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EXAMINING HUMAN RESOURCE FACTORS INFLUENCING ANALYTICAL DECISION MAKING AND ORGANIZATIONAL EFFECTIVENESS IN TECHNOLOGY DRIVEN COMPANIES

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ABSTRACT

Purpose: The primary objective of this research is to analyze and examine the factors contributing to the issues in analytical decision-making in large technology-driven Indian organizations.

Theoretical Framework: The study aims to develop an 'analytical organizational effectiveness model' and 'analytical transformation theory' for technology-driven industries.

Design/Methodology/Approaches: The study adopted a mixed methodology research design using systematic literature review (SLR), exploratory research, expert interviews and quantitative techniques to identify key variables of the study.

Findings: The SLR validated the proposed conceptual model and found that human resource factors influence analytical decision-making and organizational effectiveness.

Research Practical Social Implication: The study provides actionable insights for organizations aiming to enhance decision-making processes. This research advances analytical transformation theory by exploring and identifying key factors influencing organizational analytical transformation. This study emphasizes the human dimension in successful analytical implementation. Developing an 'analytical organizational effectiveness model' for technology-driven industries represents a significant theoretical contribution, offering a structured framework for understanding and assessing analytics within specific organizational contexts.

Originality/Value: This study is more relevant and practically applied to organizations lagging in decision-making and facing a competitive advantage.

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EXAMINANDO OS FATORES DE RECURSOS HUMANOS QUE INFLUENCIAM A TOMADA DE DECISÕES ANALÍTICAS E A EFICÁCIA ORGANIZACIONAL EM EMPRESAS IMPULSIONADAS PELA TECNOLOGIA

RESUMO

Propósito: O objetivo principal desta pesquisa é analisar e examinar os fatores que contribuem para os problemas na tomada de decisões analíticas em grandes organizações indianas orientadas por tecnologia.
Estrutura Teórica: O estudo visa desenvolver um "modelo de efetividade organizacional analítica" e "teoria da transformação analítica" para indústrias orientadas para a tecnologia.
Design/Metodologia/Abordagens: O estudo adotou um projeto de pesquisa de metodologia mista usando revisão sistemática da literatura (RLV), pesquisa exploratória, entrevistas de especialistas e técnicas quantitativas para identificar as principais variáveis do estudo.
Constatações: O SLR validou o modelo conceitual proposto e descobriu que os fatores de recursos humanos influenciam a tomada de decisões analíticas e a eficácia organizacional.
Pesquisa de Implicação Social Prática: O estudo fornece percepções acionáveis para organizações que visam melhorar os processos de tomada de decisão. Esta pesquisa promove a teoria da transformação analítica explorando e identificando fatores-chave que influenciam a transformação analítica organizacional. Este estudo enfatiza a dimensão humana na implementação analítica bem-sucedida. O desenvolvimento de um "modelo de eficácia organizacional analítica" para as indústrias orientadas para a tecnologia representa uma contribuição teórica significativa, oferecendo um quadro estruturado para a compreensão e avaliação da análise em contextos organizacionais específicos.
Originalidade/Valor: Este estudo é mais relevante e praticamente aplicado a organizações com atraso na tomada de decisões e que enfrentam uma vantagem competitiva.

Keywords: Tomada de Decisão Analítica, Capacidade de Mudança Organizacional, Orientação Analítica, Liderança Digital, Eficácia Organizacional Analítica, Transformação Organizacional Analítica.

EXAMEN DE LOS FACTORES DE RECURSOS HUMANOS QUE INFLUYEN EN LA TOMA DE DECISIONES ANALÍTICAS Y LA EFECTIVIDAD ORGANIZACIONAL EN EMPRESAS TECNOLÓGICAS

RESUMEN

Objetivo: El objetivo principal de esta investigación es analizar y examinar los factores que contribuyen a las cuestiones en la toma de decisiones analíticas en las grandes organizaciones indias impulsadas por la tecnología.
Marco Teórico: El estudio pretende desarrollar un 'modelo analítico de efectividad organizacional' y 'teoría de transformación analítica' para industrias impulsadas por la tecnología
Diseño/Metodología/Enfoques: El estudio adoptó una metodología mixta de diseño de investigación utilizando revisión sistemática de la literatura (RPS), investigación exploratoria, entrevistas a expertos y técnicas cuantitativas para identificar las variables clave del estudio
Hallazgos: La RPS validó el modelo conceptual propuesto y encontró que los factores de recursos humanos influyen en la toma de decisiones analíticas y en la efectividad organizacional.
Implicación Social Práctica de la Investigación: El estudio proporciona información útil para las organizaciones con el objetivo de mejorar los procesos de toma de decisiones. Esta investigación avanza en la teoría de la transformación analítica explorando e identificando factores clave que influyen en la transformación analítica organizacional. Este estudio enfatiza la dimensión humana en la implementación analítica exitosa. El desarrollo de un 'modelo analítico de efectividad organizacional' para las industrias impulsadas por la tecnología representa una contribución teórica significativa, ofreciendo un marco estructurado para la comprensión y evaluación de la analítica dentro de contextos organizacionales específicos.
Originalidad/Valor: Este estudio es más relevante y se aplica de manera práctica a organizaciones rezagadas en la toma de decisiones y que enfrentan una ventaja competitiva.

Palabras clave: Toma de Decisiones Analítica, Capacidad de Cambio Organizacional, Orientación Analítica, Liderazgo Digital, Efectividad Organizacional Analítica, Transformación Organizacional Analítica.

INTRODUCTION

Organizations globally face the challenge of adapting to rapidly changing and unpredictable environments; however, the underlying conception of the change process remains simplistic (Buono & Kerber, 2008). Data-driven decision-making is critical to thriving in competitive environments, and such organizations perform far better than intuitive decision-making companies (McAfee *et al.*, 2012). Orlikowski's (2000) structuration theory proposes reforming the relationship between technology and organization. Human resource functions require better decision-making by leveraging analytics (Kiran et al., 2023). Analytical organizations intend to make decisions and create value based on data as their organizational culture to achieve their goals, as also advocated by (Raghunathan *et al.*, 2017). Gochhayat *et al.* (2017) research explores different cultural dimensions that impact operational effectiveness and investigates how a strong or weak organizational culture influences organizational effectiveness. Analytical effectiveness focuses on the ability of the firm to utilize data and analytics to gain insights and implement better decision-making processes (Sarkar & Mohapatra., 2015). Becker (1978) says that the analytical decision-making concept is derived from rational choice theory, which suggests that individual decision-makers evaluate optimum choices to maximize effectiveness to make efficient decisions. Analytics is a tool that helps to know the weaknesses and strengths of Kulkarni *et al.* (2017) say that in order to make analytical decision making as an organizational culture and belief system, leaders need to make systematic shifts in their current belief system; hence, the attitudinal barrier is key to transformation.

