Exploring Factors Influencing Analytical Decision-Making Impacting Analytical Transformation in Global Organizations

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Abstract: Organizational transformational journey begins with radical changes in the decision-making process. Global organizations explore ways of achieving superior organizational efficiency to create a competitive edge in the target market. This study examines the pivotal role of data analysis and its influences on decision-making and transformation. Leaders are increasingly embracing data-driven analytical decision-making rather than the reliance on intuition to achieve transformational changes. Analytics is emerging as a catalyst for bolstering an organization's decision-making capabilities, efficiency, and overall effectiveness. The study extensively reviews peer-reviewed academic literature and identifies critical factors such as analytical orientation, information processing capability, centralization of information, data availability, data infrastructure, and decision-making capacity. The study adopted a mixed methodology approach. This research aims to develop an 'analytical transformation decision-making model' for global organizations. The study involved 617 participants and empirical validation using structured equation modeling to add robustness to the insights gleaned and reinforce the generalizability of the proposed model.

Keywords: Analytical decision-making, analytical transformation, organizational effectiveness, analytical orientation centralization, data-driven decision making

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Global organizations achieve sustainable development by incorporating novel approaches and radical methods and addressing newer challenges. Transformational approaches are key to making informed decisions based on data-driven insights to stay ahead of the competition (Wong, 2012). Organizations that effectively leverage analytics and digitalization can devise efficient strategies that mitigate risks, enabling competitive advantages, thus driving transformational changes and yielding newer opportunities. Prabhakar and Joshi (2019) say that the actual transition to analytics-driven decision-making is critical for enhancing the decision-making capability of global organizations. Analytics empower leaders to solve problems, gain detailed business insights into multiple organizational functions, and prepare for new-age challenges, creating sustained competitive advantage, leading to better results and improved decision-making abilities through various tools and techniques. Innovative strategies assist global organizations in accomplishing analytical transformation, which is pivotal for fostering economic growth.

Analytical transformation enables global market access for global organizations, resulting in blue ocean opportunities. Wong (2012) explains that analytics involves using data to generate meaningful insights, allowing firms to make fact-based decisions and enhance performance. Kapoor and Kabra (2014) suggest that organizations need to collect more data and use it to predict outcomes and automate decision-making. Using advanced analytics, global organizations can handle risks and uncertainty and make informed decisions based on analyzed data instead of relying on instincts.

Lawler and Mohrman (2004) also emphasized the importance of adopting advanced analytics for superior organizational efficiency and sustainable competitive advantage. Nandan Nilekani, the Chairman of Infosys a pioneer in the Indian IT industry (ET report, 2021), notes that the Indian technology industry has recently begun utilizing advanced analytics, data, and digital technologies within their organizations. Lepenioti et al. (2020) observed limited research on advanced analytics, particularly regarding the transition from predictive to prescriptive analytics for achieving organizational effectiveness. Consequently, additional research is needed to ascertain leaders' challenges during the transition toward advanced analytics. Technology drives analytical

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transformation and effective decision-making, and a successful transformational organization should concentrate on technology, people, processes, strategy, and structure.

This research identifies the research gaps in Kapoor and Kabra (2014) and Wong (2012) and extends the future research directions of Lepenioti et al. (2020). The study seeks to understand analytics, people's inclinations, decision-making, and transformation, underscoring the significance of further research in this domain. This study aims to pinpoint the essential factors influencing decision-making, efficiency, effectiveness, and transformation within large global companies. The study also investigates the benefits of transitioning towards advanced analytics to achieve optimal organizational performance. In line with these research objectives, the authors have formulated the following research questions:

Research Question 1: Which factors play key role in organizational transformation?

Research Question 2: What influences decision-making in global organizations?

Thus, the research objectives of the study are:

Objective 1: To identify the key factors that play crucial role in transforming global companies.

Objective 2: To examine the influence of key factors on decision-making in global organizations.

The authors adopted a mixed methodology research design (Aaker 2013, 11th Ed) (exploratory, qualitative interviews, and quantitative analysis) to address the research questions and objectives. This study conducted an in-depth analysis of peer-reviewed ABDC-ranked and Scopus-indexed journals. The study began with an extensive literature review, followed by a structured literature review (SLR) using a systematic review approach (Cooper et al., 2012. 11th Ed). The authors identified critical research gaps and future research directions from select research articles and selected key constructs based on SLR. The study then conducted in-depth unstructured qualitative interviews with human resource executives and technology experts from global organizations based in Bangalore. The open-ended interviews then validated the concepts and constructs emanating from SLR. The below subsections present a comprehensive literature review.

Organizations are experiencing significant changes due to the adoption of technology and analytics. Research on organizational transformation has prompted the examination of human resource, organizational, and technological factors. Effective decision-making is facilitated through data collection and analysis, leading to superior financial performance and sustained development (Davenport, 2016). Transformation process of an organization is primarily focused on the performance parameters of the company while mediating between the group and individual performances (Palmer et al., 2009). Further examination of factors identified in exploratory LR is crucial to enable effective decision-making by adopting advanced analytics, specifically prescriptive analytics. The subsequent sub-sections explore emerging key concepts and constructs from the SLR.

