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Factors influencing dynamic capabilities of entrepreneurial-led organisations to achieve analytical transformation

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Abstract: Entrepreneurial spirit transforms the economic scenario resulting in a significant contribution to society. Analytical transformation enables entrepreneurs with superior effective decision-making capability through information gathering, advanced technology adoption and data analysis. Effective analysis leads to superior organisational performance. However, in entrepreneurial-led large Indian organisations, the adoption of analytics is limited to predicting results. The study aims to identify the key factors that impact analytical transformation. The study also aims to identify key dynamic capabilities to achieve such transformation. This article identifies base theories related to the identified concepts. This article aims to develop an 'analytical transformation capability model' for entrepreneurial-driven large industries. This study also empirically validates the proposed research model. The study concludes that entrepreneurial-led large Indian technology-driven industries lag behind their technology peers in adopting prescriptive analytics. The study also proposes an 'analytical transformation theory' that aims to provide necessary techniques to improve organisational effectiveness.

Keywords: analytical decision making; dynamic capability; prescriptive analytics; analytical transformation; organisational effectiveness; information processing; organisation efficiency; entrepreneur led organisation; analytical orientation; data centralisation; data infrastructure; networking capability; evidence-based decision making; advanced analytics; predictive analytics.

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1 Introduction

Entrepreneurship creates an activity that involves incubating, creating and managing an organisation (Gartner, 1989) based on the spirit of the original idea. The concept of entrepreneurship has become a phenomenon with new-generation technologists. Casson (1982) says that entrepreneurs are the ones who specialise in making judicious decisions on utilising scarce resources to build sustainable organisations. Entrepreneurs go beyond scientists to understand and solve real-world issues by creating solutions to add value. Shane and Venkataraman (2000) describe entrepreneurship as identifying and utilising profitable opportunities to maximise economic value. Liu et al. (2002) say understanding the interrelationships between attitude, orientation, decision-making, and entrepreneurship is critical in volatile market conditions. Entrepreneurial-led organisations are the key drivers of nations' economic prosperity. Entrepreneurial journey creates a long-term positive impact on society. Entrepreneurship has gained its status as a legitimate scholarly research subject (Vesper, 1998).

Entrepreneurial companies go through forming, norming, storming and performing phases of organisational development (Jois and Chakrabarti, 2020). This article focuses on the performing phase of entrepreneurial-led large organisations. Data-based decision-making brings stability into entrepreneurial-led organisations enabling long-term survivability (Vaaler and McNamara, 2004). Digital technologies and analytics play a vital role in reforming, reshaping, reskilling and transforming entrepreneurial-led organisations (Jois and Chakrabarti, 2020). Sustainability and digitalisation are two central discourses in entrepreneurship research, but only recently have they been discussed jointly (Holzmann and Gregori, 2022). Digital technologies have changed the way entrepreneurship is defined. Soluk et al. (2021) highlight that few studies investigate the role of digital technologies on entrepreneurship. However, the aspect of analytical transformation is not extant in recent research.

Organisational transformation is key for entrepreneurial-led technology companies to be globally successful. The transformation has been key to the success of entrepreneurs-led organisations like Infosys, Meta (Facebook), Mindtree and Twitter. Khurana et al. (2022) say that entrepreneurial dynamic capability (EDC) also helps in the resilience of organisations. EDC enables the creation of a framework for identifying large opportunities. Organisations' journey towards digital transformation results in exponential growth, the creation of newer jobs, increased trade outcomes and improved quality of life, as the OECD Report (2018) advocates. The ability to gather, network, assimilate and analyse data at a centralised location is also part of dynamic capability (DC). Data provides possible value to the organisation through meaningful insights, and the study of analytics provides in-depth data insights.

This article covers the impact of dynamically changing capabilities on organisational transformation. Emerging transformation models that are data and analysis-driven need to be innovative and sustainable (Komm et al., 2021). Thus, the authors combine all three aspects of analytical transformation, data-based decision-making, and organisational DC into the research. Johnston et al. (2019) and Chen et al. (2012) highlight that in large industries, there are inefficiencies in data and information gathering and aggregation, resulting in reduced statistical analysis and computational capabilities. David et al. (2021), Nam et al. (2019) and Davenport et al. (2001) research showcase the importance of data infrastructure (DIFR) and analytics for improving organisational effectiveness.

Analytics is key to understanding the decision-making process to achieve superior organisational outcomes. Analytics involves transforming intuitive decisions into information and data-based decision-making, a notable change in entrepreneurial behaviour. Analytics uses extensive information and data by leveraging quantitative analysis, programming, operation research, and statistical and mathematical modelling techniques (Kapoor and Kabra, 2014). Kohavi and Simoudis (2002) say that descriptive, diagnostic, predictive, and prescriptive analytics (PA) are different types available for organisations to achieve effective results. Descriptive analytics is the primitive stage of analytical transformation based on historical data, also advocated by Shi-Nash and Hardoon (2017). Diagnostic analytics deal with observations and correlations (Shi-Nash and Hardoon, 2017). Predictive analytics tools are used for detailed analysis by considering historical data for projections to provide automated decisions (Kapoor and Kabra, 2014). The predictive analytics stage helps entrepreneurial organisations improve organisational performance by leveraging tools and techniques like business intelligence tools, data mining, statistical modelling and machine learning to make predictions (Fitz-enz, 2010). However, PA is the most advanced stage of analytical transformation, enabling solutions to the identified issues by propagating multiple solutions.

Lepenioti et al. (2020) say PA has generated significant interest in academic circles. NASDAQ Report (2020) also highlights that PA enables technology-oriented organisations to achieve desired results by adopting statistical analysis, mathematical modelling, machine learning, networking, simulation and complex event processing. Sapp et al. (2019) highlight the need for organisations to move from predictive to PA to achieve organisational maturity, effective decision-making and sustainable development. NASDAQ Report (2020) and Lepenioti et al. (2020) also bring in the need for entrepreneurial-led organisations to transform from basic decision-making to advanced data-based decision-making by building dynamic capabilities.

Lepenioti et al. (2020) and Deloitte Report (2022) showcase that large multinational corporations have transitioned from basic forms of analytics to PA, leapfrogging them to become sustainable organisations. However, organisations with limited DC of decision-making teams inhibit the employees from adopting statistical and mathematical modelling techniques (Lepenioti et al., 2020; Deloitte Report, 2022). Mohrman and Lawler (2004) and SuccessFactors (2015) say that adopting analytics across the entrepreneurial-led organisation has not kept pace with the market needs. Current progress in academic research on advanced analytics is limited to a few technology-related factors. Thus, the authors' research has focused on analytical transformation, dynamic capabilities, employee orientation, decision-making and DIFR.

2 Research objective

There is a need to investigate why entrepreneur-led technology organisations lag in advanced analytics implementation compared to their global peers (Sapp et al., 2019). Lepenioti et al. (2020) highlight the need for more research on attitudinal barriers that make entrepreneurs rely more on intuition than analytical decision-making. Akhtar et al. (2017) call for more examination of the benefits of advanced analytics implementation in large organisations. Large Indian technology-driven services organisations know the benefits of advanced analytics as they implement complex solutions for end clients. However, entrepreneur-led Indian technology organisations lag behind their global peers in adopting transformation models within their own organisations, as highlighted by Lepenioti et al. (2020), Deloitte Report (2022), Mohrman and Lawler (2004) and SuccessFactors (2015). This study aims to identify key factors impacting large technology-driven organisations' analytical transformation. The research intends to cover aspects related to attitudes that inhibit employees from transitioning from intuitive decision-making to statistical modelling and mathematical algorithm-based decision-making.

