectors. The results indicated that each factor's importance varies according to an expert from a company sector, but they prioritize organizational factors. The differing views among experts may occur because companies have different technological maturity levels, regulatory and ethical environments, change management and culture, organizational goals and strategies and sector-specific needs. For example, it was noted that experts from the education and manufacturing/automotive sectors prioritize stakeholders, public policies and governance. Thus, they perceive that their environment and regulatory and ethical issues directly impact effective GenAI adoption. According to Stahl and Eke (2024), developing GenAI applications requires multiple stakeholder engagement, considering benefits and risks, and multilevel policy interventions to foster positive results. Experts from the services/IT consultancy and services/insurance sectors agree that adoption risks and alignment with the business processes are more critical to ensure effective GenAI adoption. On the other hand, experts from different sectors prioritize internal organizational factors (except data and IT infrastructure) for successful adoption.

5.1 | Theoretical Contributions

For academia, this work significantly contributes to the existing literature regarding GenAI adoption in companies. First, a TBOE framework has been presented to explore the effective GenAI adoption in companies, considering not only technological, organizational and environmental contexts proposed by TOE but also a business context to offer a holistic perspective on adoption intention in companies. This research also answered the importance of each context for the adoption process in companies, which was unexplored by previous research. Second, a new set of 13 factors influencing effective GenAI adoption in companies was proposed and validated by AI and business experts. In particular, the results revealed the importance of governance (not addressed by previous works) and most organizational factors for successful GenAI adoption. Third, most previous works have focused on general AI adoption or specific company sectors. This study offers a holistic perspective on GenAI adoption in all company sectors while identifying the importance of factors and contexts in specific sectors. Fourth, the proposed work can be applied to future studies for determining the critical and influential factors considering points of view from different business experts with different roles (e.g., CEOs) and other regions/countries.

5.2 | Implications for Practice

This study provides valuable practical insights for companies and their managers and suggests strategies to contribute to more effective GenAI adoption. Companies can use these insights to identify and prioritize enablers to a favourable environment for successful GenAI adoption, assess their readiness for adoption, determine barriers and develop strategies to handle them. Policymakers may also find relevant insights in these results to design incentive schemes or regulations to improve the GenAI adoption process.

First, the findings suggest that most companies should prioritize strategies to foster their internal organizational capabilities. To leverage the GenAI benefits, managers should analyse whether their organizational culture aligns with the new requirements arising from GenAI technologies. Change management is important to help employees and top managers understand and deal with organizational changes and minimize misconceptions regarding GenAI (e.g., possible job loss). In addition, encouraging an innovative/collaborative culture and developing an AI strategic alignment is crucial to incorporating GenAI properly. Also, preparing a governance structure to guarantee the correct GenAI use is essential to prevent a company from failing in compliance. Moreover, aligning the organizational structure regarding jobs, systems and people/teams is important for successful GenAI adoption. Organizational size also impacts GenAI adoption. Thus, large companies can concentrate efforts to impede bureaucratic and old systems/processes, complex organizational structures and change resistance that hamper GenAI's introduction. On the other hand, SMEs tend to have few resources to introduce new technologies. This can be overcome by embracing open GenAI platforms. Companies that want to experiment and/or innovate with GenAI should apply it to create new business processes/services and solve problems not yet solved by humans or previous AI algorithms. Nevertheless, as stated before, the final effective use of this technology in a corporative environment will likely require deploying orchestrated specific agents on the premises, which will pose downstream difficulties.

The interactive mechanisms between factors (furnished by the weighted matrix) provide valuable insights for enterprises and policymakers. For instance, the strong link between business processes and technology acceptance suggests that organizations aiming to adopt GenAI should prioritize process redesign and integration readiness to facilitate GenAI implementation. Similarly, the influence of culture on organization size highlights the importance of fostering an innovation-oriented culture, especially in larger enterprises where structural inertia may hinder adoption. Finally, the impact of organization size on public policies reveals how policymakers can tailor regulatory frameworks to address the needs of different company sizes.

From the policymaker perspective, our results suggest that regulations oriented to foster collaboration between companies may be less effective than policies that set the focus on mitigating organizational problems. In this line, defining a clear legal framework that clarifies the responsibilities of GenAI providers and users can be a key factor in reducing corporate uncertainties related to GenAI governance.

5.3 | Limitations and Future Results

Despite the valuable insights, this study has some limitations that need to be considered in future research. This research focuses on the CTOs' perspectives and may not be directly extrapolated to all managers' perspectives. Future research can be performed to incorporate and compare other managers' perspectives (e.g., CEO). For instance, it is also crucial to recognize that this study focuses on companies with robust operations in Spain (despite their international nature) and may not be extrapolated to other countries in other developing stages. For this reason, future works can also be devoted to replicating this study in other countries with different contexts and technology infrastructures.