Organizations adopting data-driven decision-making tend to make informed, effective decisions, leading to better outcomes and improved organizational effectiveness (Davenport, 2006). Gangwar and Date's (2016) research examines and empirically validates the critical factors influencing analytic adoption intentions using the technology acceptance model (TAM). Analytics can assist leaders and organizations in gaining insights into customer behaviors, preferences, and needs through data analysis. The emergence of new technologies influences transformation towards advanced analytics (Penpokai, 2023). Li *et al.* (2015) say analytical insights enable organizations to personalize their offerings, tailor their marketing strategies, and improve customer service, resulting in improved customer experience and increased effectiveness in customer interactions. Analyzing data patterns and trends can help organizations identify inefficiencies in their processes and operations. By identifying effective areas of efficiency improvements, organizations can optimize their operations, reduce costs, and enhance productivity, leading to increased effectiveness (Davenport, 2006). Organizations that adopt advanced analytics techniques, such as predictive and prescriptive analytics, can gain a competitive advantage by leveraging data insights to make proactive decisions and optimize outcomes to improve organizational effectiveness (LaValle *et al.*, 2011). The following sections list the research objectives and questions from the initial literature review.

The research examines the critical factors that affect the efficiency, decision-making, transformation, and effectiveness of global multinational organizations. Additionally, the study seeks to determine the reasons behind the slower adoption of prescriptive analytics by Indian technology-driven organizations. The research also analyzes the benefits of implementing advanced analytics for improving organizational performance.

RO1: To identify and analyze the crucial factors in building an analytically oriented organization.

RO2: To analyze the critical factors influencing organizational and analytical effectiveness in large technology-driven organizations.

RO3: To examine the influence of analytical decision making on organizational effectiveness.

RO4: To explore the factors contributing to the infective implementation of analytical decision-making processes in most large technology-driven organizations.

The authors formulated the research questions below based on the above research objectives. The authors have adopted a structured literature review (SLR) to address the research objectives and questions in the following section.

RQ1: What factors play a key role in analytics-based decision making to improve organizational effectiveness?

RQ2: How can the critical factors contributing to organizational effectiveness be analyzed?

RQ3: Why do most Indian technology-driven organizations fail to implement efficient analytical decision-making?

RESEARCH METHODOLOGY

The authors adopted a mixed methodology research design using SLR, exploratory research, expert interviews and quantitative techniques to identify key variables of the study. The study began with an exploratory literature review (LR) and search with select keywords to identify important concepts related to the topic of the study. Further, a structured literature review was conducted, utilizing a systematic review and meta-analysis approach (Jois *et al.*, 2022). The authors utilized the information gathered from this LR methodology to identify research gaps and key constructs. As the next step, unstructured, open-ended interviews with fifteen (15) technology-driven industry experts were conducted to validate the identified concepts and constructs. The authors also conducted a structured literature review to explore the relationships between each variable and to identify relevant theories, scale development articles, and recent advancements in key concepts. The above approach also resulted in the identification of scales and dimensions for the constructs. The research developed a structured questionnaire based on the selected scales and dimensions. Structured interviews were conducted with large technology-driven industry experts using pre-determined criteria and questionnaires. The sampling theorem and thumb rule determined a sample size of at least 800. The survey was administered to over 1000 industry experts, HR executives, and senior executives using various methods such as face-to-face, email, Google™ form, and WhatsApp™. The research conducted a statistical analysis using the IBM SPSS tool, and a statistical model was developed using the IBM AMOS structure equation modeling (SEM) tool, resulting in an analytical organizational effectiveness model. The SEM goodness fit index and model fit were tested to validate the findings.

THEORETICAL REFERENTIAL

The researcher of this article focused on selecting some of the best academic contributions from various reputed journals, wherein the researcher also focused on identifying theoretical background and research gaps from each of such selected papers. The researcher here would like to present a comprehensive literature review while conducting an in-depth analysis of peer-reviewed journals.

Analytical Organizational Change Capacity (AOCC)

The organizational change capacity (OCC) framework, proposed by Zhao and Goodman (2019), comprises three dimensions: context, change process, and learning, each with several components that impact an organization's ability to achieve the desired change. Sastry (1997) suggests additional explanations for successful change processes, which present avenues for future research. Pettigrew *et al.* (2001) emphasize the significance of organizational change and propose that change capacity is an organization's ability to produce solutions that respond to environmental and organizational evolution and implement change processes successfully. When a change initiative is announced, managers are typically responsible for its implementation (Business Insights, 2020). Poole and Van-de-Ven (2004) argue that the topic of organizational change requires a broader view and comparison with literature on innovation and design thinking.

Widianto *et al.* (2021) propose that dynamic capability theory provides a dynamic perspective on the capabilities required for successful change, with managers needing to be agile in leading the process. McClelland and Atkinson (1948) stress the importance of individual behaviors, needs, values, and motivation in influencing the success of organizational change efforts. Judge and Douglas (2015) define OCC as a combination of managerial and organizational capabilities that enable a company to adapt more quickly and effectively to changing situations than its competition. Judge and Elenkov (2005) define OCC as a broad dynamic organizational capability that allows companies to adapt traditional capabilities to new threats and opportunities and create new dynamic capabilities. Based on such an extensive literature search on OCC, this study tries to define analytical organizational change capacity (AOCC) in the research model sub-section.

Managerial Attitudinal Barrier

Victor and Cullen (1988) discovered that managers significantly influence the organizational culture as employees often take cues from their supervisors' behavior to determine how they should behave in the workplace. Wong and Li (2015) suggest that managerial obstacles such as a lack of skills, cultural barriers, and inadequate top management support can impede the adoption of new technologies. The Upper Echelons theory posits that managers' cognitive bases and values also shape their overall perceptions, not just their impact on organizational outcomes (Navneet, 2020). In analyzing internal barriers to export activity, the study identified informational, managerial, financial, and marketing obstacles, with a lack of managerial, human, and financial resources being the primary hindrance to initiating or increasing export activity.

Senior and lower-level managers can use business analytics (BA) for strategic decision-making and improving efficiency in performing daily tasks (Akin & Bayram, 2020). However, a structured literature search shows managers create many barriers to adopting newer technology due to various altitudinal issues. Mumford's (1998) work on classifying barriers to learning for managers highlighted that emotional or motivational blocks arise when demotivated managers are less willing to take risks in learning activities. Previous experiences with learning can also create cognitive blocks (Mumford, 1988). Several studies have highlighted the impact of managerial behavior on employees' job performance in organizations, including Andersson and Florén (2011). Zakrzewska *et al.* (2021) emphasize the significance of recognizing factors that facilitate or hinder the effective implementation of agile management systems. Zhu *et al.* (2006) highlight managerial obstacles as a major barrier to organizational and analytical transformation.