3 Research methodology

The research began with a comprehensive and extensive literature review utilising a systematic review methodology (Emory and Cooper, 1991). A systematic literature review (SLR) approach identified critical research gaps and key constructs. Each concept and construct derived from the SLR was validated with a set of open-ended and unstructured questionnaire-based interviews with five C-level executives. In order to gain a holistic understanding, the study employed a mixed methodology research design, incorporating both exploratory qualitative research and quantitative analysis. The study formulated hypotheses based on the identified key constructs and explored their interrelationships. The study identified key-scale development articles and base theories for each construct. Further, the unstructured questionnaire and identified dimensions of the scales resulted in the adaption of items for the questionnaire. The structured questionnaire was then administered to 15 top-level executives to check content validity and face validity. The correlation matrix was analysed to remove the negatively correlated items and select the most suited dimensions and items for the study. Further, the pilot testing and statistical analysis using IBM SPSS resulted in composite reliability (CR), convergent validity (CV) and divergent validity (DV) scores. Further, the questionnaire was finalised based on the expert opinion, content and face validity scores, CR, CV and DV scores.

The development of the model was based on the literature review, hypotheses development and the interconnectedness of the key constructs. This research adopted a simple random sampling method to select global organisations and survey respondents from those organisations. The selection of global organisations was based on criteria such as their global revenue size and industry sector. Data collection was carried out using surveys and interviews. Surveys were aimed at gathering quantitative data on the challenges faced by global organisations. The research utilised IBM SPSS and IBM AMOS statistical software for quantitative analysis and structured equation modelling (SEM). Survey participants were comprehensively informed about the study's objectives and confidentiality clauses, and then their consent was obtained. Collected data were treated with confidentiality and solely used for only research purposes. A total of 617 valid responses were collected from over a thousand survey questionnaires administrations. The questionnaires were distributed through multiple methods, including face-to-face interviews, e-mail, Google™ Forms and WhatsApp™. The authors employed factor analysis using principal component analysis with varimax rotation to identify key variables and group them for further analysis. Based on the scree plot analysis, it was determined that the optimal number of factors was five. Subsequently, regression analysis was conducted to examine the relationship between the identified key factors. Further, the SEM was used to calculate the CMIN/DF, goodness fit index, PCLOSE and RMSEA scores to test whether the model was fitting.

4 Review of literature

The authors conducted an extensive literature review by analysing top-quality peer-reviewed articles from ABDC, ABS, JQL and Scopus-ranked journals. Entrepreneurial organisations are experiencing many changes due to technology-led transformation in the market space. Parisa et al. (2020) highlight the following factors that play a vital role in transformation, organisational factors: top management support, readiness in the organisation, technology factors like compatibility, risk factor in the management, trialability, observability and environmental factors such as support from outsiders, government policy, rules and regulations, pressure from competitors. Akhtar et al. (2017) say that organisations that utilise dynamic data collection using technologies such as internet of things (IoT), sensory networking and information processing capability (IPC) achieve superior competitive advantage in the marketplace. Grant (1996) highlights the importance of analytical insights, business networks and informed, evidence-based decision-making in IPCs.

The authors further explore and extend concepts such as dynamic capabilities and decision-making proposed by Teece et al. (1997). Parida et al. (2017) proposes networking capability as critical to achieving relational abilities by improving communication and engagement. Chuang and Lin (2013) highlight the importance of infrastructure capability to effectively deploy organisational resources, keeping customer relationship management in mind. Hence, this research adopts a structured literature review with a systematic reviews approach by focusing on concepts such as: management capability, information gathering and processing capability, DC, analytical orientation (AO), centralisation of data and information, networking capability, DIFR, data quality management, analytical transformation and organisational effectiveness.

4.1 IPC as a DC

Information processing systems play a crucial role in dealing with unexpected operational challenges and providing actionable insights (Akhtar et al., 2022). IPCs improve knowledge generation based on large amounts of data (both structured and unstructured) and information (Gubbi et al., 2013; Akhtar et al., 2017). Information processing theory propagates the need for gathering accurate information and organisations' capability to analyse information by correlating between the two resulting in excellence in organisational performance (Galbraith, 1974). The organisation's dynamic capacity is key to analysing available data and information to assimilate to acquire insights for decision-making (Cao et al., 2015). This article examines an entrepreneurial-led organisation's IPC as DC.

IPC directly impacts the decision-making capability of an organisation, enabling sustainable development based on policy, procedure, strategy, structure and business processes (Cao et al., 2015). IPC as DC of the organisation is based on the information technology structures of the organisation that assist various organisational activities (Premkumar et al., 2005). IPC as DC leads to the effective collection of data and information aggregation, resulting in improved DIFR and quality management. IPC as a DC plays a critical role in managing multilevel data and understanding complex information emerging from analytical algorithms. Any lack of system capabilities leads to non-transformation. Organisations cannot build DC without orienting their leadership, decision-makers and employees toward a centralised decision-making process to achieve analytical transformation. The following section addresses employees' AO as a DC. Therefore, the research proposes the following hypothesis:

H1 IPC-DC positively influences DIFR quality and data management capability (DQM).

4.2 AO centralisation as DC in entrepreneurial-led organisations

AO is defined by organisations' analytical culture, building skills, enabling talent, providing insights from analysis, and efficient data management (Dias et al., 2021; Kiron et al., 2014). AO also refers to the decision-making capability and process based on information, facts and data (Holsapple et al., 2014). Dias et al. (2021) refer to non-analytical decision-making as a process based only on intuition and previous experiences. Most entrepreneurial-led IT organisations highlight only the technology and DIFRs while discussing digital transformation but disregard changes required in organisation, culture, strategy and employee orientation. Experiences and skills may vary according to the policies, procedures, processes and capacities of companies' AO (Davenport et al., 2001). Employee analytical orientation (EAO) is an important factor in the organisational ability to adopt advanced analytics (Navneet, 2020) to improve efficiency. Kiron et al. (2014) say that analytical culture is a 'secret sauce' which enables AO to create value. A lack of AO hinders the transition from predictive to PA. Entrepreneurs and leaders of Indian IT organisations have a common opinion that it is essential to transform the organisation towards PA. Most decision-makers feel organisations must learn new statistical and mathematical modelling skills to survive in a globally competitive market.

Centralising information and data leads to improved analytical decision-making capability resulting in an organisational transition toward advanced analytics. Centralisation can smoothen analytics adoption by minimising friction and uncertainty (ASHE-ERIC, 1988). Data decentralisation may make data prioritisation harder, leading to ineffective analytical decision-making (Komm et al.. 2021). Analytical centralisation (AC) is a key system factor in the organisational context that considers data availability, analytics scope, organisational needs and partnerships (Grossman and Siegel, 2014). AC coupled with EAO leads to effective data collection and aggregation at a central place by enabling effective DIFR and efficient data quality management. AO enables leaders, decision-makers and employees to make efficient decisions in planning, organising, analysing, and creating DIFR to achieve effective data quality management and sustainable development. Therefore, the research proposes the following hypothesis:

H2a EAO as DC positively impacts DIFR quality.

