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Conceptual model for establishing the relationship between digital transformation and organizational performance in electrical power companies

Javier Rosero-Garcia[1+]
William Montano-Salamanca[2]

[1]*Department of Electrical and Electronic Engineering, Universidad Nacional de Colombia, 111321, Bogota, Colombia.*
Email: jaroserog@unal.edu.co
[2]*Electrical Machines & Drives Research Group, Universidad Nacional de Colombia, 111321, Bogota, Colombia.*
Email: wmontanos@unal.edu.co

(+ Corresponding author)

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ABSTRACT

The purpose of this study is to establish a conceptual model of structural equations that examines the relationship between digital transformation and organizational performance in the electric power sector, using the theories of Dynamic Capabilities (DC), Resources-Based View (RBV), and Knowledge-Based Vision (KBV). The study proposes a conceptual model of 27 relationships (hypotheses) that incorporates the theories of DC, RBV, and KBV, which are used to evaluate the relationship between digital transformations and organizational performance in the electric power sector. We conducted surveys with industry professionals to validate the model. Through the analysis of the survey data, the study establishes the relationship between digital transformations and organizational performance, highlighting the crucial role of knowledge in generating value for organizations. The study findings showed that the proposed model, which incorporates the theories of DC, RBV, and KBV, effectively models and measures organizational processes in the electric power sector. Our results show that digital transformation, particularly in Big Data, has a significant positive impact on organizational performance. Furthermore, the study highlights the important role of knowledge creation and management in driving organizational value in the context of digital transformation. Specifically, the study allows us to conclude that we can express organizational processes in causal relationships and measure them through data, with the interaction of these elements producing knowledge as a key element in generating value in organizations.

Contribution/Originality: This research contributes by proposing a comprehensive conceptual model that integrates Dynamic Capabilities Theory, Resource-Based View, and Knowledge-Based Vision, specifically tailored to the electric power sector. It offers novel insights into how digital transformation impacts organizational performance, guiding firms to optimize their digital strategies effectively.

1. INTRODUCTION

Digital transformation, defined as the strategic use of digital technologies to enhance organizational performance (Teng, Wu, & Yang, 2022b) is a multifaceted process integral to achieving organizational objectives efficiently and effectively. This transformation is underpinned by significant theoretical frameworks, notably the "Dynamic Capabilities Theory," "Resource-Based View" (RBV), and "Knowledge-Based View" (KBV) (Hershanty & Jafrizal, 2021).

"Dynamic Capabilities Theory" emphasizes an organization's adaptability to environmental changes as a key determinant of success (Schriber & Löwstedt, 2020). The RBV posits that a firm's competitive advantage lies in its distinct and valuable resources (Iyanda, Awawdeh, Al-Hiyari, & Isiaka Jimba, 2021) while the KBV underscores the centrality of knowledge management for gaining a competitive edge (Hu, Sarfraz, Khawaja, Shaheen, & Mariam, 2022). In the realm of organizational performance, various methodologies and models have emerged to gauge the impact of digital transformation. These tools aid organizations in comprehending their current digital maturity and pinpointing areas for enhancement. Navigating the intricate relationship between digital transformation and organizational performance requires a nuanced consideration of both short-term and long-term effects.

In a globalized and competitive market, organizations must constantly evolve to respond to external changes. The intersection of sustainable competitive advantage and digital transformation enhances an organization's resilience to change, fostering significant capabilities and sustainable performance (Stroumpoulis & Kopanaki, 2022). Big Data, an integral component of digital transformation, optimizes internal operations, enhances process performance control, and identifies bottlenecks and inefficiencies (Rialti, Marzi, Ciappei, & Busso, 2019; Sestino, Prete, Piper, & Guido, 2020).

Achieving these benefits necessitates operational flexibility in processes, IT systems, and Big Data applications. This flexibility supports organizational responsiveness to change and elucidates how digital transformation augments operational performance for a competitive advantage (Yu, Wang, & Moon, 2022). Crucially, organizational decisions, process optimization, and adaptation to real-time decision-making necessitate a holistic transformation. This transformation involves changes in processes, functions, organizational culture, and professional capabilities to harness the potential of real-time information and enhance overall performance.

Building on research grounded in RBV, DC, and KBV, this paper delves into the value of IT, Big Data, and competitive advantage. RBV's application to IT capabilities highlights that a firm's competitive advantage stems from distinct, valuable, and inimitable resources and capabilities (Asikhia, Osinowo, & Kassim, 2021). KBV explores a company's potential for competitiveness in a dynamic market (Tajpour, Hosseini, Mohammadi, & Bahman-Zangi, 2022) while DC theory addresses the challenge of maintaining a competitive advantage in turbulent external environments (Mikalef, Pateli, & Van De Wetering, 2021).

In the Colombian context, the electric power sector's collaborative efforts under the *Colombia Inteligente* initiative signify a concerted push toward digitalization. This initiative, spearheaded by various companies and technological development centers, aims to leverage Smart Grids and advance decision-making aligned with government policies and technological adoption. Prioritizing the implementation of smart metering technologies, the initiative recognizes the pivotal role of data management and application development for electric grid companies (CIRCE Foundation University of Alcalá de Henares Technological University of Pereira Creara Consultores, Afi – International Financial Analysts Universidad del Valle Regulation Experts, & ICT Regulation Expert, 2016). Ensuring the benefits of data management, real-time information, and knowledge requires a holistic transformation of organizational structures, cultures, and strategies (Kovalenko, Kovalenko, & Yakovleva, 2021).

The broader significance of digitalization extends beyond transformation, focusing on technology's value addition to business and decision-making. This shift toward data-centric approaches poses challenges across organizational domains, including personnel, processes, and technology (Anand & Krishna, 2019).

Notably, existing research highlights a gap in understanding the factors influencing digital and technological changes in organizations, particularly concerning Big Data analytics (BDA). It is imperative to investigate the potential effects of digital transformation on BDA capabilities and organizational performance, marketing strategies, impediments to BDA adoption, and the synergy between digital transformation and organizational structures (Rialti et al., 2019).

This paper's objective is to establish a relationship between new digital technologies, digital transformation, and organizational performance. Drawing on RBV, DC, and KBV, a conceptual model is constructed to elucidate the intricate dynamics of this relationship and to explore how digital transformation influences organizational performance in electric power companies. This study, using a positivist research approach, posits the casual relationships, measureable through data, reflect an objective reality.

The study contributes to organizational administration and management theory by identifying the pivotal relationship between organizational management, decision-making, and digital transformation. Methodologically, we collect data through surveys from Colombian electric power sector companies to determine the relationship between digital transformation and organizational performance.

This paper's structure unfolds with a literature background about digital transformation, organizational performance, DC, RBV, and KBV theories. Moving forward, the methodology section unfolds, introducing the structural equation model and hypotheses designed to establish the relationship between Digital Transformation and Organizational Performance in electric power companies. This proposed model maps the associations between various domains, including digital transformation, physical and human resources, knowledge management, and organizational performance. By integrating a vision based on resources, knowledge, and some dynamic capabilities of organizations. We presents the study's results, discussion, and conclusions at the end.

2. LITERATURE BACKGROUND

This section presents the conceptual framework of the proposed model. It contextualizes Digital Transformation and Organizational Performance and describes RBV, DC, and KBV theories to identify the methodology that best fits the construction of the proposed model. It also describes methodologies and models to evaluate Organizational Performance with Digital Transformation and provides some considerations about their relationship.

2.1. Digital Transformation

Digital transformation can be defined as the process that includes the data cycle, information and communication technologies, personnel associated with production, and decision-making; this process facilitates the development of change in operations, business models, and the way of working to add value to the organization (Gong & Ribiere, 2021).

Digital transformation refers to a thorough restructuring of both internal and external operations, production procedures, and managerial approaches within the contemporary digital economy. It is propelled by advanced technologies such as big data, the Internet of Things, cloud computing, and various other information technologies. This transformation encompasses three principal pathways: digitization of production services, digitization of marketing models, and digitization of industrial processes (Li, 2022).

One of the paradigms of digital transformation is the use of data produced by various sources, such as in industrial environments, to obtain information to create knowledge for subsequent decision-making. The data considered assets, digital replicas, and systems should have characteristics such as definition, function, format, time, and relevance to make reports that will become valuable information for companies. It is possible to conduct an analysis that conduct an analysis that creates knowledge using analytical functionalities included in new management systems, aiming to make decisions that promote innovation in productive processes (ElMassah & Mohieldin, 2020; Vaska, Massaro, Bagarotto, & Dal Mas, 2021).