Psychological Attitudinal Barrier

Navneet (2020) says that decision-makers are unable to observe every aspect of an organization and its environment, which means that their perceptions of the organization and environment are influenced by their cognitive bases and values. These psychological constructs are often measured by observable indicators such as demographics and personality traits (Navneet, 2020). When an organization adopts analytics, employees are expected to have a positive attitude. However, since analytics is new, uncertainty surrounds it, leading to individuals engaging in activities that reduce their uncertainty before adopting the innovation (Vargas *et al.*, 2018). Feng *et al.* (2019) propose an intertwined model that explains how the forced adoption of self-service technology can result in users experiencing psychological reactance. The intertwined model conceptualizes psychological reactance as a latent construct with two second-order indicators: cognitive and emotional reactance. According to the psychological reactance theory, people are motivated to restore their freedom of choice when threatened, leading to a state of psychological reactance where individuals act against the source of the threat to redeem their freedom (Rosenberg & Siegel, 2017; Brehm & Brehm, 2013).

Hirshleifer (2001) discovered that psychological factors are crucial in making strategic decisions. Among the common habits in human history, the preference for specific numbers can significantly influence investment behavior (Li *et al.*, 2023). The psychological reactance theory explains the relationship between persuasive messages, freedom threat, and reactance, providing valuable insights into playable ads' efficacy. Furthermore, perceived control is a fundamental concept in understanding reactance because humans highly value choice and control, as assumed by the psychological reactance theory (Quick *et al.*, 2013). A positive psychological attitude strengthens motivation, resilience, collaboration, innovation and productivity, enhancing organizational effectiveness. This study considers the psychological attitudinal barrier (PAB) one of the key constructs and an independent variable as part of building a model. The research model sub-section discusses the linkages of each identified construct.

Analytical Orientation Centralization

Analytical orientation (AO) comprises analytic culture, analytic skill, employee talent, insights from analysis, and data infrastructure and management (Dias *et al.*, 2021; Kiron *et al.*, 2014). In order to achieve superior results, data must be transformed into knowledge, and leaders in the organization must understand the strategy, skills, and culture required to achieve analytical orientation (Davenport *et al.*, 2001). Organizations must possess appropriate skilled and expert employees to analyze and interpret the data effectively (Alotaibi, 2023).

Kiron *et al.* (2014) say that analytical culture is the secret sauce that creates business value. Analytical orientation is a critical construct that analyzes analytical skill and culture, which can impact transitioning organizations towards the analytical organization. AO helps guide leaders in the organization to make better decisions, organize, analyze, and promote efficient organizational growth. An in-depth structured literature review highlights that analytical orientation (AO) and analytical centralization (AC) are crucial factors in decision-making instead of intuition-based decisions, which is also suggested by Navneet (2020). A comprehensive understanding of analytical orientation (AO) is crucial to acknowledge that decision-makers rely on technology and information systems to optimize their business data and variables. Furthermore, for AO to thrive, the entire organization must value data-based analysis and decision-making, as Davenport *et al.* (2001) suggested. Incorporating design thinking in management implies a human-centered approach to decision-making, where user behavior and habits significantly influence the process. It is worth noting that design thinking may not necessarily be systematic in nature.

Focusing on enhancing analytical decision-making is key to driving transformation and improving effectiveness. Centralizing analytical operations can help organizations transition smoothly by reducing friction and uncertainty, according to the ASHE-ERIC Higher Education Report in 1988. It is essential to centralize data to enable effective analytical decision-making within the organization. Komm *et al.* (2021) highlight the importance of centralization in bringing data scientists together in a single unit, allowing them to support decision-making better and resolve issues that arise. Decentralization can make managing data scientists in different units challenging when issues arise, and decision-making can suffer. Each business unit must customize its models to maximize efficiency in optimizing analytical decision-making.

Prioritizing analytical opportunities and centralization can help organizational leaders drive the transformation toward advanced analytics, as emphasized by Grossman and Siegel

(2014). The process of analytical transformation results in a proficient analytical mindset, a sound data infrastructure, and effective data quality management. Leaders in large organizations think it is imperative to shift towards advanced analytics and provide the workforce with the necessary skills to learn new techniques and models to achieve organizational efficiency through a centralized and analytical approach.

Analytical Decision-Making Effectiveness

In today's world, the decision-making process in organizations is undergoing a significant transformation. While managers in the past relied on their intuition and instincts to make decisions, organizations increasingly use data-driven analytics to support their decision-making (McAfee *et al.*, 2012). According to Sapp et al. (2019) and Gartner's report, digitalization involves improving existing business models, creating new revenue streams, and identifying value-adding opportunities through the use of digital technologies. This complex process involves several areas, including changes in thinking, leadership, technology adoption, resource digitalization, and innovation acceptance. To build an effective analytical organization, greater access to structured, unstructured, proprietary and un-proprietary data across multiple levels has to be greater. The data processing is carried out using various business rules and regulations, and the data is made available for analytics after applying these rules. Big data analytics must be dynamic and adaptable to provide the best possible cause-effect relationship for decision-makers in the organization (Deshpande *et al.*, 2019); the same can be achieved through an adaptive mechanism that utilizes predictive and prescriptive analytics at a given time (Deshpande *et al.*, 2019).

For many years, the classical theory of decision-making was the dominant belief regarding how experts made decisions. According to this theory, individuals have exceptional memory and computational abilities that enable them to perform complex decision calculations (Satz & Ferejohn, 1994; Scott, 2000; Bonabeau, 2003). However, recent research has shown that some employees of all expertise levels tend to use intuitive and analytical decision-making styles to solve difficult problems (Okoli & Watt, 2018). Knowledge workers who prefer analytical decision-making styles are more likely to utilize an organization's information systems and data to a greater extent than those who prefer conceptual decision-making styles. In terms of organizational decision-making, an analytical decision-making culture is characterized by the existence and understanding of a decision-making process and the use of available information for each decision, regardless of its nature (Popovič *et al.*, 2012).

Popovič *et al.* (2012) and Akin and Bayram (2020) argue that in organizations with a culture of analytical decision-making, employees are encouraged to utilize data and information, including advanced statistical and analytical techniques, in their decision-making processes. The use of prescriptive analytics has become increasingly important in data-intensive enterprise environments, as it aims to convert valuable insights into actionable recommendations to meet business objectives. The fundamental concept is to move beyond the findings of descriptive data analysis and predictive modeling to answer questions such as what should be done and why it should be done. However, there is often inconsistent comprehension of the constituent elements of prescriptive analytics, which can impede the development of appropriate information systems (Stefani & Zschech, 2018). This study also aims to determine whether Indian technology-oriented organizations are ready to transition from descriptive and predictive analytics to prescriptive analytics within their own organization. This research also analyzes where Indian technology-oriented organizations stand compared to their global peers. The research aims to test and identify the key factors that hinder Indian technology-oriented organizations from recognizing the importance of prescriptive analytics-based decision making driven by mathematical and statistical modeling using analytics tools.