H2b Employee orientation analytical centralisation as dynamic capability (EOAC-DC) positively correlates with DIFR management capability.

4.3 Impact of networking capability as a DC on analytical transformation

Networking capability can be defined based on organisational infrastructure and human resource capability to initiate, collect, organise, centralise and analyse information and data to make effective analytical decisions. Entrepreneurs' credibility is tested by their ability to build networks to establish successful organisations and track records (Churchill and Lewis, 1983). Networking capability is one of the organisational variables initiated towards managing relationships between various stakeholders (Mitrega et al., 2012) and organisational assets. Walter et al. (2006) define networking capability as the organisational ability to initiate, maintain, and utilise relationships with various stakeholders. Another key element of organisational networking capability is the sensory network and data management, the brain behind analytics (Sendi et al., 2020).

Networks based on sensors and internet-enabled devices (IoT) have always assisted in asset data collection, information gathering and analysis of characteristics (Oppermann et al., 2014). Paul et al. (2018) highlight that appropriate sensors must be strategically designed, installed and managed to collect data and information to optimise organisational utilisation efficiently. The lack of sensors at strategic locations severely inhibits efficient sensory networks, resulting in a collection of compromised information and data and reduced analytical decision-making capability. Advanced analytical capabilities like PA-based decision-making impact organisational efficiency (Zadorojniy et al., 2018). Yang et al. (2019) highlight the need for efficient and sustainable sensory networks, an effective DIFR capability and a DQM. Hence, the study hypothesises that:

H3 Network capability as dynamic capability (NC-DC) is positively correlated to data infrastructure quality management capability (DIFRC).

4.4 Significance of DIFR and management capability as DC in analytical decision-making and transformation

Large entrepreneurial-led enterprises do not focus on efficient data collection and feel that information gathering at multiple levels is an additional expenditure (Johnston et al., 2019; Chen et al., 2012). The organisation's data may be structured, unstructured, exclusive, or shared, and different rules and laws govern how that data is processed (Deshpande et al., 2019). Organisations' computational, IT, statistical, and analytical capabilities are key to effectively maintaining data (Chen et al., 2012). According to David et al. (2021), analytics effectively uses input data using arithmetic algorithms and statistical analysis to resolve business issues, identify linkages, forecast ambiguous outcomes and automate choices. DIFR can provide the necessary data to produce real insights into any organisation (Nam et al., 2019).

Based on the research of Nam et al. (2019), Johnston et al. (2019), Chen et al. (2012) and Deshpande et al. (2019), it can be inferred that a lack of DIFR, DIFRC and DQM results in a reduced organisation's capability to switch from predictive to PA. Advanced analytics implementation can overcome such inhibitions to transform data into useful information. Therefore, DIFR and DQM are combined to propose the DIFRC concept. Discussions in the last two previous subsections show that DIFRC mediates between IPC-DC and AT, as also suggested by Cao et al. (2015). IPC has a positive and indirect effect on AT through a mediating effect of DIFRC. Davenport et al. (2001) state that effective DIFR is key to rigorous data collection, validation, and data cleansing processes based on standardised frameworks to achieve transformation. An AO promotes a systematic and detail-oriented approach to data quality management (Davenport et al., 2001).

Employees' orientation and AC are key to capturing the right information, data availability, understanding organisational needs, developing networks and transforming organisations (Grossman and Siegel, 2014). Thus, the study concludes that DIFRC also mediates EOAC and analytical transformation capability (ATC). DIFRC is a key mediator enabling organisations to establish an interrelationship between NC and ATC by maintaining efficient DIFR, implementing data governance, and ensuring data integration and interoperability. DIFRC also assesses and monitors data quality, fosters collaboration and knowledge sharing, ensures data security and privacy, and drive data quality improvement initiative. Such interrelationships between NC-DC, IPC-DC, EOAC-DC, DIFRC and ATC ensure the availability, accessibility, and reliability of data. Therefore, the research proposes the following hypotheses:

H4a DIFRC has a mediating relationship between NC-DC and ATC.

H4b DIFRC has a mediating relationship between IPC-DC and ATC.

H4c DIFRC has a mediating relationship between EOAC and ATC.

4.5 Analytical transformation capability

One of the main challenges faced by entrepreneur-led Indian IT organisations is the switch from predictive to PA, which hinders crucial decision-making capability and affects organisational effectiveness. The method through which businesses make decisions are radically altering and entrepreneur-led large Indian IT organisations also need to adopt them. Managers are used to making intuition and gut instinct-based decisions; however, global competition is forcing decision-makers to make decisions based on data and analytics (Kryscynski et al., 2018). Orlikowski (1992) highlights the importance of analytical decision-making processes to accomplish transformation and superior outcomes, reassuring decision-makers of organisational backing when rational decisions are made. Big data analytics provides decision-makers with powerful tools and techniques to deliver effective decisions based on predictive and PA (Deshpande et al., 2019). Popovič et al. (2012) and Akin and Bayram (2020) also propagate similar thought processes by advocating that decision-makers encourage employees to adopt advanced technologies to transform organisations analytically.

Wong (2012) says that analytical capabilities enable open innovation within an organisation. PA helps firms turn their decisions into actions (Gokalp et al., 2022) to achieve analytical transformation. Macias-Lizaso (2018) highlights that the analytics journey begins excitedly but quickly become frustrated as there is a lack of strategy; hence, there is a need for a better research model. Therefore, the research proposes the following hypothesis:

H5 DIFRC is positively related to ATC.

H6 IPC-DC significantly influences ATC.

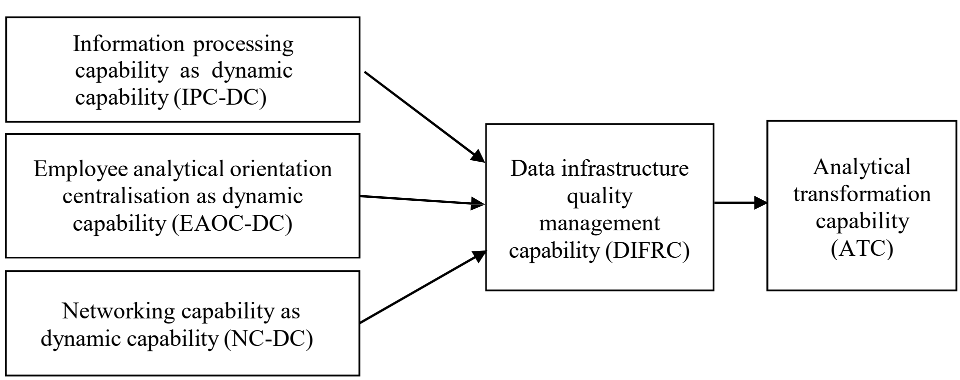
H7 EOAC-DC has a significant correlation with ATC.

H8 NC-DC has a significant relationship with ATC.