Additionally, while a large set of factors from three contexts was considered in this research, other factors influencing GenAI adoption in companies may not be considered. For instance, as GenAI technologies are new and may evolve rapidly, new factors may appear. Thus, in the future, additional studies may be needed to incorporate new factors for analysis. In addition, as ANP requires a large number of pairwise comparisons, other studies can be done to reduce the number of pairwise comparisons (e.g., using the Fuzzy Delphi method (Li and Wang 2020)) and/or apply other MCDM methods (e.g., the rough-SWARA technique (Dora et al. 2022)).

6 | Conclusion

This study extends the research on GenAI by addressing the most critical and influential factors for effective GenAI adoption in Spanish companies. Guided by previous works/theories, systems thinking and qualified experts on business and AI, this work revealed that most technology experts agree that the organizational context is highly important compared to technological/business and environmental contexts. Culture, governance, organizational structure, organizational size and business processes are the most important and influential factors in GenAI adoption.

Analysing the responses of a small fraction of experts, organizational factors did not appear to be the most relevant ones. Nevertheless, in all cases, the organizational cluster was very close to the alternative most relevant one (environmental in two cases and technological/business in one case). This slight disagreement between experts may be explained by companies with different technological maturity levels, regulatory and ethical environments, change management and culture, organizational goals and strategies and sector-specific needs.

Finally, policymakers may find relevant insights in our results that suggest that policies to improve GenAI adoption should target organizational barriers.

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Data Availability Statement

The data that supports the findings of this study are available in the supplementary material of this article.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Data S1:** Supporting information. **Data S2:** Supporting information.

Appendix A

Factors' Description

Technology Acceptance (f1)

It is the technological aspects that affect the organizational and customers' acceptance of GenAI, such as perceived usefulness and ease of use (TAM). Users are likelier to use ChatGPT if they perceive it as a valuable and easy tool. However, other users can find it challenging to use, fail to see its worth and value and obtain inaccurate or superficial outcomes (Gupta et al. 2024). This can be overcome by investing in training and upskilling courses to enable users to obtain knowledge and skills about GenAI.

Adoption Risk (f2)

They are risks related to GenAI adoption, such as costs, failure in the return on investment, compliance risks and data privacy. Implementing a GenAI solution can benefit a company but also bring risks and challenges, mainly because of its disruptive and new nature. The *cost* (e.g., talents and training) and return on investment to adopt GenAI solutions are a concern. GenAI also poses challenges to *security and data privacy* (Jagatheesaperumal et al. 2022). To deal with these issues, companies must implement security plans/systems to avoid unauthorized access to data and ensure data protection according to regulations.

Nonadoption Risk (f3)

It addresses the loss of *competitive advantages* of a company over its competitors when GenAI is not incorporated into its business. Thus, it analyses the impact of the nonadoption of GenAI on a company. It can be stated that when a company achieves one or more business objectives with lower costs and higher profits than its competitors, it already has a competitive advantage (Laudon and Laudon 2014). In this manner, GenAI has an important role in fostering innovations by creating new products/services and business models, improving customer/supplier experiences and furnishing operational efficiency and excellence.

Business Processes (f4)

They are related to the compatibility and adaptation ability of the business processes in a company to the new requirements and characteristics arising from GenAI adoption. A company's performance depends on how well its business processes are developed and co-ordinated, and they are competitive forces that enable a company to innovate or execute tasks better than its competitors (Laudon and Laudon 2014). For successful GenAI adoption, previous business processes that depend on other technologies or processes should be adapted or compatible with the new requirements and disruptive characteristics of GenAI.

Culture (f5)

It is cultural aspects that influence GenAI adoption, such as top management support, innovative and collaborative culture and AI strategic alignment. *Top management support* can foster GenAI adoption since top managers can help establish the requirements for successful GenAI use in their organizations. An *innovative culture* is important to incorporate new technologies (Pumplun et al. 2019) since innovative behaviour comprises experimentation, risk-taking and multiple problem-solving skills (Jöhnk et al. 2021). A *collaborative culture* is important to promote communication and cooperation between employees with different skills to complement and help each other. To handle these aspects, a company's *AI strategic alignment* is crucial to properly incorporate technological advances, knowledge, change management, individuals and motivation to change work and the company (Horani et al. 2023).