The data lifecycle associated with digital transformation is considered an important aspect of the process of converting Big Data into information. This data life cycle can be classified into creation, maintenance, and use. Data can be converted into useful information for decision-making, by combining these three phases (Hutchinson et al., 2021).

Digital transformation as a process of change at the productive, business, and social levels is facilitated by the development of Information and Communication Technologies (ICT). In this way, Information and Communication

Technologies are technological tools, such as the cloud, social networks, mobile applications, Big Data, streaming, network collaboration tools, robots, artificial intelligence, and others, that help implement technological changes in the productive processes of companies (Stroumpoulis & Kopanaki, 2022).

These information management technologies include systems for storing, retrieving, and processing information, performing calculations, and preparing reports (Widiastuti, 2020). Therefore, it is necessary to ensure the implementation of distributed services, data management analysis, the development of customized applications, and the implementation of cybersecurity systems.

Furthermore, one of the goals of digital transformation is to make decisions based on online information in real-time, with the challenge of transforming the data associated with business production into valuable information and knowledge (Love, Zhou, & Matthews, 2019). To carry out this, digital transformation can be supported and founded on technologies such as the Internet of Things (IoT), Industrial Internet of Things (IIoT), blockchain, Big Data, algorithms, and expert systems (Sestino et al., 2020). A larhe collection of sensors, databases, emails, websites, images, and social networks can develop Big Data. The challenges of Big Data are data visualization, mining, analysis, collection, storage, search, and sharing (Shamim, Zeng, Shariq, & Khan, 2019).

The implementation of digital technology, especially Big Data systems, requires extremely large, interconnected hardware architectures, cloud data management, highly fast, high-speed Internet connectivity, and system interoperability. In addition, it is necessary to build complex infrastructures and architectures along with analytical computing methods that are difficult to understand for managers and employees, who may reject their implementation and oppose the use of analyzed data for decision-making (Rialti et al., 2019). Therefore, it is essential to promote "the development of technical, managerial, and personnel capacities related to BDA with an understanding of the complexity of the infrastructure, the methodologies of data analysis, and the contributions and potential effects of data use on the processes" (Rialti et al., 2019).

Big Data is characterized by several key attributes, known as the "Seven V's of Big Data": volume, velocity, variety, veracity, value, variability, and visualization. Volume denotes the absolute size of the dataset, while velocity pertains to the speed of data generation and analysis. Variety refers to diverse sources and formats of data, and veracity relates to data reliability. Value represents the economic benefits of data analysis, whereas variability refers to fluctuations in data flow and sources. Visualization enables the presentation of insights from Big Data analytics (Munawar, Qayyum, Ullah, & Sepasgozar, 2020; Rialti et al., 2019).

Organizations that embrace digital transformation can leverage data when they have adaptability, technology adoption, and new methods to operate their business along with the interrelationship with the organization's culture, leadership, processes, structures, and communications. This requires continuous evolution and innovation in digital technologies, collective learning, and updated capabilities, as well as a reinvention of the organization in change management processes (Stroumpoulis & Kopanaki, 2022; Wessel, Baiyere, Ologeanu-Taddei, Cha, & Blegind Jensen, 2021). The Small- and Medium-Sized companies that invest in digital transformation experience higher profitability, productivity, and market value. Digital transformation can help companies achieve cost reduction, efficiency improvement, and innovation, which are the ultimate goals of digital transformation for enterprises (Teng, Wu, & Yang, 2022a).

Big Data Analytics (BDA), as part of digital transformation, offers companies business-centric practices and methodologies and provides a competitive advantage in data-driven decision-making to improve business efficiency and effectiveness and create organizational value due to its high operational and strategic potential (Mirarab, Leili Mirtaheri, & Amir Asghari, 2020). It makes it necessary to build Big Data capabilities with innovative ways of organizing, learning, and innovating. This may help improve customer relationships, operational risk management, operational efficiency, and business performance (Behl, 2022).

The concept of Organizational Transformation (OT) refers to fundamental changes in characteristics such as structure, process, culture, and capability that add value to the organization (Warner & Wäger, 2019). OT continuously transforms the organization by changing its range of products and services, reconfiguring its resources, capabilities, and supply structures, and shifting from planned control to opportunistic experimentation, all of which improve organizational performance (Guo & Xu, 2021).

2.2. Organizational Performance

The actual outcomes of a company or organization, measured against planned goals or objectives, determine its organizational performance (Kaur & Kaur, 2021). According to Richard et al., organizational performance comprises three specific areas of outcomes (Richard, Devinney, Yip, & Johnson, 2009):

- Financial performance: profits, return on assets, return on investment, etc.
- Product market performance: sales, market share, etc.
- Shareholder return: total shareholder return, economic value-added, etc.

The evaluation of a company's organizational performance includes various indicators such as value for money, customer retention rate, sales growth rate, company profitability, and overall competitive position (Fauziah & Jamal, 2020; Ong'esa & Kinyua, 2020).

Organizational performance is measured using a variety of criteria, including average return on investment, average profit, average returns on sale, average market share growth, average sales volume growth, and average sales growth in dollars (Sklyar, Kowalkowski, Tronvoll, & Sörhammar, 2019).

Furthermore, organizational performance, which is closely linked to stakeholders, heterogeneous product market circumstances, and time, is emphasized as one of the key constructs in management research.

Nevertheless, it is important to note that organizational performance is not a unidimensional theoretical construct, and it is unlikely to be characterized by a single operational measure. The measurement of organizational performance can vary depending on the research domain and may involve discipline-specific measures (Vieira, Neves, & Dias, 2019).

Recent research emphasizes that the long-term growth and survival of organizations are paramount. Prioritizing continuous improvement in performance, they define "effectiveness" as achieving objectives, underscoring competitive advantage and resilience during crises as critical to long-term survival (Chatzoudes, Chatzoglou, & Diamantidis, 2022). Two key factors can evaluate organizational performance: alignment with external environments and internal contributors. This approach recognizes the significance of customer satisfaction in defining organizational performance (Tunyi, Agyei-Boapeah, Areneke, & Agyemang, 2019).

Furthermore, the introduction of the definition that emphasizes means an ends underscores the ability of a company, functioning as a resource-rich social system, to achieve its objectives without depleting resources or jeopardizing employee well-being. The concept of organizational performance is associated with high productivity rates, high levels of satisfaction and motivation among members, and low rates of turnover, costs, and labor unrest (Jenatabadi, 2015).

The definition of organizational performance may include common elements such as "effectiveness in the organization's objectives," "efficiency in organizational resources," and "relevance in stakeholder satisfaction." Other definitions used over time are listed below (Jenatabadi, 2015):

- "The extent to which an organization, as a social system, could consider both its means and its ends was a frequent definition in the 1980s."
- Cherrington defined organizational performance as a concept of an organization's success or effectiveness.
- The quality of employees' performance and knowledge closely relates to organizational performance.
- According to Harrison, Freeman, and Adam, "an effective organization with a high level of performance is one that keeps the demands of stakeholders (shareholders, customers, and its own) satisfied."
- "In the first decade of the 21st century, the definition focused on an organization's ability to efficiently use available resources to achieve accomplishments consistent with set goals."

Finally, we mention some performance measurement (PM) activities that enhance motivation, monitor performance, improve communication, and diagnose problems, enabling business management to excel. In addition, they help identify and propose actions to improve the management strategy. Some proposed measurements are listed below (Jenatabadi, 2015):

- Monitoring business progress.
- Monitoring the effect of strategies and plans.
- Diagnosis.
- Support decision-making.
- Facilitation of motivation and communication.

2.3. Dynamic Capabilities Theory

Dynamic capabilities guide organizations seeking to harness big data, promoting resource integration for sustainable and repeatable initiatives. This necessitates agility in sensing environmental shifts, ongoing market surveillance, and a commitment to best practices. By continually adapting, organizations enhance their competitive edge, leveraging skills, data, and technology to drive efficiency and innovation (Lee & Yoo, 2019). The relationship between big data and dynamic capabilities underscores the need for organizational evolution to capitalize on insights. This entails dynamic adjustments in big data processes to align with internal and external dynamics. Such adaptability forms the foundation for organizational transformation and strategic alignment with insights gleaned from big data initiatives (Mikalef, Van De Wetering, & Krogstie, 2021).

Dynamic capabilities can be considered to represent a suitable approach to studying the effects of information systems and big data analytics (BDA). BDA can be used in different situations and can provide the organization with competitive advantages in the face of a changing market and high global competitiveness. BDA capabilities can help an organization tailor an existing resource base to address different information needs that support decision-making (Rialti et al., 2019). BDA progressively influences the competitiveness of organizations and their organizational and financial performance by creating organizational capability to identify and seize new opportunities, seek collaborations and strategic partners, improve knowledge flow, and facilitate knowledge sharing (Rialti et al., 2019). However, these positive effects of Big Data arise from the organizational decision to implement them and to establish change management strategies and dynamic capabilities to better use data in the organization.