5 Research model

Organisations that have barriers to innovation are averse to transformation as per the diffusion of innovation theory (DOI) (Rogers, 1962). Entrepreneurial-led Indian IT organisations are also facing similar issues in transforming their organisation despite their employees being technologically advanced, as suggested by Nam et al. (2019) and Davenport et al. (2001). AO is a key factor that inhibits such organisations from transforming. Decision-makers in large organisations have limited capability in statistical and mathematical modelling, as also suggested by Kapoor and Kabra (2014); hence there is a lack of analytical culture (Kiron et al., 2014). Such a lack of culture builds an aversion to change, obstructing new initiatives and shifting from predictive to PA, as also suggested by Lepenioti et al. (2020). An organisation's IPC significantly impacts its ability to build data IT infrastructure and management capability.

Figure 1 ATC model

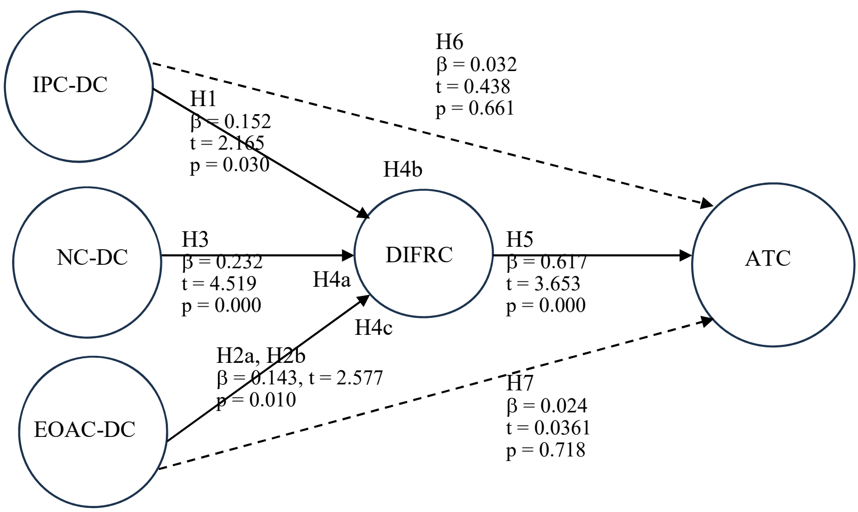


Employee orientation towards analytics coupled with centralisation DC results in better DIFR management capability which is also advocated by Kiron et al. (2014). The sensory networking capability of an organisation is directly proportional to DIFRC (Oppermann et al., 2014). Information processing and organisation networking capability coupled with employee orientation centralisation capability push data management towards building dynamic capabilities, thus achieving ATC. The study considers IPC, AO, AC, and network capability as independent variables, DIFR and quality management as mediating variables and analytical transformation as dependent variables. The ATC model is proposed in Figure 1.

5.1 Hypotheses

This study proposes that IPC as DC coupled with employee orientation and centralisation as DC impacts data collection capability, data integration, data aggregation, data IT infrastructure and management capability. In conjunction with employee orientation towards analytics, networking capability as DC leads to better DIFR management, thus, analytical transformation as a DC. Such transformation results in adopting advanced analytics, compelling organisations to go beyond predictive to PA, thus impacting analytical decision-making quality. Hence, the study proposes the hypothesised model as in Figure 2.

Figure 2 Hypothesised ATC model



6 Results and analysis

The study validated scale unidimensionality (SU) using exploratory factor analysis (EFA) to test whether items are loading heavily on one factor (Hair et al., 2008). EFA was conducted using the IBM SPSS tool and with the 'principle component analysis method' selection with eigenvalue as one and rotation as varimax (Ritter et al., 2001). Kaiser-Meyer-Olkin (KMO) Bartlett test reveals the sphericity appropriateness of data for factor analysis. The sample size was adequate for pilot testing as the KMO score was larger than 0.5 (Field, 2000; Pallant, 2013; Kaiser, 1970). Hence, the SU of IPC-DC, analytical orientation centralisation capability (EAOC-DC), NC-DC, DIFRC, and ATC are acceptable for their respective dimensions. Based on the KMO communalities extraction values, the items which did not indicate SU was dropped.

Table 1 Dimensions of scales and indicator variables mapped to latent variables

Indicator variables	*Latent variables*
Organisation IPC is useful	Information processing capability as DC
IPC important	
IPC useful	
IT team – AOAC	Employee analytical orientation centralisation capability as DC
Statistical techniques – AOAC	
Competitors – AOAC	
Relevant information – AOAC	
Intuition rather than d-a-AOAC	
Specific goal – AOAC	
Selection – NC	Networking capability – DC
Build attention – NC	
Communication information – NC	
Socialise network – NC	
Train employee for conflict – NC	
Reason for termination – NC	
Data collection technology – DIFR	Data infrastructure quality management capability
Data distributed – DIFR	
Big data process and technology – DIFR	
Automatic method to collect data – DIFR	
Company investment in dig data infra – AT	Analytical transformation capability
Company adopts dig data operation – AT	
Empowers talent and personnel – AT	

6.1 Composite reliability

The scales were adapted with little modification from well-established research articles to suit this study. Further, confirmatory factor analysis (CFA) was conducted to assess SEM-based CR using IBM AMOS and IBM SPSS tool-based validity of unidimensional scales, which is discussed in the following sections of the article (Cronbach, 1951; Netemeyer, 2003). The study extracted the standard loadings λ from the factor groupings. The latent variables are the constructs of the study, and indicator variables are the items-dimensions as per the pattern matrix and rotated component matrix table (Jois et al., 2022). Table 1 denotes the dimensions of the scales considered in the study and as well shows the indicator variables mapped to latent variables. The standard loadings and measurements error values are as shown in Table 2. The Cronbach alpha and average variance (AVE) are above 0.7, as per Table 3. Hence, all 22 items can be treated as reliable to measure the respective scales. Based on Table 1, Table 2 and Table 3, the CR scores are above 0.8; hence, scales: information processing capability (IPC-DC), EAOC-DC, networking capability (NC-DC), DIFRC, and ATC are reliable.

Table 2 Standardised loadings and measurement error

Latent variables	*Standardised loadings (λ)*	*Square of standardised loadings (λ2)*	*Measurement error (ME = 1 – λ2)*
Information processing capability as DC	0.943	0.89	0.11
	0.946	0.89	0.11
	0.812	0.66	0.34
Employee analytical orientation centralisation capability as DC	0.908	0.82	0.18
	0.912	0.83	0.17
	0.926	0.86	0.14
	0.897	0.80	0.20
	0.883	0.78	0.22
	0.906	0.82	0.18
Networking capability – DC	0.912	0.83	0.17
	0.942	0.89	0.11
	0.926	0.86	0.14
	0.910	0.83	0.17
	0.907	0.82	0.18
	0.936	0.88	0.12
Data infrastructure quality management capability	0.967	0.94	0.06
	0.965	0.93	0.07
	0.982	0.96	0.04
	0.976	0.95	0.05
Analytical transformation capability	0.916	0.84	0.16
	0.966	0.93	0.07
	0.937	0.88	0.12

6.2 CV and discriminant validity

The study has demonstrated CV based on the correlation coefficient between items within the construct (Azmi and Mushtaq, 2013). Based on the analysis of the correlation coefficients between items of different constructs, the authors acknowledge that rarely items will have perfect convergence. Hence, the range would be between 0.3 and 0.95. The study shows that all values are between 0.3 and 0.95. The authors also calculated VIF scores which were found to be below the acceptable value of 10 (Neal and David, 1998). Hence, based on correlation coefficient matrix analysis and VIF scores, the study rules out multicollinearity issues (Senaviratna and Cooray, 2019). Thus, the CV of all the scales information processing capability (IPC-DC), EAOC-DC, networking capability (NC-DC), DIFRC, and ATC are established. Table 4 demonstrates variance between all scales is 86%, which is higher than the correlation squares of the respective scales. Based on no correlation between most items outside the measures (Hair et al., 2008, 2009), the discriminant validity of scales is established.