Analytics Dynamic Capabilities

Organizations gain competitive advantage by improving decision-making and organizational effectiveness and by leveraging dynamic analytics capabilities to gain valuable insights from big data (Cao et al., 2015). Despite the potential benefits, there is a lack of empirical research on the mechanisms of improving analytics capabilities, decision-making effectiveness, and competitiveness (Cao et al., 2015). Analytics 1.0 was the era of business intelligence, while Analytics 2.0 was the era of big data, and Analytics 3.0 (advanced analytics) was the era of data-enriched solutions (Davenport, 2013). Advanced analytics utilizes multidimensional data, centralized data discovery, technology-enabled data management, diverse data analysis methods, embedded analytics, cross-disciplinary data teams, and analytics on an industrial scale. Prescriptive analytics is a key tool for achieving organizational efficiency and performance.

Analytical transformation as dynamic capabilities creates new opportunities, higher collaboration, and superior decision-making interactions to improve organizational efficiency. Data management, warehousing, mining, operations research, and visualization are key areas contributing to analytics. Songkajorn et al. (2022) investigated the relationship between dynamic capabilities, transformation, strategic intuition, and organizational performance; this study extends

such organizational development research to explore the relationship between decision-making, analytics, and transformation. The study identifies 'analytics dynamic capabilities' as a key factor backed by dynamic capabilities theory, wherein this management and organizational theory focuses on a company's ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments (Teece et al., 1997). Orientation towards change is key to decision-making and transformation. Hence, the following subsection discusses such aspects.

Analytical Orientation and Centralization

Adelman and Hagiu (2021) examined the role of analytical orientation in driving competitive advantage and defined orientation as the extent to which an organization uses data and analytics to make informed decision-making across all levels of the organization. According to Navneet (2020), analytical orientation (AO) is crucial for decision-makers, managers, and associates to make data-driven decisions instead of intuition. Navneet's (2020) research examines the role of associates of the delivery teams and their attitude toward designing and executing statistical models and mathematical algorithms. Analytical orientation promotes collaboration within an organization while adopting technology with a common objective, identifying analytical skills, talent, culture, decision-making, and values as key to transformation (Dias et al., 2021; Srinivas and Kumar, 2022). Organizational culture theory acts as the theoretical background for AO, wherein the theory focuses on the shared values, beliefs, and practices within an organization and how they contribute to organizational effectiveness (Schein, 2010).

Organizations that develop analytical capabilities and leaders who nurture strategies, skills, and culture to attain analytical orientation achieve sustainable competitive advantage (Davenport et al., 2001). Decentralization makes it difficult for data scientists to make decisions as they must be simultaneously in different places. The business units have to tailor each model based on analytical decision-making for each department, which is almost impossible without centralization and redundancy of data. Analytical centralization (AC) is the dynamic organizational capability to centralize data, significantly impacting organizational decision-making, morale, and efficiency. AO and AC prioritize analytical opportunities to build models to measure business values in the organization.

According to the ASHE-ERIC Higher Education Report (1988), AC reduces friction and uncertainty, enabling a smooth transition toward highly efficient organizations. Analytical centralization leads to improved data quality, accurate decision-making, increased efficiency, and on-time execution of analytics projects and governance. Analytical orientation centralization refers to the degree to which an organization relies on data analytics teams to provide centralized analytical services to various business units. Analytical orientation centralization (AOC) theoretical base is derived from contingency theory (Lawrence & Lorsch, 1967; Scott, 1981) and the contingency model (Fiedler,1993), which suggests that the effectiveness of organizational structures and processes depends on the fit between the organization and its environment. Centralization may be contingent on the organization's size, complexity, and other factors (Lawrence and Lorsch, 1967). Leaders must take the initiative based on AOC to undertake transformation toward advanced analytics (Grossman & Siegel, 2014). Effective analytical orientation, centralization, data infrastructure, and data quality management lead to analytical transformation. Hence, the study hypothesizes that:

H1a: Analytical orientation among decision-makers positively impacts data infrastructure quality-based information aggregation.

H1b: Analytical centralization enables improvised data quality management.

Analytical Information Processing Capability

Organizational dynamic capabilities depend on effectively capturing data and information to gain insights for effective decision-making (Akhtar et al., 2017). Joseph and Gaba (2020) highlight the importance of organizational design and information processing in decision-making. Wang (2001) examines the role of information processing on organizational development, wherein the research highlights the role of organizational context on the information processing-related variables. Information processing, cognitive style, and decision-making behavior are vital in organizational development and transformation. Myers–Briggs type indicator (MBTI; Myers & Myers, 1980) acts as the theoretical background for the information processing capability of an

organization, wherein the information, leadership, learning, and decision style significantly influence decision-making. Cao et al. (2015) define the dynamic capabilities of global organizations as the ability to understand, aggregate, and analyze data and information to derive meaningful insights in the context of analytical decision-making. This capability is called Analytical Information Processing Capability (AIPC), which allows organizations to collect information that significantly impacts decision-making leading to sustainable development.