Digital Leadership

Digital leadership, which refers to the ability of leaders to navigate and leverage digital technologies in their decision-making processes effectively, has a significant impact on the adoption of analytical decision making. Bonnin *et al.* (2018) highlight that digital leaders intend to create an organizational culture that encourages continuous improvement and learning, assisting in adopting analytical decision making as employees are empowered to learn from data and improve decision-making practices. Digital leadership is the ability to bring about change within organizations and is in high demand due to a shortage of leaders in the field (Martins, 2019). Achieving business objectives through digital transformation requires skilled workers and effective leadership to optimize technology, analytics, and digitization. A diverse workforce is crucial in introducing and sustaining digital transformation, and effective policies and decision-making are more important than the amount of money spent (Martins, 2019). Decentralized leadership that leverages collective intelligence is ideal for the digital economy, but traditional management tools may still be necessary (Petry, 2018). Identifying digital leaders is vital for successful digital transformation, requiring consistent involvement at all levels and employee commitment (Gudergan *et al.*, 2021). To keep pace with technological progress, leaders must develop agile business models and articulate a clear and ambitious digital vision encompassing all areas of the company and its stakeholders (Harrison *et al.*, 2010).

According to a study by Shumei *et al.* (2019), digital leaders emphasize developing analytical skills and capabilities among their employees, as having a workforce skilled in data analysis is crucial for adopting analytical decision-making practices. As Marr (2016) highlighted, digital leaders invest in advanced analytics technologies that enable them to collect, analyze, and interpret data in real time, enhancing their ability to make analytical decisions based on evidence. The influence of a leader plays a vital role in organizational performance. According to a study by Westerman *et al.* (2014), digital leaders realize the importance of data and analytics in decision-making and encourage using data and evidence-based research to inform decision-making processes to reach organizational effectiveness.

Analytical Organizational Effectiveness

Organizational effectiveness is a broad term that encompasses multiple aspects of organizational performance, including increased output, quality, quantity, adaptability, and efficiency. Efficiency is the optimal use of organizational resources and is measured as the ratio of output to input. The concept of organizational effectiveness has been studied extensively in organizational science for over 80 years, and it is considered a central theme in management practice. It is defined as the company's ability to consistently achieve its strategic and operational goals over the long term. According to Kataria *et al.* (2013), organizational paradigms of employees' work engagement are related to organizational effectiveness. Organizations must be effective to develop and sustain a competitive advantage in the contemporary business world. Organizations are built to be the most effective and efficient social units (Cetin & Cerit, 2010). Managerial effectiveness varies widely from company to company and from job to job, and the criteria for effectiveness must be defined carefully and objectively (Seeta, 2016). Balaraman (1989) defined managerial effectiveness in behavioral terms and evaluated it on job-oriented criteria such as communication, cost awareness, delegation of work, labor relations, planning and scheduling, securing interdepartmental cooperation, training subordinates, and utilization of capacity.

In most organizational research, organizational effectiveness is the dependent variable, defined as the degree of congruence between organizational goals and observable outcomes (Hannan and Freeman, 1977). Effective organizations, resilient while facing adverse conditions, tend to produce better-quality products (Kataria *et al.*, 2014). Mott (1972) defined

OE as the ability of an organization to mobilize its centers of power for action, production, and adaptation. However, an organization can be judged effective by one criterion and ineffective by another (Kataria *et al.*, 2014). Overall, organizational effectiveness is a critical concept in organizational science and management practice, encompassing multiple constituents of organizational performance. Analytical organizational effectiveness (AOE) importance lies in organizations' ability to achieve their goals consistently over the long term and to adapt to dynamically changing circumstances effectively. This research tried to develop a model based on the constructs proposed till now. This research delved deep into each concept and tried to understand the linkages between the constructs. The following sections present the analytical organizational effectiveness framework, which is further converted as an SEM model and validated in the following sections.

RESEARCH MODEL

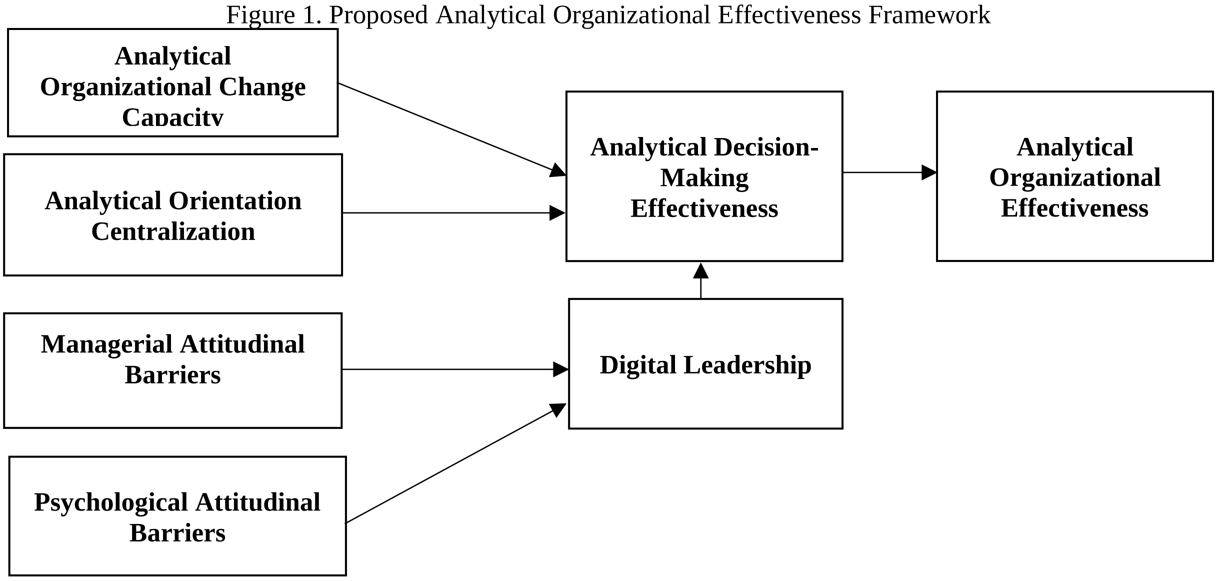
Mid-level leaders and managers who are supposed to transform have limited knowledge of statistical modeling and mathematical algorithms, and lower-level decision-makers exhibit a negative attitude toward change. Inhibiting new initiatives can be referred to as psychological attitudinal barrier toward innovation that can be proved based on the diffusion of innovation theory (DOI) (Rogers, 1962). This psychological attitudinal barrier toward new ways of doing business limits organizational efficiency, resulting in a reduced return on investment. The proposed analytical organizational effectiveness framework emphasizes analytical decision-making by considering attitudinal barriers, leadership, and statistical, mathematical, and computational models. Digital leadership intention is key to ensuring data is captured across various departments and at multiple levels to transform the organization into an analytical organization. Digitally aware leadership coupled with a positive attitude without barriers and intention drives analytical decision-making. Davenport (2013) advocates that organizations must create a value chain for analytics that surrounds all the steps from data acquisition to decision-making. Analytical organizations understand the value of that data and information and build processes to capture and analyze that data. Dawar and Bagga (2020) discuss the challenges of organizations becoming more data-driven and providing a transition framework. Analytical organizations must build the right data infrastructure, develop data literacy, overcome attitudinal barriers, and integrate data-based decision-making into organizational culture.