Table 3 CR 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*
Information processing capability as DC	0.56	2.44	5.97	6.53	0.91	3	0.81	0.93
Employee analytical orientation centralisation capability as DC	1.08	4.92	24.18	25.27	0.96	6	0.82	0.82
Networking capability – DC	0.90	5.10	26.04	26.94	0.97	6	0.85	0.85
Data infrastructure quality management capability	0.22	3.78	14.32	14.54	0.99	4	0.95	0.72
Analytical transformation capability	0.35	2.65	7.02	7.37	0.95	3	0.88	0.79

Table 4 Discriminant validity of scales

Factor grouping name variables	*Average loading*	*Variance extracted*	*Variance between all*	*Correlation*	*Correlation square*
Information processing capability as DC	0.900	0.811	86%	0.364	13.2%
Employee analytical orientation centralisation as DC	0.905	0.819		0.188	3.5%
Networking capability – DC	0.922	0.850		0.184	3.4%
Data Infrastructure quality management capability	0.973	0.946		0.259	6.7%
Analytical transformation capability	0.940	0.883		0.386	14.9%

6.3 Test of hypothesis

By analysing Table 5, Hypothesis H1 values ($\beta = 0.152$, $t = 2.165$, $p = 0.030$), the study concludes that H1 is supported, which is also suggested by Cao et al. (2015). H1 proves that there is a significant relationship between IPC-DC and DIFRC. Effective information-gathering DC leads to efficient DIFR and quality management. Efficient DIFR attains a meaningful state only when the information is accurate, consistent and reliable. Davenport et al. (2001) say there is a correlation between EAOC-DC and DIFRC, supported by H2 values ($\beta = 0.143$, $t = 2.577$, $p = 0.010$). Employee orientation towards adopting analytical capability leads to efficient DIFR design and superior data quality management. Walter et al. (2006) suggest that there is a significant connection between NC-DC and DIFRC, which contributes to H3 values ($\beta = 0.232$, $t = 4.519$, $p < 0.001$). Networking DC, employee orientation, and information-gathering mechanisms improve DIFR and quality management capability. Hence, Hypotheses H1, H2 and H3 can be accepted as the path coefficients are above 0.1, and in the social sciences studies, path coefficients above 0.1 can be accepted if the p-value is below 0.05.

Based on the analysis of Table 5, the direct, indirect, and total effects at significance levels with a 95% confidence interval are significant, and the mediating role of DIFRC between NC-DC and ATC is established. As both effects between NC-DC and ATC were statistically significant. Further, Hypothesis H4a was tested to check whether the indirect effect value is outside the upper bound and lower bound levels. Then, the bootstrap confidence value (two-tailed significance using the bias-corrected percentile method) was checked for significance. As the significance value was below 0.05, the mediating role of DIFRC between NC-DC and ATC is established; hence, the H4a is supported, which was supported by the research article of Cao et al. (2015). Networking capability powered by efficient DIFR leads to analytical transformation.

Table 5 Test of hypotheses

Hypothesis – path posited		*P. coef (β)*	*t-value*	*p-value*	*Sig. level*	*Results*	*References*
H1	IPC-DC -> DIFRC	0.152	2.165	0.030	$p < 0.05$	Supported	Cao et al. (2015)
H2a, H2b	EAOC-DC -> DIFRC	0.143	2.577	0.010	$p < 0.05$	Supported	Davenport et al. (2001)
H3	NC-DC -> DIFRC	0.232	4.519	0.000	$p < 0.001$	Supported	Walter et al. (2006)
H4a	NC-DC ->DIFRC -> ATC	β(direct) > 0.1		$p < 0.05$		Supported	Cao et al. (2015)
H4b	IPC-DC -> DIFRC -> ATC	β(indirect) > 0.3		Ha out of upper bound or lower bound		Supported	Cao et al. (2015)
H4c	EOAC -> DIFRC -> ATC	Diff β (direct) and β (direct) > 0.3				Supported	Davenport et al. (2001)
H5	DIFRC -> ATC	0.617	3.653	0.000	$p < 0.001$	Supported	Orlikowski (1992)
H6	IPC-DC -> ATC	0.032	0.438	0.661	$p > 0.001$	Not supported	Wong (2012)
H7	EAOC-DC -> ATC	0.024	0.0361	0.718	$p > 0.001$	Not supported	Gokalp et al. (2022)
H8	NC-DC -> ATC	Minimisation could not be achieved				Not supported	Akhtar et al. (2017)

Based on the analysis of direct, indirect and total effects, the mediating role of DIFRC between IPC-DC and ATC is also established. As both effects between IPC-DC and ATC were statistically significant. Hypothesis H4b was tested to check whether the indirect effect value is outside the upper bound and lower bound levels. As the significance value was below 0.05, the mediating role of DIFRC between IPC-DC and ATC is established; hence, the H4b is supported, which is also indicated in the research of Wong (2012) and Cao et al. (2015). Similarly, based on the analysis of direct, indirect and total effect values, the mediating role of DIFRC between EOAD-DC and ATC is established. As the significance value was below 0.05, the mediating role of DIFRC between EOAC and ATC is established; hence, H4c is supported, which is advocated by the research article of Davenport et al. (2001).

DIFR management capability and AO are critical to gathering information and collecting and centralising data for effective analysis. Hypothesis H5 values ($\beta = 0.617$, $t = 3.653$, $p < 0.001$) show that there is a significant relationship between DIFRC and ATC, which is also suggested by Orlikowski (1992). Effective DIFR management DC leads to superior analysis resulting in efficient analytical decision-making, thus achieving analytical transformation. Hypothesis H6 values ($\beta = 0.032$, $t = 0.438$, $p = 0.661$) prove that IPC-DC does not directly affect ATC, as also indicated in the research of Wong (2012). Hypothesis H7 values ($\beta = 0.024$, $t = 0.361$, $p = 0.718$) show that there is no direct correlation between EAOC-DC and ATC; hence Hypothesis H7 is rejected, which is indicated in the research of Gokalp et al. (2022). Table 5 shows that the minimisation could not be achieved in SPSS for the model when there is a relationship between NC-DC and ATC, thus, this study concludes that Hypothesis H8 is not supported. Networking DC alone cannot result in ATC, but when coupled with employee orientation, AC, information gathering DC, and DIFR lead to transformation.