The importance of AIPC is also emphasized by Cao et al. (2015), who state that information processing should align with organizational policy, strategy, structure, and business processes. The theoretical background of AIPC is based on Galbraith's (1973) Information Processing Theory (IPT), which highlights the importance of organizational analysis, information processing needs, and IPC in achieving sustainable competitive advantage. Efficient IPC is crucial in executing tasks on time and achieving sustainable competitive advantage (Liu, 2022). AIPC is a key factor in achieving competitive advantage in unpredictable situations, as emphasized by Akhtar et al. (2017). AIPDC, organizational systems' analytical information dynamic processing capabilities, enables teams to capture multilevel data and information from analytical algorithms. Therefore, the authors hypothesize that effective AIPC and AIPDC positively influence organizational decision-making and lead to sustainable development and competitive advantage.

H2: Information processing capability positively influences data infrastructure quality management.

Analytical Decision Making

Sharma et al. (2014) argue that organizational transformation to achieve a higher valuation depends on decision-making, business analytics, and resource allocation processes. The big data revolution has improved decision-making performance, resulting in competitive advantages based on the availability of large volumes of data with varied information, speed, and agility. Davenport (2006) also stresses the importance of human resources and resource allocation in making universal fact-based decisions when competing in analytics. This research extends Bharadwaj's (2000) research to focus on a framework for analytical decision-making (ADM), emphasizing the importance of resources, capability, data and information infrastructure, and analytics competency. Organizational learning theory (Argyris and Schön, 1978) is the theoretical basis for ADM. It says that organizations learn from experience and adjust their decision-making processes based on analysis of past outcomes. Based on the Deloitte report (2013) and Capgemini consulting technical report (2023), the authors state that ADM is enabled by taking full advantage of data analytics tools, techniques, information capability, data quality, and analytical skills.

Networking Capability

Networking capability (NC) is an ongoing process of selecting, attracting and building resolutions based on elements of the network and data size. Network capability based on information technology, network architecture and people is the backbone of any global organization to achieve sustainability (Low, 2013). Gemünden et al., (1996) also advocate on similar lines, wherein developing network capability is key to achieving sustainable competitive advantage. This study extends the research of Mitrega et al. (2012) to propose NC as a key construct in an organizational development context. The empirical study of Reinartz et al. (2004) provides enough evidence that dynamic organizational capabilities that enable initiating, organizing, and developing relationships are strongly linked to organizational performance. Network Resource-Based View (NRBV) extends the resource-based view by emphasizing the strategic importance of network relationships as valuable resources that contribute to a firm's competitive advantage (Inkpen and Tsang, 2005). NC can also be defined based on the organization's infrastructure and the human resource capability to take the initiative to manage, collect, centralize and analyze information and data to make effective analytical data-based decisions.

Networking capability is the complicated organizational capability that aims towards organizational development and managing relationships among business partners (Mitrega et al., 2012). Another key element of organizational networking capability is the sensory network, the brain behind analytics (Sendi et al., 2021). NC serves as a core for network relationships in the organization. It is also defined as the capability that helps achieve organizational efficiency by

making better decision-making (Parida et al., 2017). Network theory drives organizations to understand how relationships and collaborations within and outside the organization contribute to decision-making and the transformative process in a global context (Granovetter, 1973).

Network capability (NC) has to be analyzed as a whole, and NC is key to global organizations' transformation based on analytics (Gemünden et al., 1996). Yang et al. (2019) bring in a unique aspect of sensors and sensor networks that enable datafication of the physical world. Technology-based communication empowers large data and information exchange, resulting in organizational effectiveness. Advanced analytics leverage data from a sensor to analyze and recommend informed decisions. NC is a transformational process wherein the creation phase focuses on building relationships, and the operational phase focuses on sustaining and improving organizational effectiveness (Johnsen et al., 2000). Networking capability creates a framework that impacts decision-making in the organization. The study of sensory network capability and people-based networking capability is critical to the quality management of data infrastructure. These factors influence decision-making and the transition towards advanced analytics, aiding organizational effectiveness. Hence, the study hypothesizes that:

H3a: Networking capability coupled with data infrastructure impacts analytical decision-making effectiveness.

H3b: Organizational networking capability positively influences data/information collection/aggregation.

Data Infrastructure

Effective data quality management is crucial for data collection and usage, organizational capability, data consistency and completeness, and adoption of advanced analytics (Kwon et al., 2014). The complex data collection, assimilation, and integration processes significantly impact sustainable competitive advantage (Missi et al., 2005). Data quality considers several managerial, strategic, organizational, and operational factors influencing analytical decision-making (Missi et al., 2005). Data quality can be defined based on the data fitness for use, with accuracy crucial for successful transformation. Effective analytical data infrastructure and quality management are crucial for organizations to adopt advanced analytics and transform themselves (Grossman & Siegel, 2014).