Managers can decide and adopt suitable strategies according to the available information regarding internal operations, supply chain processes, personnel performance, and consumers' behavioral patterns (Rialti et al., 2019). Therefore, BDA is a resource with multiple usability potentials to solve diverse problems. Achieving those solutions involves routines, processes, and capabilities to transform such data into meaningful insights, and the expertise of analysts and managers can increase the efficiency of the analysis. BDA can create huge knowledge flows that must be funneled into a data management process. Based on the knowledge created by BDA, it is important to address the impact of data on decision-making processes and organizational performance (Rialti et al., 2019).

In conclusion, BDA can create knowledge and change the way managers think and act based on an appropriate information management system. This makes it necessary to ensure that managers receive the right information when making decisions to enhance performance, respond to sudden changes, or identify new business models (emerging opportunities) and, consequently, choose the best way forward for the organization (Rialti et al., 2019).

2.4. Resource-Based View (RBV)

The integration of Big Data and Predictive Analytics (BDPA) within supply chain (SCP) and organizational performance (OP) is depicted as a three-stage process: acceptance, routinization, and assimilation. Drawing from the resource-based perspective, this study identifies connectivity and information sharing as key resources influencing organizational performance. It also comes to the conclusion that resources, through the support of top management, have a positive effect on OP, SCP, and BDPA acceptance (Gunasekaran et al., 2017; Mishra, Luo, Hazen, Hassini, & Foropon, 2019).

Connectivity and information sharing, under the mediation effect of top management commitment, improve BDPA acceptance, performance, and business processes, measured through RBV theory and online surveys of company managers (Gunasekaran et al., 2017).

Top management should be able to acquire IT resources, invest in them to build BDA capabilities, and commit to the process to achieve high organizational performance (Gunasekaran et al., 2017). Assessing the impact of Big Data on marketing activities through RBV is also important; this comprises the process of collecting records of consumer activities, the process of extracting information, and the process of using consumer knowledge to enhance the dynamic and adaptive capabilities of the organization (Suoniemi, Meyer-Waarden, Munzel, Zablah, & Straub, 2020).

To create a competitive advantage with resources, leaders should develop capabilities and structure resources to be used in the processes, acquisition methodologies, and implementation of Big Data analytics in business (Gunasekaran et al., 2017). Capabilities are a necessity for organizations, and they depend on their context, because these capabilities are a subset of non-transferable resources and are aimed at enhancing the productivity of other resources (Gunasekaran et al., 2017; Suoniemi et al., 2020).

According to the above, in a digital organization, leaders should ensure their strategic priorities, cultural values, and organizational norms and transmit them to their collaborators. Human aspects such as charisma, motivation, adaptability, and the ability to be facilitators are the most important characteristics of leaders of digital organizations. These leaders should facilitate the design and execution of actions, be open to employee initiatives, and be responsive to feedback as strengthening tools (Cortellazzo, Bruni, & Zampieri, 2019).

In conclusion, sustaining management focused on employee experience, with systemic learning mechanisms and strategies linked to the vision of the organization, simplifies working life, and instills innovative behaviors based on shared leadership. Organizational culture is based on values, behavior, member relationships, power relations, and existing competencies that can lead to a culture of achievement based on expected outcomes or a culture of support for personal motivation (Cortellazzo et al., 2019; Zacharias, Rahawarin, & Yusriadi, 2021). Therefore, the importance of strong leadership, effective communication, and organizational culture to drive successful digital transformation initiatives is highlighted (Aghayari, Valmohammadi, & Alborzi, 2022).

2.5. Knowledge-Based View (KBV)

The examination of Big Data Analytics (BDA) in the business value chain reveals that it can contribute to enhancing organizational performance by establishing links between knowledge assets, organizational agility, and productivity, through empirical testing of a new theoretical framework that combines Knowledge-Based View (KBV) and Dynamic Capabilities (DC) theories. Highlighting the understanding of the BDA value chain using a model founded on KBV and DC theories, and providing insights into knowledge assets, impacts on process performance, and competitive advantage of BDA initiatives. However, the effectiveness of BDA initiatives may vary depending on the level of environmental dynamism, which underscores the importance of considering external factors in the analysis (Wamba, Dubey, Gunasekaran, & Akter, 2020).

Knowledge management is critical to strengthening the mechanisms that facilitate it, such as codification, sharing between individuals and teams, and stimulation of knowledge generation, sharing, and protection. In addition, it is necessary to provide the infrastructure and strengthen the structured coordination of knowledge management process in an effective manner. Knowledge management facilitates the creation of open and collaborative ecosystems and the exploitation of knowledge flows, and increasing the capacity for innovation. In this context, knowledge management suggests that big data can provide organizations with a deeper understanding of their strategic actions (Chierici, Mazzucchelli, Garcia-Perez, & Vrontis, 2019; Wang & Wang, 2020).

Integrating digital technology-based administrative management with knowledge management allows organizations to make decisions focused on their strategic objectives and preserve knowledge as the company's most important asset. Knowledge management should aim to present and use information promptly, ensuring the availability, consistency, and quality of data (Alvarenga, Matos, Godina, & CO Matias, 2020).

2.6. Methodologies and Models for Assessing Organizational Performance through Digital Transformation

A multivariable statistical method called structural equation modeling (SEM) test a hypothesis for the analysis of a structural theory related to a given phenomenon. It can also be used to look at the relationships between variables using diagrams (Owolabi, Ayandele, & Olaoye, 2020). The potential of SEM is highlighted, particularly, for theory development and construct validation in areas such as psychology and social sciences. More and more evidence shows that this modeling approach is useful for estimating parameters of unobservable constructs and testing hypothesis in casual models (Owolabi et al., 2020).

As for the model proposed, the twelve hypotheses assessing the entire supply chain were tested using a survey conducted in several countries by European organizations. Academic researchers and two language experts validated the content, scope, and purpose of the study's instrument, a literature review-based survey. Subsequently, a pilot study was conducted with thirty executives from companies different from the main survey application group to implement modifications to the final instrument, eliminate ambiguities, and simplify interpretation (Côrte-Real, Oliveira, & Ruivo, 2017).

The conceptual models also used empirical validation methods, primarily through surveys. For instance, in Côrte-Real et al. (2017) a survey involving 500 European companies and their IT business executives was conducted, revealing the potential of BDA to enhance business value across various stages of the company's value chain. Utilizing the partial least squares (PLS) method, the proposed conceptual model was estimated and the validity of the hypotheses examined. The findings supported the assertion that BDA applications can foster effective knowledge management, leading to organizational agility (Côrte-Real et al., 2017).

Furthermore, a comprehensive model is proposed to evaluate the implementation of Big Data Analytics (BDA) and its impact on decision-making processes. Three key dimensions from the foundation of this model: organization, people, and technology. The organization dimension addresses how the organization implements a data strategy. The people dimension includes the collaborative knowledge worker factor, which consists of three criteria: analytics personnel skills, organizational relationships, and analytics culture. Finally, the technology dimension includes four criteria: IT infrastructures, information processing, data governance, and data quality management (Adrian, Abdullah, Atan, & Jusoh, 2018). Other studies employ RBV to conceptualize BDPA assimilation as a capability that impacts SCP and OP, facilitated by connectivity and information-sharing resources, and mediated by top management commitment (Côrte-Real et al., 2017; Gunasekaran et al., 2017). The method used a Likert-scale survey approach that was tested by a group of six experienced researchers. Subsequently, the survey was sent by email to 45 consultants and supply chain managers for them to review structure, readability, ambiguity, and completeness and have a final instrument modified based on comments.

In terms of model validations, there are models validated through a three-stage improvement cycle to develop measures that meet all reliability, validity, and uni-dimensionality requirements; through the validation, both scale composite reliability (SCR) and Cronbach alpha (Gunasekaran et al., 2017). This comprehensive validation approach helped establish the robustness and effectiveness of the models in accurately assessing the targeted constructs. By employing validation techniques, the studies reinforce the reliability and validity of the measures used to evaluate the relationship between data-driven practices and organizational performance.

3. METHODOLOGY

This paper proposes an SEM that associates digital transformation with big data and OP as its central axis, presenting the related elements or variables. This model presents the relationship between resources, big data-based elements of digital transformation, and organizational performance and shows the role of decision-making in creating competitive advantages as a mediator of BDA implementation. Lastly, we used an instrument to validate the proposed model and identify its dominant relationships.

