RESEARCH ARTICLE

EXPLORING FACTORS INFLUENCING ANALYTICAL DECISION MAKING AND TRANSFORMATION IN GLOBAL ORGANIZATIONS

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Abstract : Organizational transformation journey begins with radical changes in the maneuvering decision-makingprocess. The ability of an organization to analyze data has a significant impact on transformation and decision-making. Global organizations exploreways of achieving superior organizational efficiency to create a competitive edge in the target market. Decision-makers traditionally depended on intuition rather than data-driven analytical decision making. Analytics gives organizations a deeper understanding of critical processes, allowing for transformational changes. Although multinational organizations have been early adopters of analytics, technology-led organizations in emerging economies have slowly embraced analytics. Advanced analytics can enhance an organization's decision-making capabilities, efficiency, and effectiveness. The study extensively reviews relevant literature and identifies critical factors such as managerial behavior, data availability, collection and processing capabilities, data infrastructure and Management, centralization of data, and decision-making capacity. The study has adopted a mixed methodology approach. This research aims to develop an ‘analytical transformation decision-making model’ for global organizations. This research has adopted structured equation modeling to validate the proposed model empirically. The research demonstrates that the ability to collect and analyze data depends on the team’s analytical skills and centralized data analysis structure, which can improve decision-making capabilities and drive analytical transformation.

Keyword: Analytical decision making, analytical transformation, organizationaleffectiveness, sustainable competitive advantage, data driven decision making

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INTRODUCTION

Global organizations achieve sustainable development by incorporating novel approachesand radical methods and addressing newer challenges. Transformational approachesarekey to making informed decisions based on data-driven insightsto stay ahead of the competition(Wong, 2012).Organizations that effectively leverage analytics can devise efficient strategies that mitigate risks enabling competitive advantages. The growing significance of analytics and digitalization drives transformational changes in the socioeconomic landscape, yielding newer opportunities. However, the actual transition to analytics-driven decision-making is yet to happen, which is critical for enhancing the decision-making capability of global organizations (Prabhakar& Joshi, 2019). Analytics empower leaders to solve problems and prepare for new-age challenges, creating sustained competitive advantage.Innovative strategies assist global organizationsin accomplishinganalytical transformation,which is pivotal for fostering economic growth.Analytical transformation enables global market access for global organizationsresulting in newer opportunities.

Analytics gives businesses detailed insights into multiple organizational functions, leading to better results and improved decision-making abilities through various tools and techniques. Wong (2012) explains that analytics involves using data to generate meaningful insights, allowing firms to make fact-based decisions and enhance performance. Kapoor et al. (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 emphasize 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 In`dian 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 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 et al. (2014)and Wong (2012) and extends the future research directions of Lepenioti et al. (2020). The studyseeks to understand analytics, people's inclination, 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:

RQ1: Which factors are key to superior organizational effectiveness inglobal companies?
RQ2:Which key factors influence analytical decision-making in global organizations?
RQ3: What are the benefits of transforming organizations based on advanced analytics?

Thus, the research objectives of the study are:

RO1:To identify the key factors which play a crucial role in the organizational effectiveness of global companies.
RO2:To examine the influence of key factors on analytical decision-making in global organizations.
RO3: To examine the benefits of transforming organizations using advanced analytics to achieve sustainable development.

The authors adopted a mixed methodology research design (Aaker at el., 2013, 11th Ed) (exploratory & 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 gapsand future research directions from select research articles and selected key constructs based on SLR. The study then conducted unstructured interviews with human resource executives and technology experts from global organizations based out of Bangalore.The interviews then validated each of the concepts and constructs that emanated 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). 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.

A. Analytics Dynamic Capabilities

Organizations can improve their decision-making effectiveness and gain a competitive advantage 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 is the era of big data, but Analytics 3.0 (advanced analytics) is the era of dataenriched 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.

B. 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. Bharadwaj's (2000) research focuses on an IT-based framework for analytical decision-making (ADM), emphasizing the importance of resources, data strength, data infrastructure, and analytics competency. Based on the Deloitte 2013 report and Capgemini consultingtechnical report, authors conclude that ADM is enabled by taking full advantage of data analytics tools, techniques, information capability, data quality, and analytical skills. Therefore, this study focuses on key factors such as analytical orientation and centralization, analytical information processing capability, networking capability, data infrastructure quality management, and analytical transformation.

C. Analytical Orientation and Centralization

Analytical centralization and orientation refer to the degree to which an organization relies on data analytics teams to provide analytical services to business units. Adelmanand Hagiu (2021) examined the role of analytical orientation in driving competitive advantage and defined analytical orientation as the extent to which an organization uses data and analytics to inform 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. However, some team members of the delivery teams feel uneasy about designing and executing statistical models and mathematical algorithms, even though they are comfortable with computer-based programsNavneet (2020). AO 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).