The data infrastructure required for analytics consists of software components, services, utilities, platforms, and applications that manage processes and prepare models for decision-making and analytical processes (Srinivas and Kumar, 2022). Analytics processes rely on models and infrastructure to achieve operational effectiveness and transformation. Georgiadou et al., (2015) provides useful research insights into the institutional and technical complexities of spatial data infrastructures in the information infrastructure domains. Flamholtz's (1995) proposed framework acts as the theoretical background for data infrastructure, providing an organizational development model, life cycle model, and infrastructure growth model. Total Data Quality Management (TDQM) is an approach that integrates data quality management into an organization's overall quality management system, which involves processes, standards, and practices for ensuring and improving data quality (Wang, 1998).

Proper data organization is essential for better decision-making (Deshpande et al., 2019). Missi et al. (2005) emphasize the importance of data integration, network-related capability, processes, and data quality management. Therefore, the authors hypothesize that:

H4a: Data collection positively influences analytical decision-making.

H4b: Data aggregation enabled by data infrastructure impacts data quality management while positively influencing analytical decision-making transformation.

Organizational Efficiency

The ability of an organization to efficiently use its resources in line with its requirements can be described as organizational efficiency. Watson (2009) and Al-Eisawi et al. (2021) suggest that organizational systems should be driven by strategy and focused on the business to improve organizational efficiency. Intelligent systems based on technology and procedures can translate raw data into useful information for decision-makers, creating a large potential for improved

organizational efficiency. Any process disruptions can result in significant gaps between planned and actual performance outcomes, affecting competitiveness and organizational efficiency and resulting in organizational transformation. Angle and Perry (1981) suggest that organizational efficiency is a dimension of organizational effectiveness and can be measured using various performance indicators. The leadership's influence and employee alignment with organizational objectives is critical in establishing a favorable environment for achieving organizational efficiency, effectiveness and analytical transformation.

Organizational Effectiveness

Large global enterprises strive to establish a data-driven culture and utilize data analysis to gain a competitive advantage and valuable insights for prompt and accurate decision-making, achieving organizational effectiveness (Vassakis et al., 2017). Galbraith (1973) emphasizes that precise information based on data analytics can significantly aid decision-making and improve organizational performance. Institutional theory acts as the theoretical base for organizational effectiveness, which suggests that organizations conform to expectations and norms to gain legitimacy and enhance effectiveness (Scott, 1981). OECD report (2018) states that data-driven innovation, big data, and investment in data infrastructure can enhance organizational effectiveness. The transformation of data and information into knowledge forms the basis of data-driven decision-making. Dension and Mishra (1995) highlight the crucial role of analytical cultural dynamics and orientation in achieving superior decision making and organizational effectiveness. Intelligent systems based on analytics comprise human elements, technological components, and a profound understanding of processes, leading to converting data and information to knowledge while achieving organizational effectiveness and analytical transformation. Cameron (1986) identifies the absence of models for researching and theorizing organizational effectiveness and transformation as a critical issue. Therefore, this research aims to develop a model for analytical decision making and transformation.

Analytical Transformation

Analytical transformation (AT) is the movement from traditional or basic analytical methods focusing on radical changes using digital technologies. Transformation empowers organizations to leverage resource capabilities effectively using analytics and digital technologies (Fitzgerald et al., 2013). (Adams et al., 2023; Srinivas et al., 2024) highlight that the organizational development mindset enables transformational change, wherein the transformational change processes are emergence, narrative and generativity. Organizations must utilize all the opportunities; hence, analytical transformation is essential to convert data into valuable insights (Deshpande et al., 2019). The digital transformation framework includes various aspects of analysis, which is critical for building analytical transformation in the organization to reach organizational effectiveness (Ross et al., 2018).

The way organizations make decisions is fundamentally changing; in the past, decisions were made instinctively based on a gut feeling of the manager; however, futuristic organizations are using data-based analytics to empower decision-making (Srinivas and Kumar, 2022). One of the significant challenges in large organizations is transforming from the basic form of analytics to advanced forms that hinder critical decision-making, thus reducing organizational effectiveness. Data analytics based on big data enables informed decision-making in the organization with the help of predictive and prescriptive analytics (Deshpande et al., 2019). Implementation teams are encouraged to use information and data for decision-making while utilizing advanced statistical, mathematical, and analytical tools in firms to accomplish analytical decision-making (Bayram & Ateş, 2020). Transformation is key to smart analytical centers to maximize digitalization benefits and organizational success.

Analytical transformation is the strategic change top management seeks in this digital age. Leaders and managers should adopt analytical decision-making to become successful in the digital age. Increasing analytical skills within an organization is key to transforming into an analytically oriented organization. The analytical transformation guides organizational development while achieving digital maturity (Solms et al., 2021). Analytical transformation provides valuable information on various organizational levels while improving information quality that supports critical decision-making. Table 1 shows the theoretical background for each concept and construct discussed.