The construction of the SEM considered variables associated with digital transformation and with elements of the organization to develop hypotheses that relate to each element of the model. Each variable was considered as an element of the proposed model. Next, we analyzed the significant connections (relationships) between each variable using the proposed hypothesis. Finally, a group of experts from the electricity sector evaluated the model using an instrument to validate it.

The construction of the conceptual model involved the identification of variables associated with digital transformation and elements of the organization to develop hypotheses that relate to each element of the model. Each variable was considered an element of the proposed model, and the relationships between these elements were analyzed.

Professionals in the electric power sector participated in a survey that collected data to validate the proposed model. The survey questionnaire consisted of items that measured the identified variables and hypotheses. We used a purposive sampling technique to select participants who represented a diverse range of roles and responsibilities within the sector. The data collection procedure involved distributing the survey electronically to the selected participants, ensuring confidentiality and anonymity.

The collected data was then subjected to statistical analysis using techniques such as Principal Component Analysis (PCA) and Partial Least Squares (PLS) to assess the validity and reliability of the measurement scales and to examine the proposed relationships between variables.

Furthermore, a group of experts from the electricity sector, including professionals and researchers with expertise in digital transformation and organizational performance, evaluated the model. They provided feedback and insights regarding the relevance and applicability of the proposed model and its constructs.

The methods used included the following steps:

1. A survey was conducted with experts in the electric power sector to validate the proposed Structural Equation Model, which depicts the relationship between resources, Big Data-focused elements of digital transformation, and organizational performance.
2. The survey tool let people give each of the 27 relationships (hypotheses) that show how the parts of the proposed model are connected a weight. The goal was to find the most important relationships in the model.
3. Participants rated each relationship (hypotheses from H1 to H27, relating two elements of the model) on a scale from 0 to 10, according to the indicative scale provided inTable 1.

Table 1. Scale to evaluate each hypothesis of a conceptual model. Indicative scale for grouping the survey responses.

Sparse or null link						Weak link					Medium to strong link						Strong link			
0.0	0.5	1.0	1.5	2.0	2.5	3.0	3.5	4.0	4.5	5.0	5.5	6.0	6.5	7.0	7.5	8.0	8.5	9.0	9.5	10.0

4. Hypotheses with a median score equal to or above 8.0, falling within the Strong Relationship range of the indicative scale, were considered valid and included in the model.
5. The model excluded hypotheses with a median score below 8.0. Additionally, hypotheses with a wide interquartile range (Q3-Q1) indicating substantial dispersion of ratings within the moderate to strong relationship scale were also excluded.

6. We performed a pairwise correlation matrix analysis on the proposed hypotheses, identifying positive correlations with coefficients greater than 0.6.
7. For output variables dependent on more than two input variables, two types of analysis were conducted: Principal Component Analysis (PCA) and Partial Least Squares (PLS).
8. Hypotheses with the highest simple linear correlations were identified, highlighting the importance of decision-making and process performance in achieving sustainable competitive advantage.

We validated the proposed model and established the predominant relationships between the interrelated variables by incorporating the feedback from the experts and analyzing the survey data.

In summary, the methodology involved the collection of data through a survey from professionals in the electric power sector, statistical analysis of the collected data, and evaluation of the model by domain experts. These steps ensured the reliability and validity of the proposed structural equation model and provided valuable insights into the relationship between digital transformation, big data, and organizational performance in the sector.

The following are the interrelated variables that gave rise to the hypotheses proposed for this model's development:

The variables associated with Digital Transformation used as elements in the proposed model are:

1. Big Data (BD): A vast array of sensors, databases, emails, websites, images, and social networks, can construct Big Data. The challenges of Big Data are data visualization, mining, analysis, collection, storage, search, and sharing (Sestino et al., 2020).
2. Big Data Analytics (BDA): It is associated with the transformation and analysis of raw data into valuable information, as well as knowledge for the creation of business value. It includes determining factors such as the quality of data and information that are critical to organizational impact; this will facilitate top management in decision-making. Previous studies have shown that BDA quality factors include data quality, information quality, and system quality (Adrian et al., 2018; Awan et al., 2021).
3. BDA Capabilities: The ability of an organization to use the resources associated with large volumes of data and information to meet strategic objectives and improve business processes (Gu, Zhou, Cao, & Adams, 2021). BDA capabilities can help an organization tailor an existing resource base to address different information needs that support decision-making (Rialti et al., 2019).
4. BDA implementation: It includes processes for managing Big Data analytics capabilities and resources (such as technologies, people, and analytics processes) and for transforming Big Data into valuable and understandable information by using analytics applications to gain insights for effective decision-making and to enhance organizational performance (Adrian et al., 2018).

The variables associated with Organizational Performance used as elements in the proposed model are:

1. Organizational Agility: Dynamic capability accelerating or simplifying how work is done to foster agility from a strategic, operational, and cultural point of view. It aims to develop the ability to detect and respond to major changes in the environment by leveraging diversity to exploit opportunities, learn to prototype rapidly, and institutionalize success stories (AlTaweel & Al-Hawary, 2021).
2. Decision Making: (Brous, Janssen, & Herder, 2019) divided it into three categories: performance management, perception management, and infrastructure service improvement.
3. Sustainable competitive advantages: They are assumed to exist when a company proves to be more successful than its current or potential competitors. Competitive advantage comprises better strategic performance (qualitative dimension) and financial performance (quantitative dimension) in comparison with competition (Baah & Jin, 2019).
4. Process level performance: It is determined, including other factors, by continuously enhanced production and operations, increased labor productivity and flexibility, and use of equipment and tools that streamline operations (Li, Van Zelst, & Van Der Aalst, 2020).

5. Financial Performance: It refers to measures of an organization's operations and policies in monetary terms, such as profitability, return on assets, return on investment, growth, value-added, and others (Hada, 2020).
6. Strategic Performance: This includes gaining strategic advantages over competitors, a large market share, and more success than major competitors as indicators of better strategic performance (Nwachukwu & Chladkova, 2019).
7. Organizational Performance (OP): Average market share, average sales volume, and average sales growth are indicators that reflect the degree to which the organization performs better than its competitors. Organizational performance involves strategic planners, operations managers, financial directors, legal advisors, entrepreneurs (owners of the organization), and others, in its development (Ong'esa & Kinyua, 2020).

The variables associated with resources used as elements in the proposed model are:

1. Technology and infrastructure: Dimension that integrates the elements of data analytics execution, including IT infrastructures, information processing, data governance, and data quality management (Adrian et al., 2018).
2. Human resources: It includes the collaborative knowledge worker, determined by the people dimension that refers to the analytics personnel skills, the organizational relationship, and analytics culture (Adrian et al., 2018).
3. Information Sharing (IS): Organizational capital that focuses on information flow. Resources aim to create capabilities; since information sharing makes this possible in the organization, Information Sharing is considered a resource (Fosso Wamba, Akter, & De Bourmont, 2019).
4. Connectivity (c): Organizational resource that focuses on meeting the communication requirements of information systems, the integration of information applications within the organization, and the supply chain. It also aims to ensure the existence of links between adequate information systems and supply chain network partners (Fosso Wamba et al., 2019).
5. TD Strategy (Organization): The Digital Transformation Strategy is an important factor in the organization dimension. It refers to the organizations' assurance in performing strategic analytics alignment, managerial commitment, and resource management (Adrian et al., 2018).
6. Knowledge Management: It is a discipline that facilitates the creation, storage, transfer, and application of knowledge in organizations. Knowledge management is multidisciplinary, and there are different perspectives on knowledge management models (Centobelli, Cerchione, & Esposito, 2019).

The variable related to Digital Transformation Strategy (Organization) used as an element in the proposed model represents:

The Digital Transformation Strategy is an important factor in the organizational dimension. It refers to the organization's ability to ensure strategic alignment, management commitment, and resource management. The management of these big data and analytics (BDA) resources includes technology and infrastructure, human resources, and competency development (Adrian et al., 2018).

The variable related to Knowledge Management used as an element in the proposed model represents:

Knowledge management is a systematic process that generates value from an organization's collective experience and personal, technological, and organizational competencies. Knowledge management plays a fundamental role in the efficient management of data and its appropriate delivery to end-users to support business processes. Knowledge management enables dynamic capabilities by providing specific functional competencies that can improve business performance (Li et al., 2020).

3.1. Hypotheses

Hypotheses are established for the above variables to demonstrate the relationship between each of them to determine if there is a correlation between Digital Transformation and Organizational Performance by examining the dependent relationships between independent and dependent variables and evaluating the contribution and reliability of each variable in the established constructs and hypotheses.