Organizations must develop analytical capabilities to achieve a sustainable competitive advantage, and leaders must develop strategies, skills, and culture to attain analytical orientation (Davenport et al., 2001). AC, or analytical centralization, is the dynamic organizational capability to centralize data, significantly impacting organizational decision-making, morale, and efficiency. AC results in improved analytical decision-making, aiding organizational transformation and analytical decision-making effectiveness (ADME). According to ASHE-ERIC Higher Education 1988 Report, 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.

Decentralization makes it difficult for data scientists to make decisions as they must be simultaneously in different places. According to McKinsey's 2021 report, 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. AO and AC prioritize analytical opportunities to build models to measure business values in the organization. Leaders must take the initiative based on AO and AC 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.

D. Analytical Information Processing Capability

According to Akhtar et al. (2017), an organization's dynamic capabilities depend on effectively capturing data and information to gain insights for effective decision-making. This ability is called Analytical Information Processing Capability (AIPC), which allows organizations to collect information that significantly impacts decision-making and leads 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).

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. 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.

E. 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. The leadership's influence and employee alignment with organizational objectives are critical in establishing a favorable environment for achieving organizational efficiency and effectiveness. Angle and Perry (1981) suggest that organizational efficiency is a dimension of organizational effectiveness and can be measured using various performance indicators.

F. Organizational Effectiveness

According to Vassakis et al. (2017), 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. Galbraith (1973) emphasizes that precise information based on data analytics can significantly aid decision-making and improve organizational performance. OECD 2015 report 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. 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. Dension and Mishra (1995) highlight the crucial role of analytical cultural dynamics and orientation in achieving organizational effectiveness. Cameron (1986) identifies the absence of models for researching and theorizing organizational effectiveness as a critical issue. Therefore, this research aims to develop a model for the same.

G. 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). Gemunden and Ritter (1996) also advocate on similar lines, wherein developing network capability is key to achieving sustainable competitive advantage. NC can also define 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). Gemunden and Ritter (1996) highlight that NC has to be analyzed as a whole, and NC is key to global organizations' transformation based on analytics (Gemunden& Ritter, 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.

H. Data Capability

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

I. Analytical Transformation

Analytical transformation (AT) is the movement from traditional or basic analytical methods, while transformation focuses on radical changes in digital technologies (Fitzgerald et al., 2013). AT empowers organizations to leverage resource capabilities effectively. Organizations must utilize all the opportunities; hence analytical transformation is essential to convert data into valuable insights (Deshpande et al., 2019). 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. One of the significant challenges in large organizations is transforming from 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. AT improves organizational information quality and supports critical decision-making. 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) acts as 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 adoptinnovation at an early stage, and laggards, such as emerging economy-based global organizations, lag in adopting new ideas due to riskaverseness. Data-driven decision-making contributes significantly and positively to organizational performance in terms of productivity and profitability. Based on Galbraith's (1973) IPT theory and Akhtar et al. (2017) research, analytical information processing capability plays a key role in decision making while transforming an organization. AIPC's theoretical background comes from information processing theory (IPT) which focuses on organizational analysis, information processing needs and IPC that impacts decision-making and organizational performance so as to achieve sustainable competitive advantage. 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. Such data, if aggregated centrally, leads to superior decision-making capability (Parida et al., 2017), transforming the organization and thus achieving sustainable competitive advantage (Gemunden& Ritter, 1996; Low, 2013). The research model is as in Figure 1.

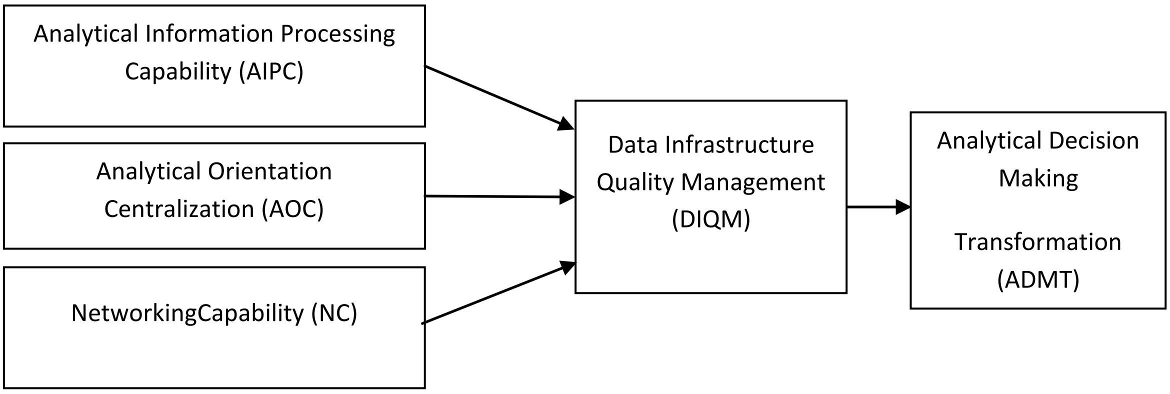

Figure 1: Analytical Decision-Making Transformation Model

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 below sub-section discusses a summary of hypotheses addressed in previous sections. The hypothesized research model is as shown in Figure 2.