Table 1: Theoretical Background

Concept/Variables	Theoretical Background	Literature Source
Analytical Transformation	Digital Transformation Frameworks Technology Acceptance Model Innovation Diffusion Theory	Ross et al., 2018; Davis,1989; Rogers, 1962
Data Infrastructure and Quality Management	Total Data Quality Management	Wang, 1998
Analytical Information Processing Capability	Information Processing Theory IPT	Liu, 2022; Anderson, 2009; Galbraith, 1973; Akhtar et al. 2017
Analytical Orientation and Centralization	Organizational Culture Theory Contingency Theory	Schein, 2010 Lawrence and Lorsch, 1967
Network Capability	Network Resource-Based View Network theory	Inkpen and Tsang, 2005; Granovetter, 1973
Analytical Dynamic Capability	Dynamic Capabilities Theory	Teece et al., 1997
Analytical Decision Making	Organizational Learning Theory	Argyris and Schön (1978)
Organizational Effectiveness	Institutional Theory	Scott, 1981

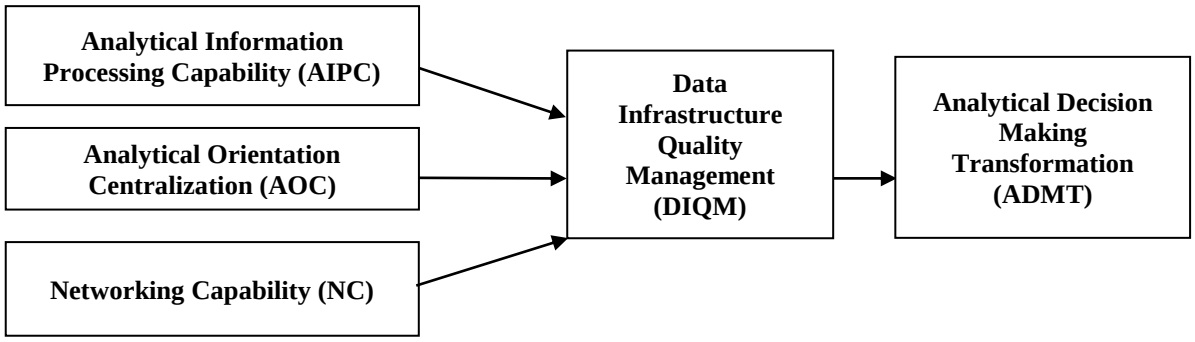
This study reveals in-depth insights into global phenomena associated with nurturing and building sustainable and successful organizations. This study gives a holistic view of organizational and human resource behavior studies about analytical decision-making effectiveness and organizational transformation. This research tries to develop the research model based on the interlinking relationship between the abovementioned constructs that emerged from the structured literature review. The discussions in the previous section have demonstrated that some of the decision-makers in charge of transformation in large global organizations have fairly limited knowledge of mathematical algorithms and statistical models due to a lack of analytical orientation and culture. People who execute transformation projects show huge resistance toward transformation, thus limiting innovative initiatives and the transition toward advanced analytics. Rogers's (1962) diffusion of innovation theory (DOI) is the theoretical base for such barriers toward innovation and transformation. Diffusion of Innovation (DOI) theory describes that early adopters (multinational corporations) take the risk to adopt innovation at an early stage, and laggards, such as emerging economy-based global organizations, lag in adopting new ideas due to risk averseness. Therefore, this study focuses on key factors such as analytical orientation and centralization, analytical information processing capability, networking capability, data infrastructure quality management, analytical decision-making and analytical transformation. Pool (2000) highlights the need for an organizational development model encompassing various constructs; hence, this study proposes an analytical decision-making transformation model as in Figure 1.

Data-driven decision-making contributes significantly and positively to organizational performance regarding productivity and profitability. Based on Galbraith's (1973) IPT theory and Akhtar et al.'s (2017) research, the study states that analytical information processing capability is key in decision-making and organizational transformation. AIPC's theoretical background comes from information processing theory (IPT), which focuses on organizational analysis and information processing needs. IPC impacts decision-making and organizational performance so as to achieve sustainable competitive advantage (Srinivas and Kumar, 2022). AIPC leads to efficient data management capabilities and an in-depth understanding of organizational information (Cao et al., 2015). Liu (2022) argues that AIPC and data infrastructure quality management shall lead to efficient decision-making and organizational transformation.

Efficient data organization and quality management (Deshpande et al., 2019) lead to improved organizational efficiency, positively impacting analytical decision-making (Missi et al., 2005) and transformation (Grossman & Siegel, 2014). Technology-based networking capability (Sendi et al., 2021) and human resources-based networking capability (Mitrega et al., 2012) lead to efficient data