Transformation into an analytical organization is linked to efficiency and effectiveness in resource hiring, fulfillment, training, sales and service delivery parameters. Transformation of analytical decision making based on statistical computational and mathematical modeling powered by technological tools will help maximize stakeholder value, as suggested by Popovič *et al.* (2012), Akin and Bayram (2020) and Davenport (2013). Zicari and Virgillito's (2019) research compares the practices of highly analytical-oriented organizations to those that are not. Analytical organizations tend to have a more centralized approach to managing and analyzing data, with teams dedicated to analytics. Analytical organizations invest more in training and development to optimize the skills needed to analyze data effectively. Prescriptive analytics needs centralized data to make effective decisions in an integrated fashion. Digitally aware organizational leadership may demand that the second leadership level identify critical parameters linked to profits and organizational levers that increase or decrease profits. Mid-level leaders and managers are responsible for creating the necessary digital and data infrastructure for advanced analysis.

Despite having technologically advanced employees, large technology-driven Indian organizations hesitate to transition to advanced analytics. This reluctance is due to the perception that analytical decision-making is complex and not user-friendly. Devenport (2013) argues that analytical effectiveness requires a mixed approach surrounding people, processes and technology. Davenport (2013) suggests that organizations should invest in training and development to develop data knowledge, establish clear data governance policies, and use technology to automate data collection and analysis. Finkle and Bingham (2019) argue that successful data analytics programs require three key elements: a clear strategic vision, a focus on business success and a culture of data-driven decision-making. Bingham (2019) suggests that organizations must clearly understand the value of analytics, align analytics initiatives with business goals, and build a culture of focus to prioritize data-driven decision-making. Davenport (2013) discusses how data-driven decision making can drive organizational performance and offers insights into the characteristics of highly effective organizations leveraging data analytics. Effective analytical organizations can align their data analytics initiatives with their business objectives, build a culture of data-driven decision making (Davenport, 2013), and leverage technology to automate data collection and analysis. Davenport and Harris (2007) discuss how analytics can provide a competitive advantage to organizations and offer insights into the highly effective characteristics of organizations that leverage data analytics.

Effective analytical organizations can identify and prioritize analytical opportunities, build analytical capabilities, and use analytics to drive innovation and improve decision making. Leaders are under the assumption that ease of use and adoption of advanced analytics can be improved, but psychological, attitudinal, and managerial barriers prevent such adoption. Additionally, the team involved in the transition towards advanced analytics is not keen on getting trained due to their inhibition towards statistics and mathematical modeling. This lack of skill and knowledge can be considered a managerial obstacle that hinders the transition toward analytics-based decision-making. Such obstacles created by managers and leaders result in organizational barriers, which impede transformation toward new initiatives and reduce efficiency. The limited knowledge of statistical modeling and mathematical algorithms among mid-level leaders and managers, coupled with their reluctance to change, creates a psychological attitudinal barrier toward innovation that can impede organizational effectiveness and result in a reduced return on investment (ROI) (Rogers, 1962). Figure 1 shows the conceptual model demonstrating ways to improve organizational effectiveness through analytical decision-making.

Figure 1. Proposed Analytical Organizational Effectiveness Framework



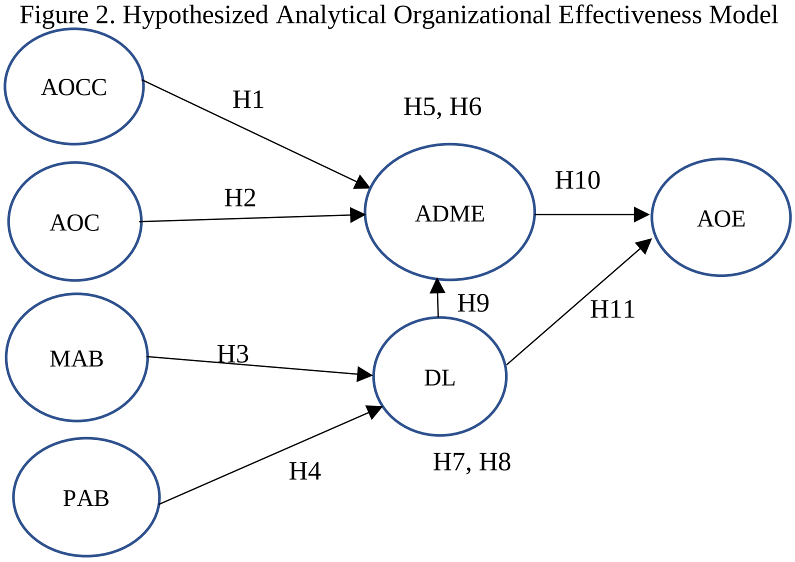
Source: Prepared by Authors (2023).

Organizational change is always constant, and agile organizations have the capacity and capability to adapt to changes. Organizational change capacity coupled with managerial and decision-maker intent leads to better analytical decision-making, thus improving analytical organizational effectiveness. The infrastructure needed for analytics, intent towards implementing advanced analytics, and culture of change based on organization change capacity lead to superior analytical decision making that positively impacts organizational effectiveness. The infrastructure needed for analytics, the intent to implement advanced analytics, and a culture of change based on organizational change capacity lead to superior analytical decision-making, positively impacting analytical organizational effectiveness, as in Figure 1. The model's independent variables are organizational change capacity, managerial attitudinal barrier, psychological attitudinal barrier, and analytical orientation centralization, and moderating variables are analytical decision-making effectiveness and digital leadership. The dependent variable is analytical organizational effectiveness.

Structural model

The key findings of the exploratory research, structured literature review, expert interviews and synthesis of the literature are translated into the following hypotheses. The hypothesized analytical organizational effectiveness model is as shown in Figure 2. The study proposes the following hypotheses:

Figure 2. Hypothesized Analytical Organizational Effectiveness Model



Source: Prepared by Authors (2023).

H1: There is a significant relationship between analytical organizational change capacity and analytical decision-making effectiveness.

H2: There is a significant relationship between analytical orientation centralization and analytical decision-making effectiveness.

H3: There is a significant relationship between managerial attitudinal barriers and analytical decision-making effectiveness.