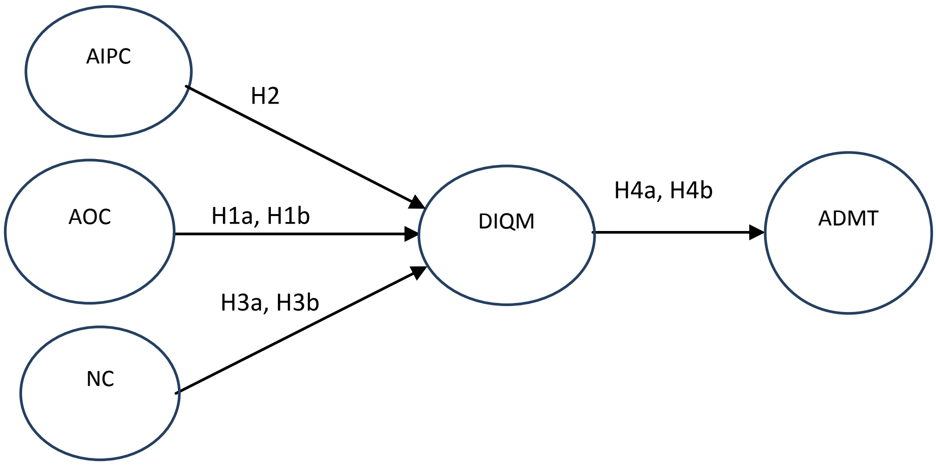

Figure 2: Hypothesized AnalyticalDecision Making Transformation Model

As the organization moves towards the implementation of advanced analytics, effectiveness in the organization 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. Hence, the study proposes the hypothesized model as in Figure 2.

Method

The study began with an extensive and structured literature review using a systematic review approach. Based on SLR, the authors identified critical research gaps and key constructs. Open-ended, unstructured interviews with five C-level executivesvalidated each 'concept' and 'construct' emanating from SLR. The authors adopted a mixed methodology research design, both exploratory qualitative research and quantitative analysis.Further, the study focused on hypotheses development based on the key constructs and their relationship with each other.The model was developed based on the hypotheses development and the interlinking relationship between key constructs.

J. Participants

The respondents were selected randomly from global organizations and technology-driven organizations. The σp(standard deviation) was calculated to be around 14 based on the test sample. As per the table, 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).

$N = z2 * N * σp2 / ((N-1) * e2 * + z2 * σp2)$

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 overa thousand industry experts, human resource executives, and senior executives from global and top technology organizations.

K. Research Design

This study chose simple random sampling to choose global organizations and experts from such organizations. The complete list of global organizationswas 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.

L. Measures

A structured approach toward literature review resulted inidentifying 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. Asthe 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.

M. Procedures

The study gathered 617 valid responses from overa 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 analysiswas 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) scorewas higher than 0.5 (Field, 2000). Hence, the SU of AIPC, AOC, NC, DIQR, and ADMT is acceptable for their respective dimensions. As per KMO values, the items that did not indicate SU was 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 items-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 scoreswere above 0.8;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.

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 valueswherein 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 ADMTare established. The discriminant validity of scales was established, as shown in Table 1. The table shows that the variance between scales is 86%, greater than the correlation squares of the scales.

Table 1

Scale	**Factor Grouping Name**	**Average Loading**	**Variance Extracted**	**Var Between All**	**Correlation**	**Correlation Square**
Component 4	Information Processing Capability	0.900	0.811	86%	0.364	13.2%
Component 2	Analytical Centralization and Orientation	0.905	0.819		0.188	3.5%
Component 1	Networking Capability	0.922	0.850		0.184	3.4%
Component 3	Data Infrastructure and Data Quality Management	0.973	0.946		0.259	6.7%
Component 5	Analytical decision-making transformation	0.940	0.883		0.386	14.9%

Discriminant Validity of Scales

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 0.130which 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, hence, hypotheses are acceptable. Table 2 demonstrates that hypotheses H1a, H1b and H2are 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 advancedanalytical 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 inanalytical transformation; thus, hypothesis H1 cannot be rejected (as indicated in Table 2). 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 andsupported. 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 2.

Table 2

Hypotheses Testing – Analytical Transformation Model

Hypothesis – Path Posited	P.coef (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

The authors of this study discovered compelling evidence that supports 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. 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 (Abbasri et al., 2016; 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.

The success of an organization's analytical orientation, culture, and centralization relies 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.

This study identifies significant factors related to human resources and technology that can help organizations transition to advanced analytics and improve their decision-making abilities. It contributes to the development of theoretical frameworks and models for analytical transformation, highlighting the importance of analytics in this process. While the study focuses on global and large Indian organizations, it is generally applicable, but future research should expand to all global market sectors. C-level executives can benefit from the study's findings by understanding what is important in analytical transformation and pushing their decision-making teams to adopt advanced analytics based on mathematical models and statistical algorithms. Implementation teams may overcome their resistance to innovation and advanced technology adoption. Researchers from other countries can apply the study's model in their own settings, and further empirical validation is necessary for non-technology-oriented industries. Future research projects can explore additional constructs such as personality traits, leadership styles, and tools and techniques.

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