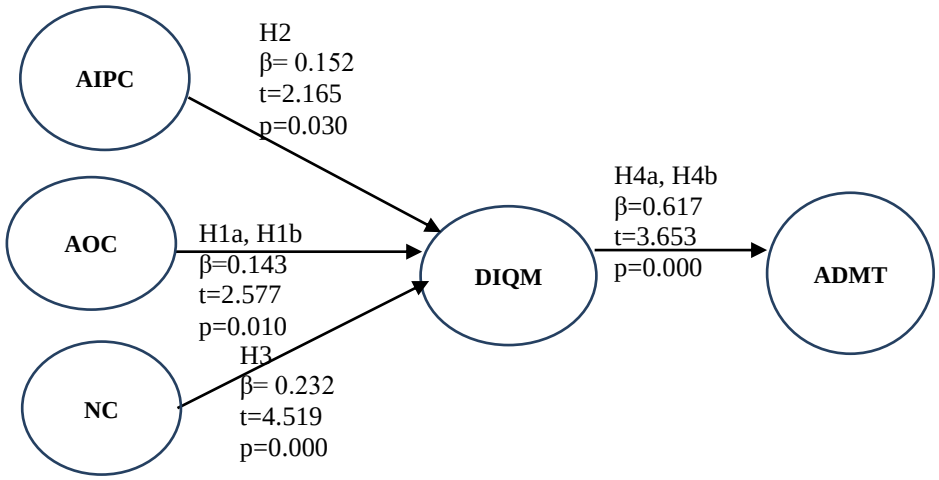
and information collection. If aggregated centrally, such data leads to superior decision-making capability (Parida et al., 2017), transforming the organization and thus achieving sustainable competitive advantage (Gemünden et al., 1996; Low, 2013). Therefore, the study considers analytical information processing capability (AIPC), analytical orientation centralization (AOC), and networking capability (NC) as independent variables, data infrastructure quality management (DIQM) as mediating variables, and analytical decision-making transformation (ADMT) as dependent variables. The research model is shown in Figure 1.

Figure 1: Analytical Decision-Making Transformation Model



As the organization moves towards implementing advanced analytics, effectiveness increases exponentially. The study finds that AIPC and NC significantly impact organizations' ability to collect, aggregate, centralize, assimilate, and manage data. Such ability leads to creating efficient data infrastructure to ensure superior data quality management and analytical decision-making quality, thus leading to increased organizational sustainability and transformation, resulting in organizational effectiveness. The key findings of the literature review can be seen in the hypotheses listed in the previous sections. The hypothesized research model is as shown in Figure 2.

Figure 2: Hypothesized Analytical Decision-Making Transformation Model



Method

The study began with an extensive and structured literature review (SLR) using a systematic review approach. Based on SLR, the authors identified critical research gaps and key constructs. Open-ended, unstructured, qualitative interviews with C-level executives validated each concept and construct emanating from SLR. The C-level executives were selected from across geographies, and industry verticals and both users and experts from analytics field. The authors adopted a mixed methodology research design: exploratory qualitative research, open-ended qualitative interviews, and quantitative analysis. The study engaged in a phenomenological reduction involving setting aside preconceptions and focusing on the essence of the participants' experiences. The research identified common themes, patterns, and essential aspects related to the use of technology in human

resource management. By incorporating phenomenological analysis, the study added a qualitative layer to the research, offering a deeper understanding of human experiences behind the qualitative measures. Further, the study focused on hypothesis development based on the key constructs and their relationship with each other.

Participants

The respondents were senior technology experts, users of analytics technologies and C-level executives selected randomly from global and technology-driven organizations across various industry verticals and geographies. The σp (standard deviation) was calculated to be around 14 based on the test sample. The z (standard variate) at the 99% confidence level was 2.57. The confidence level was chosen at 99% probability. The 'e' (acceptable error) was decided to be below 0.8. The n sample size was calculated based on the formulae suggested by Hair et al. (2008).

$$N = z2 * N * \sigma p2 / ((N-1) * e2 * + z2 * \sigma p2)$$

The simple random sample size was calculated using the sampling theorem and was decided to be above 600 (Hair et al., 2008). Then, the structured questionnaire was converted into a survey form of physical form, Google™ form, and Survey Monkey™. The survey was administered to over a thousand industry experts, users of analytics technologies, key human resource executives, and senior executives from global organizations.

Research Design

This study chose simple random sampling to choose global organizations and experts from such organizations. The complete list of global organizations was based on their global revenue size and industry sector. Prior experience in utilizing analytics was not a criterion for selection. The study utilized surveys and interviews to gather data, with surveys aiming to capture quantitative data on issues encountered by global organizations. The research used IBM SPSS and IBM AMOS statistical software for quantitative analysis and structured equation modeling. Participants were fully informed of the study's objective and asked for their consent before participating, with collected data being kept confidential and only used for research purposes.

Measures

A structured approach toward literature review resulted in identifying scales and items for select constructs. Structured questionnaire was designed based on the items adapted from key scale development articles from top-quality peer-reviewed journals. As the next step, eighteen interviews with technology experts and human resource managers were conducted using a structured approach to validate the questionnaire and calculate content validity index (CVI) and content validity ratio (CVR) values (Rutherford-Hemming, 2018). The research calculated convergent validity, discriminant validity and composite reliability to validate the scales, measures, dimensions and items. Only the measures meeting the required criteria were selected to ensure a robust questionnaire was prepared. The questionnaire was designed based on the selected measures, dimensions, and items that emerged from the reliability and validity tests.