Table 1. Proposed variables and relationships (hypotheses) for the structural equation modeling conceptual model.

Source variables	Hypotheses	Arrival variables
TD strategy (Organization)	H1: TD strategy execution has a significant positive effect on BDA	BDA
TD strategy (Organization)	H2: TD strategy execution influences the technology, infrastructure, and human resources of the organization	Technology and infrastructure and HR
Technology and infrastructure	H3: Deployment of large amounts of data is related to available technology and infrastructure	BD
Technology and infrastructure	H4: Technology and infrastructure are positively related to connectivity	Connectivity (C)
Human resources (HR)	H5: HR capabilities have a positive effect on BDA diffusion	BDA
Human resources (HR)	H6: HR capabilities have a positive effect on organizational agility	Organizational agility
BD	H7: BD allows for the creation of information exchange (IE)	Information exchange (IE)
Connectivity (C)	H8: Connectivity is positively related to information exchange	Information exchange (IE)
BD	H9: BD allows for the creation of BDA	BDA
Information exchange (IE)	H10: Information exchange is positively related to BDA acceptance	BDA
Connectivity (C)	H11: Connectivity is positively related to BDA acceptance	BDA
BDA	H12: BDA diffusion positively influences the creation of BDA capabilities	BDA capabilities
BDA capabilities	H13: BDA capabilities enable effective knowledge management	Effective knowledge management
BDA capabilities	H14: BDA capabilities enable adequate BDA implementation	BDA implementation
BDA implementation	H15: Adequate BDA implementation enables effective knowledge management	Effective knowledge management
Effective knowledge management	H16: Effective knowledge management positively impacts achieving organizational agility	Organizational agility
BDA implementation	H17: BDA implementation has positive effects on decision-making effectiveness	Decision-making
Effective knowledge management	H18: Effective knowledge management positively impacts sustainable competitive advantage	Sustainable competitive advantage
Organizational agility	H19: Organizational agility positively affects the creation of competitive advantages	Sustainable competitive advantage
Organizational agility	H20: Organizational agility positively influences process-level performance	Process-level performance
Decision-making	H21: Decision-making leveraged by BDA implementation positively affects the creation of sustainable competitive advantages	Sustainable competitive advantage
Process-level performance	H22: Process-level performance has a positive effect on competitive advantage	Sustainable competitive advantage
Sustainable competitive advantage	H23: Sustainable competitive advantages have a positive effect on organizational financial performance	Financial performance
Sustainable competitive advantage	H24: Sustainable competitive advantages have a positive effect on organizational strategic performance	Strategic performance
Process-level performance	H25: Process-level performance has a positive effect on organizational performance (OP)	Organizational performance (OP)
Financial performance	H26: Financial performance leveraged by competitive advantages has a positive impact on organizational performance (OP)	Organizational performance (OP)
Strategic performance	H27: Strategic performance leveraged by competitive advantages has a positive impact on organizational performance (OP)	Organizational performance (OP)

The relationships (hypotheses) are developed based on a review of publications and conclusions from the RSL. The 27 proposed hypotheses are presented in Table 2, where the first column indicates the variables of origin; those that are considered the starting point and the related variable as the endpoint. In this table, variables associated with Digital Transformation (DT) are identified with a gray background, those associated with Organizational Performance are in green, resources are in blue, Knowledge Management is in white, and the Digital Transformation Strategy of the Organization is in red.

The proposed structural equation model comprises the construction of constructs (elements) based on a review of publications and the conclusions of relevant articles from the literature background.

The proposed structural equation model is based on the Dynamic Capabilities (DC) theory and includes elements of the organization associated with resources and knowledge. It shows the influence of BDA based on a Digital Transformation Strategy, which impacts the management of the organization's resources.

- Effectiveness in decision-making.
- Creation of sustainable competitive advantages.
- Process-level performance enhancement through Organizational Agility.
- Impact on Organizational Performance.

Consequently, it is possible to establish the relationship between Digital Transformation (DT) and Organizational Performance (OP) with BDA as an approach. Links are established between the variables associated with DT and OP based on dynamic capabilities and strengthened through the interaction between Knowledge Management and Organizational Resources. Figure 1 shows the proposed conceptual model, indicating the hypotheses established for each variable or element of the model.

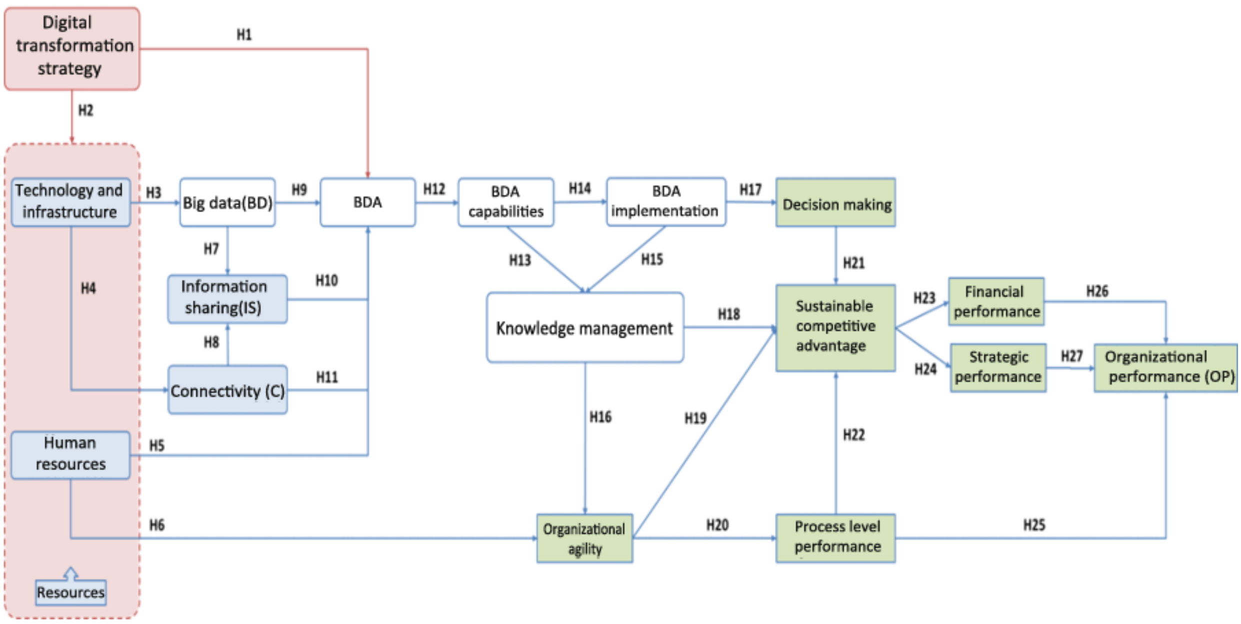

Figure 1. Conceptual model of the relationship between digital transformation and organizational performance.

4. RESULTS AND DISCUSSION

Professional experts in the electricity sector conducted a survey and provided responses to validate the structural equation model. It was possible to weigh the 27 hypotheses through this instrument. The survey presented the proposed structural equation model, which consists of 17 constructs (elements) related to each other using 27 relationships (hypotheses). We asked participants to assign a score between 0 and 10 for each construct.

To ensure the reliability and validity of the questionnaire, and provide confidence in the findings of the study, the following steps were performed:

- The questionnaire was developed based on a thorough review of the literature and the incorporation of established theories of DC, RBV, and KBV, to identify existing validated measures for the elements in our conceptual model.
- A small group of professionals in the electric power sector pre-tested the questionnaire to find any problem with its clarity or comprehension.
- The survey was administered to a large and diverse group of professionals in the industry, with a high response rate.
- The survey was administered to a group of professionals in the electricity sector at two different time points, and the responses compared ensured its consistency.

Moreover, the following input variables were analyzed: Information Exchange, Effective Knowledge Management, Sustainable Competitive Advantage, and Organizational Performance, to identify the most important constructs in the model construction. We found that H22, due to its significant variation, is the most important hypothesis for the output variable Sustainable Competitive Advantage.

Figure 2 shows the groups of scores given by the participants for each hypothesis of the proposed model. The box plot represents the scores given for each hypothesis through their quartiles; the median of the data is indicated within each box. The lines that extended from the box correspond to the scores' maximum and minimum values. For the validation of the proposed model, hypotheses with a median within the *Strong Relationship* range of the indicative scale are considered valid. Therefore, we include all the hypotheses with a median greater than or equal to 8.0.