H4: There is a significant relationship between psychological attitudinal barriers and analytical decision-making effectiveness.

H5: Analytical decision-making effectiveness has a mediating relationship between analytical organizational change capacity and analytical organizational effectiveness.

H6: Analytical decision-making effectiveness has a mediating relationship between analytical orientation centralization and analytical organizational effectiveness.

H7: Digital Leadership has a mediating relationship between managerial attitudinal barriers and analytical organizational effectiveness.

H8: Digital Leadership has a mediating relationship between psychological attitudinal barriers and analytical organizational effectiveness.

H9: There is a significant relationship between digital leadership and analytical decision-making effectiveness.

H10: There is a significant relationship between analytical decision-making effectiveness and analytical organizational effectiveness.

H11: There is no significant relationship between digital leadership and analytical organizational effectiveness.

Results and Discussions

The exploratory factor analysis (EFA) was performed by applying the principal component analysis method with an eigenvalue of one and varimax rotation, as Ritter *et al.* (2001) suggested. According to Piegorsch and Ramsey (1997), it is imperative to test that a scale measures a single construct effectively before utilizing the scale to conclude that particular construct. The study used Bartlett's test of sphericity and Kaiser-Meyer-Olkin (KMO) measures in EFA to assess the sample's adequacy for factor analysis (FA). The KMO values were higher than 0.6 and lower than 1, which are considered acceptable for factor analysis (Bartlett, 1950; Kaiser, 1974). Hence, the scale unidimensionality of AOCC (analytical organizational change capacity), MAB (managerial attitudinal barrier), PAB (psychological attitudinal barrier), AOC (analytical orientation centralization), ADME (analytical decision-making effectiveness), DL (digital leadership) and AOE (analytical organizational effectiveness) are acceptable for their respective dimensions. The study used Bartlett's test of sphericity to test whether all the items of a particular variable are uncorrelated with items of other variables. Such a test measures the null hypothesis and proves that the correlation matrix is an identity matrix. Based on factor analysis, the study tested that items within a variable are intercorrelated so that the study can reject the null hypothesis.

Table 1. Composite Reliability

Indicator Variables	Latent Variables	Stand. Ldngs (λ)	Square of Std Ldngs (λ2)	Mesrnt Error (ME=1-λ2)	Sum of ME	Sum Std Ldngs (B)	Square-Sum Std Ldngs (C)	C+ ME	Composite Reliability CR=C/(C+ME)	n	AVE= B/n	Cronbach Alpha
QOS-OE	Analytical Organizational Effectiveness	.916	0.84	0.16	0.35	2.65	7.02	7.37	0.95	3	0.88	0.93
Employees quickly adopt-OE		.965	0.93	0.07								
Productivity high-OE		.938	0.88	0.12								
Spreads the vision-AOCC	Organizational Change Capacity	.936	0.88	0.12	0.38	2.62	6.84	7.22	0.95	3	0.87	0.93
Challenged-AOCC		.918	0.84	0.16								
Various divisions-AOCC		.946	0.90	0.10								
Satisfaction-PAB	Psychological Attitudinal barrier	.972	0.95	0.05	2.94	2.88	8.29	11.23	0.74	3	0.96	0.98
Joyful-PAB		.980	0.96	0.04								
Comfortable-PAB		.986	0.97	0.03								
Collects necessary data-ADME	Analytical decision making effectiveness	.968	0.94	0.06	0.22	3.78	14.33	14.54	0.99	4	0.95	0.98
Stakeholders-ADME		.963	0.93	0.07								
methodical approach—ADME		.983	0.97	0.03								
Stakeholders-ADME		.977	0.95	0.05								
IT team-AOC	Analytical Orientation and Centralization	.945	0.89	0.11	0.45	2.55	6.50	6.954	0.94	3	0.85	0.91
Statistical techniques-AOC		.936	0.88	0.12								
Intuition rather than data—AOC		.884	0.78	0.22								
Strategic business process-MAB	Managerial Barrier	.949	0.90	0.10	0.43	2.57	6.62	7.04	0.94	3	0.86	0.91
Data-driven decision-making-MAB		.944	0.89	0.11								
Training internal staff-MAB		.883	0.78	0.22								

Digital strategy-DL	Digital Leadership	.938	0.88	0.12	0.77	5.23	27.34	28.11	0.97	6	0.87	0.97
Intuition-DL		.913	0.83	0.17								
Enthusiasm -DL		.930	0.86	0.14								
Storytelling tools -DL		.890	0.79	0.21								
Reinforce the mission -DL		.974	0.95	0.05								
Encourage employees -DL		.954	0.91	0.09								

Source: Prepared by Authors (2023).

This study adapted the scales from top-quality scale development articles. The authors conducted CFA (confirmatory factor analysis) to assess whether a significant and positive relationship exists between the latent construct (LC) and the observed variable (OV), a valid instrument for measurement models. Marsh and Hau (2007) suggest that understanding complex relationships between observed variables helps improve the reliability and validity of their measures. Kline (2011) suggests the adoption of structured equation modeling (SEM) to test the positive relationship between the identified variables. The study used IBM SPSS for CFA and IBM AMOS tool for SEM modeling. Further, the study conducted composite reliability (CR), convergent validity (CV) and discriminant validity (DV) to ensure the identified scales are reliable and valid (Lee Cronbach's alpha, 1951; Netemeyer, 2003). Based on the CFA and cross-verification in SEM, the study extracted λ (standard loadings) from the factor groupings (McDonald & Ho, 2002). Factor loadings greater than 0.70 were considered strong, between 0.40 and 0.70 were moderate, and less than 0.40 were weak (Jois *et al.*, 2022).

The Cronbach alpha and average variance (AVE) were above 0.8, as shown in Table 1. Hence, all 26 items which measure the respective scales can be treated as reliable. Based on Table 1, the composite reliability scores are above 0.8; hence, scales AOCC, MAB, PAB, AOC, ADME, DL, and AOE are reliable. Thus, the composite reliability of scales is established. Azmi and Mushtaq (2013) suggest that convergent validity can be established based on the constructs' correlation coefficient values between the related items. The study also analyzed correlation coefficient values to check whether the correlation between unrelated items of different constructs exists or not. The range between 0.3 and 0.7 is treated as perfect convergence. However, according to Hair *et al.* (2008) and Jois *et al.* (2021), the range between 0.3 to 0.95 is acceptable. Neal and Chan (1998) suggest that the VIF score should be above 10, indicating a high correlation. In this study, VIF scores are below 10, which suggests that the scales are moderately correlated.

The study found no multicollinearity regression issues based on the correlation coefficient matrix and VIF scores (Senaviratna & Cooray, 2019). Thus, the convergent validity of all the scales AOCC, AOC, MAB, PAB, ADME and AOE are established. The variance value between scales is 89% (as per Table 2), which is greater than the correlation square values of the respective scales. Hence, discriminant validity is proven. As there was no correlation between most items outside the construct (Hair *et al.*, 2008, 2009), the discriminant validity of scales is established.