7 Conclusions

Entrepreneurial-led technology organisations tend to focus on personality aspects of the business to improve effectiveness. However, the study concludes that most entrepreneurs who run large Indian technology-driven organisations (especially IT organisations) need to improve their decision-making based on advanced analytics, also advocated by Komm et al. (2021). Some key issues in critical decision-making are lack of data collection at multiple levels, analytical aggregation of data, and AO of the managerial team. AO leads to upskilling and reskilling of key decision-making teams resulting in good analytical culture within the organisation, as also suggested by Davenport (2006). Other key issues are the centralisation of analytics and data, the organisational capability to inter-network and the DIFR needed to implement effectively. Improved information, data processing, and networking capability help build effective DIFR. Data quality management capability depends on efficient sensor-based data collection, human intelligence information, data aggregation and analytics centralisation.

DIFR and quality management capability lead the transition from predictive to PA, as also suggested in the research of Markard et al. (2012). Such efficient infrastructure capability leads to the ATC of an organisation. Thus, the research proposes analytical transformation theory, which states that organisations' IPC, leadership team AO, centralisation of analytics, networking capability and data aggregation lead to the transformation of a company into an analytical organisation resulting in improved organisational effectiveness.

8 Limitations and future research directions

The study has identified various technological, human, and system factors related to the organisational transition from predictive to PA and analytical decision-making in the entrepreneurial-led Indian technology-driven sector. However, the study must be extended to other large and medium-sized Indian industries. Further, the research model must be empirically tested on various geographies and industries. This study was also restricted to the Indian IT sector and certain technology-oriented industries; however, future researchers may expand it to the global IT sector, technology sectors, heavy industries, and other industry verticals. Researchers can also expand this research to include constructs like personality traits and leadership style.

References

Akhtar, P., Khan, Z., Tarba, S. and Jayawickrama, U. (2017) 'The internet of things, dynamic data and information processing capabilities and operational agility', *Technological Forecasting and Social Change* [online] https://doi.org/10.1016/j.techfore.2017.04.023.

Akhtar, P., Osburg, V.S., Kabra, G., Ullah, S., Shabbir, H. and Kumari, S. (2022) 'Coordination and collaboration for humanitarian operational excellence: big data and modern information processing systems', *Production Planning and Control*, Vols. 6–7, pp.705–721 [online] https://doi.org/10.1080/09537287.2020.1834126.

Akin, A.M. and Bayram, N. (2020) 'The determinants of business analytics adoption: does one-size fit all', *Journal of Business Research Turk*, Vol. 12, No. 1, pp.583–598 [online] https://doi.org/10.20491/isarder.2020.864.

ASHE-ERIC (1988) *Organizations and Innovation*, ASHE-ERIC Higher Education Report, April [online] https://doi.org/10.1002/aehe.3640170304.

Azmi, F.T. and Mushtaq, S. (2013) 'Assessing the role of internal and external agents in HRM: scale development and validation', *South Asian Journal of Management*, Vol. 20, No. 3, pp.74–103 [online] https://www.researchgate.net/publication/261172981_Assessing_the_role_of_internal_and_external_agents_in_HRM_Scale_development_and_validation.

Cao, G., Duan, Y. and Li, G. (2015) 'Linking business analytics to decision making effectiveness: a path model analysis', in *IEEE Transactions on Engineering Management*, Vol. 62, No. 3, pp.384–395, https://doi.org/10.1109/TEM.2015.2441875.

Casson, M.C. (1982) *The Entrepreneur: An Economic Theory*, University of Illinois at Urbana-Champa'gn's Academy for Entrepreneurial Leadership Historical Research Reference in Entrepreneurship [online] https://ssrn.com/abstract=1496173.

Chen, H., Chiang, R.H. and Storey, V.C. (2012) 'Business intelligence and analytics: from big data to big impact', *MIS Quarterly*, Vol. 36, No. 4, pp.1165–1188 (accessed 12 January 2021).

Chuang, S.H. and Lin, H.N. (2013) 'The roles of infrastructure capability and customer orientation in enhancing customer-information quality in CRM systems: empirical evidence from Taiwan', *International Journal of Information Management*, Vol. 33, No. 2, pp.271–281.

Churchill, N.C. and Lewis, V.L. (1983) 'Growing concerns – topics of particular interest to owners and managers of smaller businesses', *Harvard Business Review*, May/June, Vol. 61, pp.30–50 (accessed 10 June 2022).

Cronbach, L.J. (1951) 'Coefficient alpha and the internal structure of tests', *Psychometrika*, Vol. 16, pp.297–334 [online] https://dx.doi.org/10.1007/BF02310555.

Davenport, T.H. (2006) 'Competing on analytics', *Harvard Business Review*, Vol. 84, No. 1, p.98.

Davenport, T.H., Harris, J.G., De Long, D.W. and Jacobson, A.L. (2001) 'Data to knowledge to results: building an analytic capability', *California Management Review*, Vol. 43, No. 2, pp.117–138 [online] https://doi.org/10.2307/4116607.

David, K., Pamela, K.P. and Renee, B.F. (2021) *MIT Sloan Management Review and SAS Institute Inc., Analytics Mandate* [online] https://sloanreview.mit.edu/project/analytics-mandate/ (accessed 15 March 2021).

Deloitte Report (2022) *The World Has Changed: Living with Covid-19 Facing Up to Climate Change. Deloitte Annual Report 2021–22* [online] https://www2.deloitte.com/content/dam/Deloitte/uk/Documents/consumer-business/deloitte-uk-travel-weekly-insight-annual-report-2021-22.pdf (accessed 15 December 2022).

Deshpande, P.S., Sharma, S.C. and Peddoju, S.K. (2019) 'Predictive and prescriptive analytics in big-data era', in *Security and Data Storage Aspect in Cloud Computing. Studies in Big Data*, Vol. 52. Springer, Singapore, https://doi.org/10.1007/978-981-13-6089-3_5 (accessed 15 May 2022).

Dias, F.M., Oliveira, M.P.V., Filho, H.Z. and Rodrigues, A.L. (2021) *Analytical Guidance or Intuition? What Guides Management Decisions on the Most Important Customer Value Attributes in the Supermarket Retail?*, April/June (accessed 21 July 2022).

Emory, C.W. and Cooper, D.R. (1991) *Business Research Methods*, Irwin, Homewood.

Field, A. (2000) *Discovering Statistics Using SPSS for Windows*, Sage Publications, London, Thousand Oaks, New Delhi.

Fitz-enz, J. (2010) *The New HR Analytics: Predicting The Economic Value of Your Company's Human Capital Investments*, AMACOM Publisher.

Galbraith, J.R. (1974) 'Organization design: an information processing view', *Interfaces*, Vol. 4, pp.28–36 [online] https://www.jstor.org/stable/25059090.

Gartner, W.P. (1989) 'Who is an entrepreneur? Is the wrong question?', *Entrepreneurship Theory and Practice*, Vol. 12, No. 4, https://doi.org/13. 10.1177/104225878801200401.

Gokalp, M.O., Gokalp, E., Kayabay, K., Gokalp, S., Koçyigit, A. and Erhan, E.P. (2022) 'A process assessment model for big data analytics', *Computer Standards & Interfaces*, Vol. 80, ISSN 0920-5489 [online] https://doi.org/10.1016/j.csi.2021.103585 (accessed 10 April 2023).