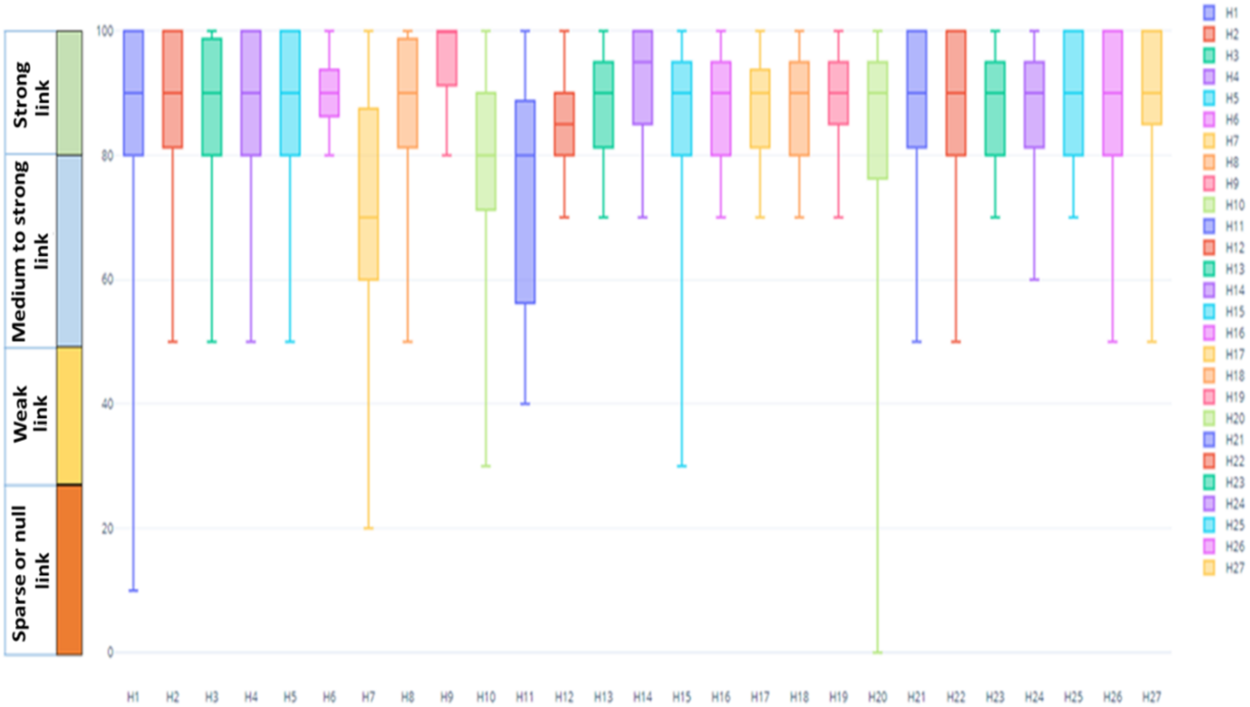

Figure 2. Analysis of the validation information of the conceptual model of the relationship between digital transformation and organizational performance.

Figure 2 shows that the H7 hypothesis has a median of 7.0; this relationship is consequently discarded in the final model. The other hypotheses of the model have a median within the range established as valid. There is a lot of variation in the data for the H11 hypothesis, though. The Q1 quartile (25% of the data) has a value of 56.25; which makes the interquartile range (Q3-Q1) very large. This means that there is a lot of variation in the score for this hypothesis on the moderate to strong relationship scale. As a result, it is not also considered for the final model.

Additionally, Table 3 presents a one-to-one correlation matrix analysis of the proposed hypotheses, where no negative correlations were found, and positive correlations with coefficients greater than 0.6 were observed (highlighted in green in Table 3). This analysis aimed to identify hypotheses with the highest simple linear correlations.

We identified the following hypotheses as having the highest simple linear correlation:

- *H_{21} and H_{22}: It is observed that decision-making and process-level performance are extremely important for achieving sustainable competitive advantage (Coefficient of 0,92).*
- *H_{27} and H_{22}: Both hypotheses are related to Organizational Performance (OP), even though they target different outcome variables.*
- *H_{27} and H_{21}: Similar to the previous relationship, both hypotheses are associated with OP, despite targeting different variables.*

Table3. One-to-one correlation matrix.

	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11	H12	H13	H14	H15	H16	H17	H18	H19	H20	H21	H22	H23	H24	H25	H26	H27
H1	1.00																										
H2	0.33	1.00																									
H3	0.03	0.40	1.00																								
H4	0.23	0.24	0.27	1.00																							
H5	0.08	0.28	0.24	0.26	1.00																						
H6	0.09	0.22	0.45	0.58	0.15	1.00																					
H7	0.20	0.15	0.37	0.24	-0.14	0.24	1.00																				
H8	0.03	0.35	0.39	0.49	-0.23	0.33	0.50	1.00																			
H9	0.03	0.32	0.32	-0.10	-0.05	0.15	-0.10	0.16	1.00																		
H10	0.13	0.17	0.00	0.30	0.43	-0.10	0.12	-0.01	0.04	1.00																	
H11	0.30	0.44	0.32	0.44	0.06	0.20	0.46	0.35	0.29	0.42	1.00																
H12	0.09	0.28	0.50	0.45	0.19	0.52	0.40	0.44	0.12	0.15	0.31	1.00															
H13	0.23	0.40	0.24	0.43	0.09	0.61	0.54	0.25	-0.05	0.02	0.39	0.55	1.00														
H14	0.30	0.26	0.25	0.28	-0.23	0.50	0.35	0.57	0.34	-0.10	0.28	0.55	0.48	1.00													
H15	-0.10	-0.06	0.39	0.48	-0.10	0.50	0.63	0.61	-0.04	0.08	0.22	0.67	0.39	0.55	1.00												
H16	0.53	0.22	0.15	0.34	0.11	0.39	0.29	0.11	0.03	0.30	0.29	0.59	0.55	0.61	0.43	1.00											
H17	0.17	0.44	0.33	0.38	0.11	0.68	0.51	0.46	0.27	-0.02	0.42	0.62	0.70	0.70	0.61	0.51	1.00										
H18	0.52	0.26	0.28	0.38	0.24	0.40	0.31	0.02	0.22	0.17	0.25	0.59	0.53	0.40	0.36	0.59	0.59	1.00									
H19	0.19	0.13	0.50	0.43	0.49	0.48	0.19	0.03	0.21	0.24	0.08	0.54	0.49	0.33	0.39	0.52	0.41	0.71	1.00								
H20	0.03	0.14	0.05	0.26	0.59	0.02	0.05	-0.08	-0.12	0.62	0.12	0.22	0.31	0.05	0.12	0.45	0.08	0.21	0.56	1.00							
H21	0.18	0.69	0.32	0.40	0.20	0.41	0.35	0.43	0.23	0.21	0.40	0.52	0.67	0.62	0.40	0.58	0.77	0.50	0.47	0.47	1.00						
H22	0.16	0.60	0.40	0.41	0.06	0.43	0.35	0.45	0.36	0.17	0.52	0.62	0.65	0.69	0.43	0.55	0.75	0.57	0.48	0.36	0.92	1.00					
H23	0.12	0.32	0.45	0.38	0.21	0.63	0.37	0.35	0.01	0.14	0.21	0.73	0.60	0.59	0.58	0.53	0.74	0.54	0.53	0.21	0.63	0.63	1.00				
H24	0.45	0.35	0.29	0.42	0.09	0.37	0.20	0.24	0.26	0.32	0.35	0.46	0.44	0.35	0.27	0.59	0.43	0.67	0.53	0.36	0.58	0.60	0.52	1.00			
H25	0.28	0.34	-0.01	0.22	-0.07	0.36	0.29	0.05	0.18	0.33	0.43	0.50	0.58	0.28	0.20	0.50	0.51	0.57	0.17	0.10	0.44	0.54	0.47	0.63	1.00		
H26	0.00	0.41	0.27	0.38	0.39	0.23	0.07	0.36	0.10	0.38	0.26	0.58	0.28	0.45	0.44	0.49	0.51	0.33	0.43	0.59	0.73	0.71	0.60	0.48	0.28	1.00	
H27	0.12	0.59	0.44	0.33	0.09	0.44	0.20	0.42	0.44	-0.06	0.40	0.56	0.52	0.52	0.31	0.36	0.72	0.54	0.42	0.19	0.78	0.87	0.55	0.61	0.45	0.67	1.00

Two types of analyses were conducted for outcome variables that depend on more than two input variables: Principal Component Analysis (PCA) and Partial Least Squares (PLS). We analyzed the following outcome variables to identify the most important hypotheses for model construction.