Organizational Size (f6)

A company's size and how it impacts GenAI adoption. Large companies have access to more resources to experiment with new technologies and have more ability to absorb the costs and risks of adopting new technologies (Wang et al. 2010). Larger companies have more resources, experience in introducing new technologies and necessary data for the immediate application of AI solutions (Kinkel et al. 2022). On the other hand, large companies may exhibit more inertia to changes and additional factors that make it difficult to introduce new technology, such as more bureaucratic and old systems/processes, complex organizational structures and resistance to change.

Data and IT Infrastructure (f7)

It is the availability of high-quality data for GenAI solutions and physical or cloud-based information technology (IT) infrastructure to enable GenAI activities and integration. *Data* are the core of any AI model, and *data quality* impacts GenAI performance. Thus, errors, unbalanced sampling, biases, non-representative data, incorrect labelling and mismeasured features affect the output of a GenAI model and produce biased outcomes (Banh and Strobel 2023; Nah et al. 2023). The GenAI development involves using extensive training data and techniques for scraping public databases on the Internet. These approaches are performed unsupervised and autonomously, which damages data quality because of the large number of unstructured data (Banh and Strobel 2023). On the other hand, *IT infrastructure* refers to the hardware and software that support GenAI applications. Integrating GenAI tools requires a robust and scalable IT infrastructure to deal with complex data and investments in cybersecurity and data protocols. With the advent and popularization of cloud computing, companies can contract on-demand IT resources over the Internet instead of buying and maintaining physical components.

Organizational Structure (f8)

It can be seen as how a company is organized in terms of jobs, systems, operating processes, people and groups making efforts to achieve its goals; and it should enable decision-making, the proper reaction to the environment and conflict management (Ahmady et al. 2016). It can be impacted by goals, strategy, environment, technology and organization size. According to Pumplun et al. (2019), organizational structure is closely related to organizational culture and affects the ability to adopt AI solutions. In particular, larger companies tend to have silo or old organizational structures that inhibit the development of GenAI projects. This can be overcome by encouraging communication between teams/departments and creating hubs/laboratories.

Governance (f9)

It guarantees the correct GenAI use to prevent a company from failing in compliance with ethical guidelines, reputational standards and risk aversion. Governance can be seen as a framework that allows the responsible use of GenAI in organizations because its incorrect use may produce undesirable results and impact the organization and society. The AI governance gives alignment and clarity, thoughtfulness and accountability; consistency and organizational adoption; process, communication and tools; and trust and public perception to an organization (Gill et al. 2022). According to Nah et al. (2023), GenAI can create new risks with unintended consequences. This is mainly because their algorithms have opaque models and unpredictable outcomes, which impede human controllability, data fragmentation, lack of interoperability between systems and information asymmetries between technology giants and regulators.

Public Policies (f10)

They are public policy regulations influencing GenAI adoption and public investment support. Regulations are one of the main challenges of this transformative and disruptive technology. For example, data are employed to implement these solutions, and new data are generated, so the current data legislation influences GenAI tools. GenAI introduces new challenges since it may inadvertently use and produce content with personal information and employ multiple jurisdictions' data to train its models (Golda et al. 2024). Intellectual property rights are another concern since existing regulations do not address GenAI copyright issues. Public investment support is another important issue. In particular, the lack of financial resources for acquiring or developing new technologies is a challenge for small companies. Also, the lack of external or public funding is the major obstacle to AI adoption for enterprises (European Commission 2020).

Stakeholders (f11)

A stakeholder is any group or individual who affects or is affected by the companies' activities, such as shareholders, employees, customers, suppliers and local communities (Friedman and Miles 2006). Collaboration, alignment and dialogue among stakeholders are crucial to enable a successful GenAI adoption with ethical principles and guidelines, to support organizational change management and to minimize misconceptions about GenAI. Stakeholders, such as customers, have an important role in GenAI since their pressure and technological readiness can impact GenAI adoption. This is because GenAI solutions are essentially based on the stakeholders' interaction and engagement; so, stakeholders are not passive actors of a company's value proposition, but instead, they can promote 'co-create' and 'co-destroy' values in the company's ecosystem (Dogru et al. 2023).

Ecosystem (f12)

It is an interconnected and collaborative network of multiple actors (e.g., universities, startups and other companies) that collectively enable the development and operation of GenAI. Here, special attention is given to the collaborating external participants of a company since internal actors are considered in the *talents* and *stakeholders* factors. By viewing a GenAI project as an ecosystem, companies can understand the holistic nature of a GenAI solution and integrate goals, technologies, processes, knowledge and experts to drive operational efficiency, innovation and competitive advantage. This arrangement can be seen as an *innovation ecosystem* whose objective is to enable technology development and innovation (Jiang et al. 2020).