Table 2. Discriminant Validity of Scales

Scale	Factor Grouping Name	Average Loadings	Variance Extracted	Variance Between All	Correlation	Correlation on Square
Component 4	Analytical Organizational Effectiveness	.940	0.88	89%	.364	13.2%
Component 5	Analytical Organizational Change Capacity	.934	0.87		.359	12.9%
Component 3	Psychological Attitudinal Barrier	.980	0.96		.342	11.7%
Component 2	Analytical Decision Making Effectiveness	.973	0.95		.259	6.7%
Component 7	Analytical Centralization Orientation	.922	0.85		.370	13.7%
Component 6	Managerial Barrier	.926	0.86		.368	13.5%
Component 1	Digital Leadership	.933	0.87		.186	3.5%

Source: Prepared by Authors (2023).

By analyzing the strength of the relationship between AOCC and ADME in Table 3 and hypotheses H1 values (β=0.216, t=4.027), the study concludes that H1 is supported, which is also suggested by Popovič *et al.* (2012). H1 proves that there is a significant relationship between AOCC and ADME. Davenport *et al.* (2001) say there is a correlation between AOC and ADME, supported by H2 values (β=0.166, t=2.776, p=0.006). Westerman *et al.* (2014) advocate that there is a significant relationship between MAB and DL, which is supported by the H3 values (β=0.275, t=5.820, p<0.001).

Table 3. Hypotheses Testing – AOE Model

Hypothesis – Path Posited	P.coef (β)	t-value	Sig. level (p-value)	Results
H1: AOCC → ADME	0.216	4.027	p<0.001	Supported
H2: AOC → ADME	0.166	2.776	P=0.006	Supported
H3: MAB → DL	0.275	5.820	p<0.001	Supported
H4: PAB → DL	0.456	2.637	p=0.008	Supported
H5: AOCC → ADME → AOE	β1+β2>0.3, Diff>0.2 Total effect and Indirect Effect are significant. Alternate hypothesis is out of the upper and lower boundary, p<0.05, and the hypothesis is within the boundary			Supported
H6: AOC → ADME → AOE				Supported
H7: MAB → DL → AOE				Supported
H8: PAB → DL → AOE				Supported
H9: DL → ADME	0.1	2.776	p=0.045	Acceptable
H10: ADME → AOE	0.300	7.225	p<0.001	Supported
H11: DL → AOE	0.67	-	p>0.05	Rejected

Source: Prepared by Authors (2023).

The H4 values ($\beta=0.456$, $t=2.637$, $p=0.008$) show that there is a significant relationship between PAB and DL, which is also advocated by Vargas *et al.* (2018). The direct effect of AOCC on AOE ($\beta=0.725$) shows that the p-value is less than 0.001 at a 95% confidence interval; hence, it is significant. The indirect effect of AOCC on AOE through ADME ($\beta=0.214$, $p=0.021$) is also significant as the p-value is less than 0.05. Thus, the total effect of AOCC impacting AOE ($\beta=0.939$ and $p<0.000$) is also significant. The alternate hypothesis is out of the upper and lower boundary, and hypothesis H5 is within the boundary. Hence, the study states that ADME mediates between AOCC and AOE. Similarly, the direct effect of AOC on AOE ($\beta=0.705$, Sig(P)<0.001) and the indirect effect of AOC impacting AOE through ADME ($\beta=0.212$, Sig(p)=0.021) is also significant. Hence, the total effect of AOC impacting AOE ($\beta=0.932$, Sig(p)<0.000) is also significant. The alternate hypothesis is out of the upper and lower boundary, and hypothesis H6 is within the boundary. Thus, ADME mediates between AOC and AOE.

The direct effect of PAB on AOE is $\beta=0.730$ and $p=0.001$; as the p-value is less than 0.05, the impact of PAB on AOE is significant. The indirect effect of PAB impacting AOE through DL is $\beta=0.285$ and $p=0.027$; hence, it is significant. The total effect of PAB impacting AOE is $\beta=0.945$) and Sig (p)=0.000; hence the relationship is significant. The alternate hypothesis is out of the upper and lower boundary, and hypothesis H8 is within the boundary. Thus, DL mediates between PAB and AOE. Similarly, the direct effect values of MAB on AOE are $\beta=0.831$ and Sig(p)=0.001. The indirect effect of PAB impacting AOE through ADME is $\beta=0.258$ and Sig (p)=0.024) is also significant, and the total effect of PAB impacting AOE through DL is $\beta=0.947$ and Sig (p)=0.000; hence, DL mediates between MAB and AOE. Harrison *et al.* (2010) say there is a correction between DL and ADME, which is supported by H9 values ($\beta=0.1$, $t=2.776$, $p=0.045$). In social sciences studies, hypotheses with path coefficients above 0.1 are accepted if the p-value is below 0.05. Hence, the H9 is accepted. Kataria *et al.* (2013) suggested that there is a correlation between ADME and AOE supported by H10 ($\beta=0.300$, $t=7.225$, p-value<0.001). The H11 values ($\beta=0.67$, p-value>0.05) show no statistically significant relationship between DL and AOE; thus, hypothesis H11 is rejected.

The study finds a positive relationship between analytical organization change capacity and analytical decision-making effectiveness (hypothesis 1). A significant relationship between AOCC and ADME positively impacted analytical organizational effectiveness. The study also hypothesized (H2) that there is a positive relationship between analytical orientation centralization and analytical decision-making effectiveness resulting in analytical transformation; thus, hypothesis H2 cannot be rejected (as indicated in Table 3). Similarly, there is a positive relationship between managerial attitudinal barriers and digital leadership, which leads to analytical decision-making transformation (hypothesis 3); therefore, it is significant and is supported. Authors have also proposed hypothesis (H4) indicating a positive relationship between the psychological attitudinal barrier and digital leadership, which results in organizational effectiveness. This study also finds that analytical decision-making effectiveness has a mediating relationship between analytical organizational change capacity and analytical organizational effectiveness (hypothesis 5). Similarly (hypothesis 6) indicates that analytical orientation centralization has a mediating relationship between analytical organizational change capacity and analytical organizational effectiveness, as indicated in Table 3.

This study indicates that digital leadership has a mediating relationship between managerial attitudinal barriers and analytical organizational effectiveness (H7); likewise, digital leadership has a mediating relationship between psychological attitudinal barriers and analytical organizational effectiveness (H8). There is a positive relationship between analytical decision-making effectiveness and digital leadership (H9); similarly, there is a positive relationship between analytical decision-making and analytical organizational effectiveness (Hypothesis 10). There is no significant relationship between digital leadership and analytical organizational effectiveness (H11). Authors found substantial evidence emphasizing employee psychological behavior, leaders', managers', and decision-makers analytical skills and culture influence decision-making. This study also found that analytical organizational change capacity strongly influences analytical decision-making effectiveness with superior analytical organizational effectiveness, which helps in the transformation of technology organizations.