- Information Sharing (Hypotheses H7 and H8)

For this outcome variable, Table 4 presents the information on the contribution percentages of hypotheses H7 and H8:

Table 4. Contribution percentages for hypotheses H7 and H8 towards the information sharing variable.

Hypothesis	Contribution percentage
H7	63.81 %
H8	36.19 %

The most important hypothesis is H7, as it exhibits the highest variation. The PCA method does not generate model values for only two explanatory variables.

- Knowledge Management (Hypotheses H13 and H15)

For this outcome variable, Table 5 presents the information on the contribution percentages of hypotheses H13 and H15:

Table 5. Contribution percentages for hypotheses H13 and H15 towards the knowledge management variable.

Hypothesis	Contribution percentage
H13	26.10 %
H15	73.90 %

The most important hypothesis is H15, as it exhibits the highest variation. Only two explanatory variables generate model values.

- Sustainable Competitive Advantage (Hypotheses H18, H19, H21, and H22)

For this outcome variable, Table 6 presents the information on the contribution percentages and model values of hypotheses H18, H19, H21, and H22:

Table 6. Contribution percentages and model values for hypotheses H18, H19, H21 and H22 towards the sustainable competitive advantage variable.

Hypothesis	Contribution percentage	Model values
H18	23.50 %	0.48
H19	21.34 %	0.46
H21	26.82 %	0.52
H22	28.33 %	0.53

The most important hypotheses are H22 and H21. Unlike other cases, there is no clear hypothesis that has greater importance than the others in contributing to the output variable. All percentages are very close, indicating that all hypotheses are relevant.

To formulate a model for predicting competitive advantage (CA) scores, Equation 1 could be used:

$$CA = (0{,}48 * H18) + (0{,}46 * H19) + (0{,}52 * H21) + (0{,}53 * H22) \quad (1)$$

- Organizational Performance (Hypotheses H25, H26, and H27)

For this outcome variable, Table 7 presents the information on the contribution percentages and model values of hypotheses H25, H26, and H27:

Table 7. Contribution percentages and model values for hypotheses H25, H26 and H27 towards the organizational performance variable.

Hypothesis	Contribution percentage	Model values
H25	23.25 %	0.48
H26	35.19 %	0.59
H27	41.54 %	0.64

The most important hypothesis in determining organizational performance (OP) is H27, followed by H26, and then H25. To formulate a model for predicting organizational performance scores, the Equation 2 could be used:

$$OP = (0{,}48 * H25) + (0{,}59 * H26) + (0{,}64 * H27) \quad (2)$$

Figure 3 shows the conceptual diagram of the validated structural equation model. The validated model eliminated the relationships provided by the H7 and H11 hypotheses.

- *H_7: BD allows the creation of Information Sharing (IS)*
- *H_{11}: BDA acceptance positively correlates with connectivity.*

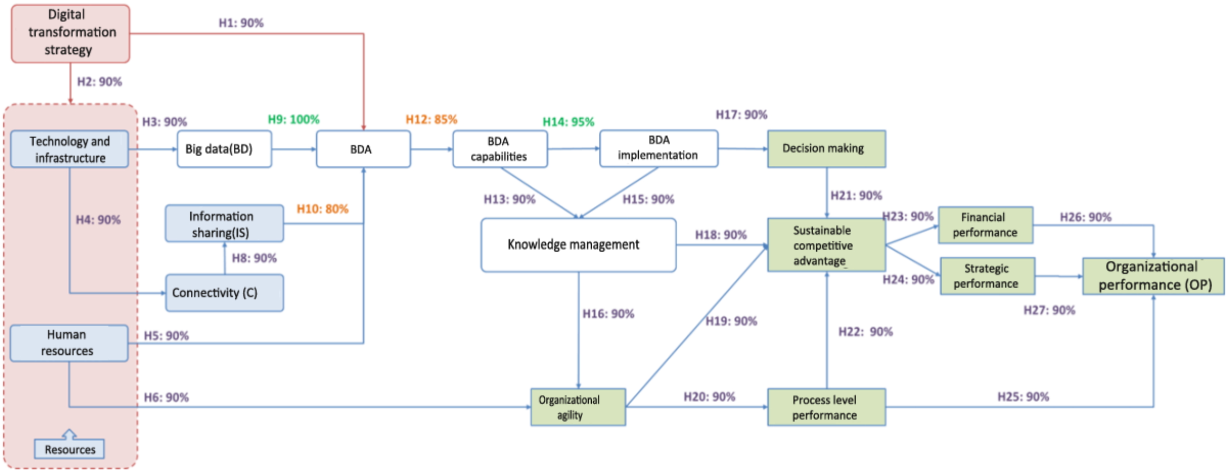

Figure 3. Validated conceptual model of the relationship between digital transformation and organizational performance.

Excluding the H7 construct, the information to be shared need not contain exclusively large volumes of information; this makes it possible to share information with any amount of data, whether or not they are part of Big Data initiatives. By eliminating the relationship given by H11, connectivity becomes a mediator between technology infrastructure and information sharing; this gives meaning to the flow of information to BDA through the link that allows connectivity.

The final model demonstrates how the Digital Transformation strategy groups the variables related to the resource management; including both physical (technologies and infrastructure) and those associated with human resources, and establish a direct relationship between variables and resources through the H2 construct. In addition, the organization's strategy is responsible for ensuring strategic IT flexibility and facilitating BDA business partnership and alignment through top management commitment and management accountability. This BDA business partnership and alignment make it possible to establish a direct relationship with Big Data Analytics through the H1 construct.

Technology and infrastructure resources include IT deployment capabilities, infrastructure flexibility capabilities, process integration and standardization, IT systems integration, and effective use of data aggregation tools, of data analysis tools, and their interpretation. This shows the relationships with BD (H3 construct) and with connectivity (H4 construct).

Human resources comprise the analytics capabilities of personnel associated with DT initiatives, the organizational relationship, personnel skills, the analytics culture, and the organizational relationship for the development of assigned activities. With these elements, it is possible to develop the analytics in BDA (H5 construct) and to create the dynamic capability of Organizational Agility (H6 construct).

After the elimination of H7 and H11 hypotheses, a relationship between technology and infrastructure and BDA was established through the mediation of connectivity (C) and information sharing (IS); data are considered assets of organizations that, by creating the right flow of information, can provide competitive advantages by taking this information into account in decision-making.

The H12 construct, which states that BDA diffusion positively influences the creation of BDA capabilities, validates the relationship between BDA and BDA capabilities with a median of 85%. These capabilities refer to data transformation and analysis and are divided into four stages: BDA acceptance, BDA routinization, BDA assimilation, and BDA diffusion. Consequently, based on BDA dissemination, the implementation of the H14 hypothesis is proposed, with the management of the capabilities created, the management of BD analysis resources, and the quality of data analytics.

As a result of BDA capabilities and their implementation, the relationships with knowledge management are established using H13 and H15 hypotheses, respectively. This management refers to the creation, storage, transfer, and application of knowledge with the functionalities of efficient data management and adequate delivery to end users (knowledge sharing).

Knowledge management has a positive influence on the dynamic capability of organizational agility (H16) to detect and respond to changes in the environment; this simplifies working methods and accelerates processes.

This agility positively impacts performance at the process level and enhances supply chain performance (SCP), production, and operations, which increases labor productivity and the offer of products and services (H20).

BDA implementation (H17 construct) mediates decision-making, thereby creating sustainable competitive advantages in organizations (H21). The use of information from Big Data initiatives has, therefore, an influence on decision-making; this is consistent with the conclusion of the experimental economics experiment, in which criteria and assertions as information supply influenced final decision-making.

Decision-making is considered a link and support for the creation of sustainable competitive advantages; this is an important element of the model as it is mediated by the direct influence of knowledge management (H18), organizational agility (H19), performance at the process level (H22), and decision making itself (H21). Then, competitive advantages group those related to improving financial performance (H23) with indicators such as the reduction of supply chain costs and the generation of efficient operations and economic policies that add value to the organization. In addition, they are associated with strategic performance (H24) with the strengthening of supplier relationships, improved planning, and strategic advantages over competitors.

The influence of performance at the process (H25), financial (H26), and strategic (H27) levels contributes positively to organizational performance, which adds value to the strategy of companies and involves planners, managers, directors, advisors, entrepreneurs, and others. It is also possible to collect performance measurement indicators against competitors, such as average market share, average sales volume, and average sales growth.

Organizational performance transversally impacts the technological and infrastructure elements associated with Digital Transformation, human resources and their skills, and data analytics capabilities and their effect on processes at the process level and on the organization's strategy. The organization integrates, builds, reorganizes, and reconfigures internal and external competencies to adapt to changing environments, as suggested by the dynamic capabilities presented above.