Grant, R.M. (1996) 'Prospering in dynamically-competitive environments: organizational capability as knowledge integration', *Organization Science*, Vol. 7, No. 4, pp.375–387.

Grossman, R. and Siegel, K. (2014) 'Organizational models for big data and analytics', *Journal of Organization Design*, Vol. 3, No. 1, pp.20–25.

Gubbi, J., Buyya, R., Marusic, S. and Palaniswami, M. (2013) 'Internet of things (IoT): a vision, architectural elements, and future directions', *Future Generation Computer Systems*, Vol. 29, No. 7, pp.1645–1660, https://doi.org/10.1016/j.future.2013.01.010.

Hair, J.F., Black, W.C., Babin, B.J., Anderson, R.E. and Tatham, R.L. (2008) *Multivariate Data Analysis*, 6th ed., Pearson Education.

Hair, J.F., Black, W.C., Babin, B.J., Anderson, R.E. and Tatham, R.L. (2009) *Multivariate Data Analysis*, 7th ed., Pearson Education.

Holsapple, C., Lee-Post, A. and Pakath, R. (2014) 'A unified foundation for business analytics', *Decision Support Systems*, Vol. 64, pp.130–141.

Holzmann, P. and Gregori, P. (2022) 'Setting the stage for digital sustainable entrepreneurship: a systematic literature review', in *Proceedings of the EURAM 2022 Conference*, Winterthur/Zurich, Switzerland, 15–17 June, pp.1–29.

Johnston, A.C., Warkentin, M., Dennis, A.R. and Siponen, M. (2019) 'Speak their language: designing effective messages to improve employees' information security decision making', *Decision Sciences*, Vol. 50.

Jois, A. and Chakrabarti, S. (2020) 'Freshdesk: bringing in freshness in startup world', *Journal of Information Technology Case and Application Research*, pp.151–156 [online] https://doi.org/10.1080/15228053.2020.1737410 (accessed 21 July 2022).

Jois, A., Chakrabarti, S. and Audrain-Pontevia, A.F. (2022) 'Exploring the impact of consumer satisfaction on the co-creation of a global knowledge brand', *Journal of Consumer Satisfaction, Dissatisfaction and Complaining Behavior*, Vol. 35, No. 1, pp.52–75.

Kaiser, H.F. (1970) 'A second generation little jiffy', *Psychometrika*, Vol. 35, No. 4, pp.401–415 [online] https://doi.org/10.1007/BF02291817.

Kapoor, B. and Kabra, Y. (2014) 'Current and future trends in human resources analytics adoption', *Journal of Cases on Information Technology*, Vol. 16, No. 1, pp.50–59 [online] https://doi.org/10.4018/jcit.2014010105.

Khurana, I., Dutta, D.K. and Singh, G.A. (2022) 'SMEs and digital transformation during a crisis: the emergence of resilience as a second-order dynamic capability in an entrepreneurial ecosystem', *Journal of Business Research*, Vol. 150, pp.623–641 [online] https://doi.org/10.1016/j.jbusres.2022.06.048.

Kiron, D., Prentice, P.K. and Ferguson, R.B. (2014) 'The analytics mandate', *MIT Sloan Management Review*, Vol. 55, No. 4, pp.1–22.

Kohavi, R. and Simoudis, E. (2002) 'Emerging trends in business analytics', *Communications of the ACM*, Vol. 45, No. 8, pp.45–48.

Komm, A., Pollner, F., Schaninger, B. and Sikka, S. (2021) *The New Possible: How HR Can Help Build the Organization of the Future*, March, McKinsey and Company.

Kryscynski, D., Reeves, C., Stice-Lusvardi, R., Ulrich, M. and Russell, G. (2018) 'Analytical abilities and the performance of HR professionals', *Human Resource Management*, Vol. 57, No. 3, pp.715–738 [online] https://doi.org/10.1002/hrm.21854.

Lepenioti, K., Bousdekis, A., Apostolou, D. and Mentzas, G. (2020) 'Prescriptive analytics: literature review and research challenges', *International Journal of Information Management*, Vol. 50, pp.57–70 [online] https://doi.org/10.1016/j.ijinfomgt.2019.04.003.

Liu, S.S., Luo, X. and Shi, Y. (2002) 'Integrating customer orientation, corporate entrepreneurship, and learning orientation in organizations-in-transition: an empirical study', *International Journal of Research in Marketing*, Vol. 9, pp.4367–4382, ISSN: 0167-8116 [online] https://doi.org/10.1016/S0167-8116(02)00098-8.

Macias-Lizaso, G. (2018) *Building an Effective Analytics Organization* [online] https://www.mckinsey.com/industries/financial-services/our-insights/building-an-effective-analytics-organization (accessed 15 December 2021).

Markard, J., Raven, R. and Truffer, B. (2012) 'Sustainability transitions: an emerging field of research and its prospects', *Research Policy*, Vol. 41, No. 6, pp.955–967 [online] https://doi.org/10.1016/j.respol.2012.02.013.

Mitrega, M., Forkmann, S., Ramos, C. and Henneberg, S.C. (2012) 'Networking capability in business relationships – concept and scale development', *Industrial Marketing Management*, Vol. 41, No. 5, pp.739–751 [online] https://doi.org/10.1016/j.indmarman.2012.06.002.

Mohrman, S.A. and Lawler III, E.E. (2004) *Useful Research: Advancing Theory and Practice*, pp.269–287, Berrett-Koehler, San Francisco, CA.

Nam, D., Lee, J. and Lee, H. (2019) 'Business analytics adoption process: an innovation diffusion perspective', *International Journal of Information Management*, July, Vol. 49, pp.411–423 [online] https://doi.org/10.1016/j.ijinfomgt.2019.07.017.

NASDAQ Report (2020) *MX's News Release Distribution Channel* [online] https://www.proquest.com/wire-feeds/predictive-amp-prescriptive-analytics-market-was/docview/2364283216/se-2?accountid=146178 (accessed 21 January 2021).

Navneet, C. (2020) *Factors Influencing Willingness to Adopt Advanced Analytics*, Grant-Dissertation, Cleveland State University.

Neal, S. and David, C. (1998) *Personnel Selection: A Theoretical Approach, Foundation for Organizational Science*, Foundations for Organizational Science, p.392, SAGE Publications.

Netemeyer, R. (2003) 'Scaling procedures: issues and applications introduction to testing & measurement', *Marketing Research*, p.224, SAGE Publications.

OECD Report (2018) 'Going digital in a multilateral world', *Meeting of the OECD Council at Ministerial Level*, 30–31 May [online] http://www.oecd.org/mcm/documents/C-MIN-2018-6-EN.pdf.

Oppermann, F.J., Boano, C.A. and Römer, K. (2014) 'A decade of wireless sensing applications: survey and taxonomy', in Ammari, H.M. (Ed.): *The Art of Wireless Sensor Networks*, pp.11–50, Springer, Berlin, Heidelberg.

Orlikowski, W.J. (1992) 'The duality of technology: rethinking the concept of technology in organizations', *Organization Science*, Vol. 3, No. 3, pp.398–427 [online] https://doi.org/10.2307/2635280.