CONCLUSION

Large technology-driven organizations in India, especially in the IT industry, need to improve their decision-making based on advanced analytics to transform their company into analytical organizations. Although human capital analysis (AHH) has recently generated much interest, most organizations struggle to move operational reporting to analytics-based dashboards (Boudreau & Cascio, 2017). Unlike their global peers, technology-driven Indian organizations lag in adopting prescriptive analytics due to inadequate data collection, lack of analytical data centralization, and low analytical orientation among executive teams. Building an analytical culture within the organization requires upskilling and reskilling decision-making teams and addressing challenges related to the centralization of analytics, organization change capacity, and dynamic capability, which is also advocated by Widianto et al. (2021) and Judge and Elenkov (2005). Leadership teas' analytical orientation, centralization of analytics, organizational change capacity, and data aggregation collectively lead to the transformation into an analytical organization, resulting in improved organizational effectiveness, as Kataria et al. (2013) and Mott (1972) suggested.

Analytics adoption provides evidence-based support for analytical effectiveness in various organizational contexts, as Mott (1972) advocates. Research studies and citations from reputable sources (Davenport, 2013; Kataria et al., 2013; Deshpande *et al.*, 2019; Dias *et al.*, 2021; Marr, B, 2016). validate the value of analytics adoption, provide insights into best practices, and help organizations build a compelling business case for investing in analytics initiatives. Sparrow and Cooper (2014) map the evolution of the organizational effectiveness field by encompassing various aspects, such as employee satisfaction, political assessments of effectiveness, power dynamics, stakeholder involvement, societal impact, social justice, resilience, adaptability, and growth. However, this study covers much more critical aspects such as analytical organizational effectiveness, Analytical organizational change capacity, psychological attitudinal barrier, managerial barrier, analytical decision-making effectiveness, analytical centralization orientation and digital leadership. Analytics adoption is essential for organizations to achieve effectiveness in today's competitive business environment. Organizations can make data-driven decisions, optimize operations, enhance customer experience, conduct strategic planning, and gain a competitive advantage by leveraging data and analytics.

Analytical organizational effectiveness relates to an organization's ability to leverage data analysis to achieve its goals and create business value. A proficient analytical organization can synchronize its analytics strategies with its business objectives, instill a culture of data-driven decision-making, and make appropriate investments in technology and skilled personnel. Effective analytical organizations are characterized by their ability to recognize and rank analytical opportunities, cultivate analytical capabilities across the organization, and utilize analytics for innovation and better decision-making. Zhao *et al.* (2018) discuss the impact of analysis on organizational performance and provide ideas on what factors contribute to analytical effectiveness. Effective analytical organizations can align their analytics initiatives with their business strategy, build a culture of data-driven decision-making, and invest in the right technology and talent.

A conceptual framework for this study was developed, incorporating empirical evidence and addressing theoretical gaps identified in the literature review. It was further demonstrated and explained from two theoretical perspectives: perspective theory and the trash can decision-making model. Prospect theory (Kahneman & Tversky, 1979) challenges the conventional view of decision-making as a purely rational, utility-maximizing process. Rather, it is believed that cognitive biases and heuristics often influence decision-making and can deviate from rational calculations of expected outcomes. Analytical transformation theory can be stated as the dynamic capability of the organization, leadership, and managers to orient and adapt to change and build an analytical organization by removing psychological attitudinal barriers to making effective decisions through digital and analytical initiatives, thus achieving organizational effectiveness. Cohen *et al.* (1972) garbage can model of decision-making theory proposes a framework interlinking problems, choices, decision-makers and solutions rather than an optimal solution.

Decision makers in this model follow a rational decision-making process instead of linear thinking and engage in a fluid and opportunistic approach. Like prospect theory and garbage can model of decision-making theory, analytical transformation theory can also significantly impact decision sciences and can be extensively studied and applied in various contexts, such as organizational decision-making, economics, finance, and public policy. The proposed theory can assist in developing a better understanding of how employees perceive and assess risk and reward and how emotions and cognitive biases influence real-world decision-making.

Analytical transformation theory underscores the complex and dynamic nature of decision-making in organizations and emphasizes the significance of considering various factors that can impact decision outcomes. The proposed theory also suggests that effective organizational decision-making may require rational analysis and understanding of the contextual factors that shape decision opportunities and decision-making. The findings of this study contribute to practical implications and applications for human resource management (HRM) practices in technology-oriented industries, especially the Indian IT industry. The adoption of analytical decision-making practices in organizations can yield tangible benefits, such as increased organizational change capacity, improved digital leadership, and overcoming managerial barriers, ultimately enhancing overall organizational performance.

Organizations prioritizing and cultivating a data-driven decision-making culture are better positioned to thrive in today's dynamic and competitive business landscape. The practical impact of analytical decision-making on organizational effectiveness is evident in improved performance, as data-driven decisions enable organizations to optimize operations, identify opportunities, mitigate risks, and achieve strategic objectives effectively. Research consistently shows that organizations prioritizing analytical decision-making tend to outperform peers in financial performance, innovation, and competitive advantage areas. By leveraging analytical techniques for data analysis and informed decision making, organizations can identify patterns, trends, and opportunities for improvement, enhancing their capacity to implement organizational changes successfully.

The study revealed several factors related to the widespread adoption of advanced analytics in technology-driven organizations in India. Organizations that embrace analytics gain a competitive advantage by leveraging data and insights on market trends, customer behaviors, and competitive landscapes. However, future researchers can extend the model by adding constructs such as competitive intensity and customer behavioral patterns. The proposed model and theory empower leadership to make key strategic decisions in order to march ahead of the competition. Analytics also facilitates strategic planning and forecasting based on historical data and predictive analytics, aiding organizations make informed decisions about future strategies, resource allocation, and market trends, thereby enhancing planning and forecasting for business growth. However, the research could not include the impact of analytics on market trends and exponential business growth as part of the study. Researchers can also expand this research to include constructs like personality traits and leadership style. Future researchers can extend this study to explore such factors.

Additionally, analytics enables organizations to identify process inefficiencies and operational trends through data analysis, leading to the optimization of operations, cost reduction, and increased productivity, thereby enhancing organizational effectiveness. The authors have proposed analytical organization as a concept that needs many future researchers to test and validate such concepts. The study must also be extended to other large and medium-sized Indian industries, not just technology-driven ones. Further, the proposed research model must be empirically tested on various geographies and industries. This study was also restricted to the Indian IT sector; however, future researchers may expand it to the global IT sector, technology sectors, heavy industries, and other industry verticals.

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