4.1. Relationship between Digital Transformation and Organizational Performance

The management of today's businesses in changing due to the increasing use of information and communication technologies (ICT), automation, and interconnection. Analyzing large amounts of business data transforms it into business advantage and performance (Grimaldi, Fernandez, & Carrasco, 2021). This requires business management to shift from intuition-based decision-making to one based on the rigor of data and evidence. According to Côrte-Real et al. (2017) data management serves various purposes such as managing customers, better understanding their interests, using marketing tools, understanding the market, and managing business performance itself.

Investing in BDA technologies alone does not create a competitive advantage. Therefore, organizations need to identify how to rearrange resources, processes, structure, leadership, etc., to build BDA capabilities and be able to measure these capabilities and business performance. To build BDA capability, companies must pay attention to different types of resources, such as tangible resources (data, technology, time, and infrastructure), human resources (management skills and Big Data techniques), and intangible resources (organizational culture, learning, structure, vision, and policy). Data-driven culture and organizational learning are the key intangible resources for developing BDA capabilities (Fosso Wamba et al., 2019; Gunasekaran et al., 2017; Yu et al., 2022).

In organizations where organizational culture, platform, and analytical skills of professionals support the effective use of BDA in the business, personnel management, technology infrastructure, organizational culture, and corporate decision-making are critical capabilities when implementing BDA (Gunasekaran et al., 2017). Researchers also propose tools that determine the balance of factors and the relationship between them to analyze an organization in Industry 4.0 and identify the actions necessary to achieve high levels of performance in the long term. Managers can use these tools to identify vulnerabilities and imbalances, aiding in critical organizational performance decision-making (Duman & Akdemir, 2021).

The process of organizational transformation towards digitalization can be compared to the process of changing a company towards globalization: both involve the need for change management along with considerations of processes, functions, professional capabilities, and others. Ensuring an integrated digital capacity in all the systems and processes, internal and external acceptance as a digital company, innovation of products and services with knowledge, and digital competence of professionals facilitate connections between digital strategy and strategic and operational objectives to bring about competitive advantage. Furthermore, digital workplaces with employee connectivity and responsive leadership can enable and support changes in digital strategies and processes, such as the commercialization of an organization (Teng et al., 2022b).

ICT capability is related to innovation and process management capabilities when defining how information systems will be implemented in businesses; this requires the organization to make changes in the different functions of its processes (Correa Ospina & Díaz Pinzón, 2018).

Studies show that it is possible to know how ICTs contribute to organizational performance; in this case, a study measured the relationship between ICT capacity, organizational capabilities, and performance of 102 MSMEs (Micro, small and medium-sized enterprises) in Bogotá based on a multimethodological model proposed by Mingers with a phased process (assessment, analysis, evaluation, and action). This study concluded that customer relationships are important in MSMEs due to market globalization and that information systems favor the identification, analysis, and understanding of customer needs (Correa Ospina & Díaz Pinzón, 2018).

Digital transformation has a positive impact on business performance, and the internal control and innovation ability mediate this relationship. Several factors affect the intensity of digital transformation, including enterprise size, industry type, and government support. Digital transformation is essential for enterprises to remain competitive in the global market, and policymakers should provide more support for digital transformation initiatives (Ye & Tong, 2022).

From a theoretical standpoint, the study advances the understanding of the relationship between digital transformation and organizational performance by proposing a conceptual model that incorporates three well-established theoretical perspectives: Dynamic Capabilities (DC), Resources-Based View (RBV), and Knowledge-Based Vision (KBV). By validating the model with empirical data, the study confirms the relevance and usefulness of these theories in explaining the relationship between digital transformation and organizational performance in the electric power sector. Moreover, the study highlights the important role of knowledge creation and management in driving organizational value in the context of digital transformation.

From a practical perspective, the study provides useful insights for firms seeking to optimize their digital strategies in the electric power sector. Specifically, the study demonstrates that digital transformation, particularly in Big Data, has a significant positive impact on organizational performance. This suggests that organizations in the electric power sector can benefit from investing in digital technologies and capabilities to improve their performance. Furthermore, the study emphasizes the importance of knowledge creation and management in generating value for organizations, which implies that firms should prioritize knowledge management initiatives to support their digital transformation efforts. Overall, the study provides a valuable roadmap for firms seeking to leverage digital technologies to enhance their performance in the electric power sector.

In the end, the proposed model shows how resource-based theories, which are managed by the DT strategy and knowledge-based vision, can be put together. This is done by combining knowledge management with BDA capabilities and putting the model into action. The model also highlights the promotion of dynamic capability of organizational agility through knowledge management by providing BD tools and its direct influence on human resources to create competitive advantages that enhance organizational performance, contextualized, and determined by the organizational, personnel, and technological dimensions.

However, it is important to acknowledge the limitations of this study. First, the data collected was self-reported and based on the perceptions of professionals in the industry. Further research should include more objective measures and longitudinal data to validate the findings of this study. Second, the sample size was relatively small, and the study was conducted in a specific industry, which limits the generalizability of the results. Future research should explore the relationship between digital transformation and organizational performance in other industries and contexts.

Despite these limitations, this study has important implications for firms seeking to optimize their digital strategies. Our results suggest that organizations should focus on developing knowledge-based capabilities to generate value from digital transformation initiatives. Furthermore, our conceptual model can serve as a framework for future research and a guide for practitioners seeking to implement digital transformation strategies in their organizations.

In summary, this study provides valuable insights into the relationship between digital transformation and organizational performance, but further research is needed to validate our findings and explore the generalizability of our results.

5. CONCLUSIONS

The proposed conceptual model, which establishes the relationship between Digital Transformation and Organizational Performance, reveals the need to group the variables associated with the management of physical resources (technologies and infrastructure) and human resources. In addition, the organization's strategy should ensure strategic IT flexibility and facilitate BDA business partnership and alignment through management commitment to establish a direct relationship with Big Data Analytics.

Human resources include the analytical capabilities of people working on the DT projects, the organizational relationship, personnel skills, the analytics culture, and the organizational relationship for the development of the assigned functions; these capabilities aim to develop the analytics in BDA and create organizational agility as a dynamic capability.

Knowledge management establishes a positive influence on the dynamic capability of organizational agility. Thanks to this influence, it is possible to detect and respond to changes in the environment, which will simplify working methods and accelerate processes. Additionally, this agility positively impacts performance at the process level and enhances supply chain performance, production, and operations, which increases labor productivity and the offer of products and services.

Organizations gain sustainable competitive advantages when BDA implementation mediates decision-making. Consequently, the use of information from Big Data initiatives has, therefore, an influence on decision-making; this is consistent with the findings of the experimental economics experiment, in which criteria and assertions as information supply influenced final decision-making.

The proposed model emphasizes the role of knowledge management, organizational agility, process performance, and decision-making in mediating the creation of sustainable competitive advantages.

Organizational performance transversally impacts the technological and infrastructure elements associated with Digital Transformation, human resources and their skills, and data analytics capabilities and their effect on processes at the process level and on the organization's strategy.

The proposed model articulates resource-based theory, managed by the DT strategy, and knowledge-based vision through the integration of knowledge management with BDA capabilities and its implementation and association with the dynamic capability of organizational agility through knowledge management by providing tools from BD initiatives.

5.1. Implications

- The proposed model reveals the need to integrate physical and human resource management for effective digital transformation.
- Organizations should prioritize strategic IT flexibility and foster BDA business partnerships to maximize big data benefits.
- Building analytical capabilities in personnel and fostering an analytics culture are crucial for developing agility and adapting to change.
- Knowledge management enhances organizational agility, simplifies workflows, and improves performance at various levels, ultimately leading to a competitive advantage.
- BDA-driven decision-making creates sustainable competitive advantages by leveraging information to make informed choices.

5.2. Limitations

- The study mainly focuses on the Colombian electric power sector, limiting the generalizability of findings to other industries and contexts.
- The research relies on survey data, which may be susceptible to biases and inaccuracies.
- The proposed model is complex and could require further validation through empirical testing.
- The study primarily focuses on BDA within digital transformation, leaving other aspects for future exploration.

5.3. Future Research Suggestions

- Replicate the study in different industries and contexts to test the generalizability of the model and to explore the temporal stability of the proposed model.
- Conduct qualitative research to gain deeper insights into the dynamics of knowledge management, organizational agility, and BDA implementation.
- Develop and validate more specific sub-models within the overall framework.
- Investigate the impact of other digital transformation elements beyond BDA on organizational performance and competitive advantage.
- Explore the ethical considerations and potential downsides of BDA-driven decision-making in organizations.

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