Procedures

The study gathered 617 valid responses from over a thousand survey questionnaires distributed through various methods such as face-to-face interviews, email, Google™ form, and WhatsApp™. The authors performed factor analysis using principal component analysis with varimax rotation to identify key variables. Based on the Scree plot, the number of factors was five. As the next step, regression analysis was conducted to explore the relationship between the identified key factors. Further, the IBM AMOS structure equation modeling (SEM) tool was conducted to propose an 'analytical decision-making transformation model'. The SEM goodness fit index and model fit were validated.

Results

The study adopted EFA (exploratory factor analysis) with the principle component analysis (PCA) method, while rotation was selected to be varimax as per Hair et al. (2008). Scale unidimensionality (SU) was validated as to whether all items are loading heavily on one factor; in this study, SU was within limits. Based on calculations, the study concluded that a sample size of 80 was adequate for pilot testing as the KMO (Kaiser Meyer Olkin) score was higher than 0.5 (Field, 2000). Hence, the SU of AIPC, AOC, NC, DIQR, and ADMT are acceptable for their respective dimensions. As per KMO values, the items that did not indicate SU were not considered further in the study. The study additionally used CFA (confirmatory factor analysis) to assess composite reliability using structured equation modeling (SEM) using IBM AMOS and IBM SPSS tools. The scales were adapted and validated based on established scale development articles. The study extracted the λ (standard loadings) from the factor groupings. The rotated component matrix table and pattern matrix resulted in latent variables being considered the study's key constructs and item dimensions as the indicator variables. The Cronbach alpha and average variance (AVE) were above 0.7. Hence, the final 22 items were treated as reliable to measure the respective scales. The composite reliability scores were above 0.8, as shown in Table 2; therefore, scales: AIPC (analytical information processing capability), AOC (analytical orientation centralization), NC (networking capability), DIQM (data infrastructure quality management), and ADMT (analytical decision-making transformation) were considered as reliable.

Table 2: Composite Reliability Table

Latent Variables	Sum of ME	Sum Std Loadings (B)	Square-Sum of Std. Loadings (C)	C+ME	Composite Reliability CR= C/(C+ME)	N	AVE= B/n	Cronbach Alpha
Analytical Information Processing Capability (AIPC)	0.56	2.44	5.97	6.53	0.91	3	0.81	0.93
Analytical Orientation Centralization (AOC)	1.08	4.92	24.18	25.27	0.96	6	0.82	0.82
Networking Capability (NC)	0.90	5.10	26.04	26.94	0.97	6	0.85	0.85
Data Infrastructure Quality Management (DIQM)	0.22	3.78	14.32	14.54	0.99	4	0.95	0.72
Analytical Decision Making Transformation (ADMT)	0.35	2.65	7.02	7.37	0.95	3	0.88	0.79

The study also calculated convergent validity scored based on the correlation coefficient matrix wherein values of items within the construct were between 0.3 and 0.7 and values of items of different constructs were below 0.299. The items not meeting the previously mentioned range were dropped for further use in the study. Further, the study calculated VIF values wherein all values were within the acceptable range of 10. Hence, based on VIF scores and correlation coefficient matrix analysis, authors concluded that multicollinearity issues are nonexistent. Hence, the study concluded that the convergent validity of scales: AOC, AIPC, NC, DIQM, and ADMT are established. The discriminant validity of scales was established, as shown in Table 3. The table 3 also shows that the variance between scales is 86%, greater than the correlation squares of the scales.

Table 3: Discriminant Validity of Scales

Factor Grouping Name	Average Loading	Variance Extracted	Variance Between All	Correlation	Correlation Square
Information Processing Capability	0.900	0.811	86%	0.364	13.2%
Analytical Centralization and Orientation	0.905	0.819		0.188	3.5%
Networking Capability	0.922	0.850		0.184	3.4%
Data Infrastructure and Data Quality Management	0.973	0.946		0.259	6.7%
Analytical decision-making transformation	0.940	0.883		0.386	14.9%

The study found no correlation between most items outside the scales (Hair et al., 2008; Jois et al., 2022). By analyzing the values of H1a, H1b (β=0.143, t=2.577, p=0.010) and H2 (β=0.152, t=2.165, p=0.030) can be accepted as the path coefficients are above 0.130 which is also advised in Hair et al. (2008) that social sciences studies may accept if the p-values are well below 0.05. As the p-values are below 0.05, the hypotheses are acceptable. Table 4 demonstrates that hypotheses H1a, H1b and H2 are accepted. Similarly, based on the significance values of H3a, H3b (β=0.232, t=4.519, p<0.001) and H4a, H4b (β=0.617, t=3.653, p<0.001), all these hypotheses are supported. The study finds a positive relationship between information processing capability, data infrastructure, and data quality management (Hypothesis 2). This results in the adoption of advanced analytical decision-making transformation. The study also hypothesized (H1) that there is a positive relationship between analytical orientation centralization and data infrastructure and data quality management, resulting in analytical transformation; thus, hypothesis H1 cannot be rejected. Similarly, there is a positive relationship between networking capability, data infrastructure, and data quality management, which leads to analytical decision-making transformation (Hypothesis 3); therefore, it is significant and supported. Authors have also proposed hypothesis (H4) indicating a positive relationship between data infrastructure quality management and analytical decision-making transformation resulting in organization effectiveness, as indicated in Table 4.