Talents (f13)

Availability in the labour market of talents with ability, skills and training for working on GenAI is an important factor. Kinkel et al. (2022) identified that the most important technical skills for a company to introduce and implement digitized solutions are software development, hardware development or adaptation/operation of the hardware needed for digital solutions and data science and AI skills. Also, soft skills for employees are needed for digital transformation, such as interdisciplinary collaboration, the ability to integrate different disciplines, intercultural communication/collaboration and teamwork. Without employees with digital skills, companies may find it challenging to implement and use GenAI efficiently. According to Ghorbanzadeh et al. (2025), organizations should prioritize AI training programmes for employees to use AI tools efficiently.

Appendix B

ANP Matrices (Aggregation Approach)

This section includes Tables B1 and B2.

TABLE B1 | Unweighted supermatrix from the aggregation approach (global results). Highlighted values are higher than the average plus two times the standard deviation.

		C1. Tech. and business				C2. Organizational					C3. Environmental			
		f1	**f2**	**f3**	**f4**	**f5**	**f6**	**f7**	**f8**	**f9**	**f10**	**f11**	**f12**	**f13**
C1. Technological and business	f1. Technology acceptance	0	0.327	0.500	0.500	0	0	0.333	0	0	0	0	0	0
	f2. Adoption risk	0	0	0.500	0.500	0	0	0	0	**1**	0	0	0	0
	f3. Nonadoption risk	0	0.260	0	0	0	0	0	0	0	0	0	0	0
	f4. Business processes	**1**	0.413	0	0	**1**	0	0.667	**1**	0	0	0	0	0
C2. Organizational	f5. Culture	0.750	0.340	0.540	0.356	0	0.500	0	0.413	0.400	0	0	0	0.319
	f6. Organizational size	0	0.140	0.163	0.124	0.260	0	0.333	0.260	0.200	**1**	0.260	0.500	0.157
	f7. Data and IT infrastructure	0	0	0	0.326	0	0	0	0	0	0	0	0	0
	f8. Organizational structure	0	0.239	0	0.194	0.327	0.250	0.333	0	0.400	0	0.327	0	0.281
	f9. Governance	0.250	0.281	0.297	0	0.413	0.250	0.333	0.327	0	0	0.413	0.500	0.243
C3. Environmental	f10. Public policies	0	0.413	0.333	0	0	0.207	0	0	0.500	0	**1**	0	0
	f11. Stakeholders	0	0.260	0.333	0	0.333	0.293	0	**1**	0.500	**1**	0	0.500	0
	f12. Ecosystem	0	0	0	0	0.333	0.207	0	0	0	0	0	0	**1**
	f13. Talents	**1**	0.327	0.333	**1**	0.333	0.293	0	0	0	0	0	0.500	0

TABLE B2 | Limit supermatrix from aggregation approach (global results).

		C1. Tech. and business				C2. Organizational					C3. Environmental			
		f1	**f2**	**f3**	**f4**	**f5**	**f6**	**f7**	**f8**	**f9**	**f10**	**f11**	**f12**	**f13**
C1. Technological and business	f1. Technology acceptance	0.041	0.041	0.041	0.041	0.041	0.041	0.041	0.041	0.041	0.041	0.041	0.041	0.041
	f2. Adoption risk	0.069	0.069	0.069	0.069	0.069	0.069	0.069	0.069	0.069	0.069	0.069	0.069	0.069
	f3. Nonadoption risk	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008
	f4. Business processes	0.119	0.119	0.119	0.119	0.119	0.119	0.119	0.119	0.119	0.119	0.119	0.119	0.119
C2. Organizational	f5. Culture	0.176	0.176	0.176	0.176	0.176	0.176	0.176	0.176	0.176	0.176	0.176	0.176	0.176
	f6. Organizational size	0.129	0.129	0.129	0.129	0.129	0.129	0.129	0.129	0.129	0.129	0.129	0.129	0.129
	f7. Data and IT infrastructure	0.016	0.016	0.016	0.016	0.016	0.016	0.016	0.016	0.016	0.016	0.016	0.016	0.016
	f8. Organizational structure	0.138	0.138	0.138	0.138	0.138	0.138	0.138	0.138	0.138	0.138	0.138	0.138	0.138
	f9. Governance	0.147	0.147	0.147	0.147	0.147	0.147	0.147	0.147	0.147	0.147	0.147	0.147	0.147
C3. Environmental	f10. Public policies	0.036	0.036	0.036	0.036	0.036	0.036	0.036	0.036	0.036	0.036	0.036	0.036	0.036
	f11. Stakeholders	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056
	f12. Ecosystem	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025
	f13. Talents	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040	0.040