Pallant, J. (2013) 'A step by step guide to data analysis using SPSS', *SPSS Survival Manual*, 4th ed., Allen & Unwin.

Parida, V., Pesämaa, O., Wincent, J. and Westerberg, M. (2017) 'Network capability, innovativeness, and performance: a multidimensional extension for entrepreneurship', *Entrepreneurship & Regional Development*, Vol. 29, pp.94–115 [online] https://doi.org/10.1080/08985626.2016.1255434.

Parisa, M., Ismail, W.K.W. and Ghobakhloo, M. (2020) 'Big data analytics adoption model for small and medium enterprises', *Journal of Science and Technology Policy Management*, pp.2053–4620 [online] https://doi.org/10.1108/JSTPM-02- 2020-0018.

Paul, M.J., Quentin, L., Pedro, T., Glenn, J.T.L., Gerardine, G.B., Srikanth. M. and Leon, W. (2018) 'A straightforward route to sensor selection for IoT systems', *Research-Technology Management*, Vol. 61, pp.41–50 [online] https://doi.org/ 10.1080/08956308.2018.1495965.

Popovič, A., Hackney, R., Coelho, P.S. and Jaklič, J. (2012) 'Towards business intelligence systems success: effects of maturity and culture on analytical decision making', *Decision Support Systems*, Vol. 54, No. 1, pp.729–739.

Premkumar, G., Ramamurthy, K. and Saunder, C.S. (2005) 'Information processing view of organizations: an exploratory examination of fit in the context of interorganizational relationship', *Journal of Management Information System*, Vol. 22, No. 1, pp.257–294, https://doi.org/10.1080/07421222.2003.11045841.

Ritter, J.M., Boone, W.J. and Rubba, P.A. (2001) 'Development of an instrument to assess prospective elementary teacher self-efficacy beliefs about equitable science teaching and learning', *Journal of Science Teacher Education*, Vol. 12, No. 3, pp.175–198 [online] http://doi.org/10.1023/A:1016747713585.

Rogers, E.M. (1962) *Diffusion of Innovations*, 1st ed., Free Press of Glencoe, New York, OCLC 254636.

Sapp, C., Brabham, D., Antelmi, J., Cook, H., Craig, T., Barot, S., Galli, D., Pal, S., Mohan, S. and Gilbert, G. (2019) *Planning Guide for Data and Analytics*, Gartner Report.

Senaviratna, N.A.M.R. and Cooray, T.M.J.A. (2019) 'Diagnosing multicollinearity of logistic regression model', *Asian Journal of Probability and Statistics*, Vol. 5, No. 2 [online] http://doi.org/10.9734/ajpas/2019/v5i230132.

Sendi, M.S.E., Pearlson, G.D., Mathalon, D.H.F., Ford, J.M., Adrian, P.T.G.M. and Calhoun, V.D. (2020) 'Multiple overlapping dynamic patterns of the visual sensory network in schizophrenia' *Schizophrenia Research*, Vol. 228, pp.103–111, https://doi.org/10.1016/j.schres.2020.11.055 0920-9964.

Shane, S. and Venkataraman, S. (2000) 'The promise of entrepreneurship as a field of research', *Academy of Management Review*, Vol. 25, No. 1, pp.217–226.

Shi-Nash, A. and Hardoon, D.R. (2017) 'Data analytics and predictive analytics in the era of big data', in Geng, H. (Ed.): *Internet of Things and Data Analytics Handbook*, pp.329–345, Wiley. https://doi.org/10.1002/9781119173601.ch19 (accessed 25 May 2021).

Soluk, J., Kammerlander, N. and Darwin, S. (2021) 'Digital entrepreneurship in developing countries: the role of institutional voids', *Technol. Forecast. Soc. Chang.*, Vol. 170, No. 120876, ISSN 0040-1625, https://doi.org/10.1016/j.techfore.2021.12087 [online] https://www.sciencedirect.com/science/article/pii/S0040162521003085

SuccessFactors (2015) *How CHROs Deliver Business Impact* [online] https://hireinsite.com/Articles/CHRO.pdf (accessed 21 February 2021).

Teece, D.J., Pisano, G. and Shuen, A. (1997) 'Dynamic capabilities and strategic management', *Strategic Management Journal*, Vol. 18, No. 7, pp.509–533, Wiley.

Vaaler, P.M. and McNamara, G. (2004) 'Crisis and competition in expert organizational decision making: credit-rating agencies and their response to turbulence in emerging economies', *Organization Science*, Vol. 15, No. 6, pp.687–703.

Vesper, K.H. (1998) 'Entrepreneurial academics – how can we tell when the field is getting somewhere?', *Journal of Business Venturing*, Vol. 3, No. 1, pp.1–10.

Walter, A., Auer, M. and Ritter, T. (2006) 'The impact of network capabilities and entrepreneurial orientation on university spin-off performance', *Journal of Business Venturing*, Vol. 21, No. 4, pp.541–567 [online] http://doi.org/10.1016/j.jbusvent.2005.02.005.

Wong, D., (2012) *Data is the Next Frontier, Analytics the New Tool: Five Trends in Big Data and Analytics, and Their Implications for Innovation and Organisations*, Big Innovation Centre, London.

Yang, S.K., Liu, C.G. and Lee, T.L. (2019) 'An efficient user authentication scheme for multiple accesses scenario in WSN based in IoT notion', *The International Journal of Organizational Innovation*, Vol. 12, No. 3, pp.10–23.

Zadorojniy, A., Wasserkrug, S., Zeltyn, S. and Vladimir, L. (2018) 'Unleashing analytics to reduce costs and improve quality in wastewater treatment', *Journal on Applied Analytics*, Articles in advance, Vol. 49, No. 4, pp.1–7.

Annexure

Scales and items

Scales		*Items*
Analytical transformation	AT1	My company invests in digital infrastructure and facilities for digital operation
	AT2	My company adopts digital technology applications for digital operations
	AT3	My company empowers talented personnel and organisations to achieve digital operation
IPC	IPC1	To what extent do you agree or disagree in your organisation information processing capability is useful
	IPC2	Information processing capability is important
	IPC3	Information processing capability is valuable
DIFR	DIFR1	My company adopts data collection technique
	DIFR2	My company adopts data storage technique
	DIFR3	My company adopts big data processing technique
	DIFR4	My company adopts automatic method to collect data consistency
Networking capability	NC1	Identifying which BP are attractive
	NC2	Build image of a reliable partner
	NC3	Communicate with BP regarding mutual expectations
	NC4	Socialise at networking events
	NC5	Train employees on how to handle conflict with BP
	NC5	Make sure BP understands reason for termination
Analytical centralisation and orientation	AOAC1	My organisation can conduct analytical tasks without the help of the IT team
	AOAC2	Employees in our organisation are familiar with many statistical techniques for data analysis
	AOAC3	Our organisation has the ability to use information faster than our competitors
	AOAC4	Organisation rely on all relevant information regardless of the type of decision to be taken
	AOAC5	In our organisation, decision-making is often based on information rather than experience and intuition
	AOAC6	Organisation making decisions will consider various options in terms of a specific goal