Table 4: Hypotheses Testing – Analytical Transformation Mode

Hypothesis – Path Posited	P. Coeff (β)	t-value	p-value	Sig. level	Results
H1a, H1b: AOC → DIFR	0.143	2.577	0.010	p<0.05	Supported
H2: AIPC → DIFR	0.152	2.165	0.030	p<0.05	Supported
H3a, H3b: NC → DIFR	0.232	4.519	0.000	p<0.001	Supported
H4a, H4b: DIFR → AT	0.617	3.653	0.000	p<0.001	Supported

Fit indices: Chi-square/df = 2.698; NFI =0.915; GFI = 0.905; AGFI = 0.905; RMSEA = 0.049

The authors of this study support the hypotheses, indicating that the analytical orientation of employees, managers, and decision-makers has a significant impact on the centralization of data, information, and decision-making. The study integrated a phenomenological analysis approach to enrich the understanding of participants' experiences during the interviews. Furthermore, the study reveals that information processing and networking capability strongly influence data infrastructure and quality management, which provides a foundation for adopting analytical decision-making transformation in global technology-oriented organizations. AIPC and NC drive the transformation of large technology organizations from predictive to prescriptive analytics, commonly known as

advanced analytics. This research underscores the importance of implementing advanced analytics for large Indian organizations to achieve global success by focusing on transformation through superior organizational effectiveness.

Discussion

Global organizations tend to concentrate on human resources-related aspects of analytical transformation to enhance organizational effectiveness. However, this study suggests that leaders of India-based global organizations fall behind their international counterparts in decision-making capability and adoption of advanced analytics. The research identifies key attributes of organizational effectiveness in technology-driven global companies, with a particular emphasis on decision-making and analytical transformation. Furthermore, the study investigates the benefits of using advanced analytics for transforming technology-driven global organizations. Data quality is a crucial element of data analytics, which relies on various factors such as the completeness, accuracy, and relevance of information gathered, data format, reliability, accessibility of infrastructure, and ease of treatability (Lin et al., 2022). Effective data management requires multi-layered data collection, aggregation, and assimilation, coupled with an analytical orientation of the implementation team, leading to informed decision-making.

An organization's analytical orientation, culture, and centralization success rely heavily on the decision-making team's intentions and the resources' skill level. According to Mani et al. (2010), having effective information processing capabilities can help organizations quickly adapt to new digital and data technologies and capitalize on opportunities while mitigating threats. Improving information processing and networking capabilities can also assist in building high-quality data infrastructure and management systems. Venkatraman (1994) proposes that technology-enabled business transformation occurs through a sequence of changes in technology functionalities, redesigning business processes based on technology capabilities, and integrating all functionalities through dynamic capabilities. Dynamic capabilities that involve technology and HR networking play a critical role in developing data infrastructure capabilities, which impact decision-making effectiveness and overall organizational transformation. Effective data infrastructure quality management leads to analytical decision-making and transformation, enhancing organizational efficiency, competitive advantage, financial performance, effectiveness, and sustainable development.

Qualitative interviews with C-level executives revealed the leadership gap in decision-making capability and the adoption of advanced analytics among leaders of India-based global organizations compared to their international counterparts. Data quality emerges as a critical factor for effective analytics, considering aspects like completeness, accuracy, relevance, infrastructure accessibility, and treatability. The significance of dynamic capabilities involving technology and HR networking is underscored for developing data infrastructure capabilities and influencing overall organizational transformation. The study also emphasizes the role of network theory in understanding relationships and collaborations within and outside organizations, particularly in the global context, impacting decision-making and the transformative process.

This study contributes to the organization development (OD) literature by providing valuable insights and analytical transformation framework for effectively understanding and managing change. This research significantly contributes to the exploration of organizational culture, orientation, its impact on behavior, and strategies for implementing culture change. Furthermore, the study contributes to the concept of action research, a foundational methodology in OD, which plays a crucial role in bridging the gap between theoretical concepts and practical application as suggested by Church et al., (2002). The study has certain limitations that need consideration. Firstly, there is contextual specificity as the focus is on global and large Indian organizations. The context may limit the generalizability of the findings to diverse industry sectors or smaller enterprises. Additionally, the study employs phenomenological analysis, which comes with its own set of limitations. It acknowledges the potential influence of the interviewer and the subjective nature of the approach, which may impact the reliability of the findings. Awareness of these

limitations is crucial for interpreting the study's outcomes. Future research should extend beyond global and large Indian organizations, explore additional constructs, and provide empirical validation, fostering a deeper understanding of analytical transformation dynamics globally. Practical implications suggest that C-level executives can benefit by leveraging the study's findings to encourage the adoption of advanced analytics, and implementation teams may overcome resistance to innovation. Researchers globally can apply the study's model in their settings, contributing to a broader understanding of analytical transformation.

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