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Leveraging Business Analytics for Operational Efficiency in Small-Scale Manufacturing Enterprises in Tamil Nadu

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ABSTRACT

This study investigates the organisational, technological, environmental, and governance challenges associated with implementing Business Analytics (BA) in small businesses in Tamil Nadu, India. While there are many benefits that business analytics can bring to evidence-based decision-making, process monitoring, forecasting and operational improvement, the adoption of analytics in small and medium-sized enterprises (SMEs) is hampered by a variety of factors, including technological infrastructure, managerial support, analytics talent, environmental conditions and external institutional support. The study is an exploratory quantitative survey involving 221 selected SMEs in the Madurai district, with 200 usable responses. The technology infrastructure capability, management support, talent management challenges, environmental support and government support are discussed as the predictors of BAI. The results of the reported regressions indicate that these factors are positively associated with BAI. The study provides context-specific evidence from Tamil Nadu and emphasises the need for organisational readiness, technological capacity, employee skills and institutional support to create a data-driven SME environment. The study also elucidates that operational efficiency is the primary motivation for adopting BA, and that BAI is the empirically measured dependent construct.

Keywords: Business analytics, infrastructure capability, management challenges, SMEs, technology adoption

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INTRODUCTION

Business Analytics (BA) is a critical capability that organisations must have to transform operational data into information to support informed decision-making, forecasting, process monitoring, and process improvement. This is especially important for small and medium-sized enterprises (SMEs), where time is crucial, and decisions

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need to be evidence-based. Recent studies in manufacturing SMEs (Harno et al., 2024) have found that data-driven analytical systems can support operational management by integrating data collection, dashboards, analytics, and managerial action. Likewise, recent data from manufacturing firms in India show that Industry 4.0 technologies, such as the Internet of Things, AI, and the cloud, are associated with positive operational performance benefits (2025).

Despite these potential benefits, BA is not being implemented uniformly across SMEs. Recent research identifies the following as important drivers of digital and analytics adoption: technological readiness, organisational support, skills, investment constraints, and external pressures. Indian manufacturing small and medium enterprises (SMEs) also indicate that significant investment, return on investment (ROI) issues, and availability of multi-skilled employees are major obstacles to digital transformation (Borana et al., 2026). A study of Indian SMEs also highlights infrastructure, financial resources, government initiatives, implementation complexity, cybersecurity, and data ownership as factors that can limit the adoption of Industry 4.0. These results confirm the importance of studying the organisational and environmental conditions under which BA can be implemented.

The Indian manufacturing setting is further complicated by the fact that SMEs are resource-constrained and under pressure to be more productive, flexible, high-quality, and responsive. Studies of discrete manufacturing SMEs in India indicate that operational measurement and real-time data capture are key priorities for the digital transformation of Indian SMEs: performance data must be captured and analysed before it can be used for manufacturing and design decision-making. The relevance of digital technologies, workforce skills, and readiness conditions is also highlighted in more recent research on the readiness of Indian SMEs for smart manufacturing (Dwivedy et al., 2025). While these studies offer valuable indicators for the country, empirical data on the implementation of BA in small-scale enterprises in Tamil Nadu is still limited. This study addresses this gap by considering five factors of BAI in SMEs in the Madurai district.

The literature also suggests that a more complete way to think about BA is as a component of a larger digital transformation initiative, one that is not just about software. Technology infrastructure provides the technological backbone of data storage, manipulation, connectivity, and analysis; management support provides strategic direction and resources; analytics talent enables the interpretation and use of data; environmental conditions influence external expectations and data-related practices; and government support can reduce obstacles to adoption. The current study thus combines these dimensions to understand the variation in the implementation of BA in small-scale enterprises.

According to Power et al. (2018), business analytics is the systematic analysis of data and the findings, using quantitative, statistical, and related analytical techniques, to support decision-making in a business. Delen and Zolbanin (2018) also position analytics

as a business research paradigm that connects data, analytical techniques, and managerial decisions. In contrast to reporting, BA goes beyond descriptive, diagnostic and predictive analysis to include prescriptive analysis. More recent studies also show that data-driven analytical systems can be developed to enhance operational management in small and medium manufacturing businesses (SMMBs) (Harno et al., 2024).

There is empirical evidence supporting the analysis of technological, organisational, and environmental factors affecting the adoption of analytics. Previous empirical research supports the study of technological, organisational and environmental factors that influence the adoption of analytics. Alaskar (2023) demonstrates that innovation capabilities are important in the relationship between business analytics and firm performance, and Qaffas et al. (2023) provide evidence that analytics talent capabilities can support business-intelligence infrastructure and firm performance. Organisational readiness, external support, top-management support, compatibility, relative advantage, data quality, and complexity are factors identified by Horani et al. (2023) as relevant determinants of BA adoption. Maroufkhani et al. (2023) also demonstrate that the factors influencing the adoption of big data analytics in SMEs are both technology- and organisation-related (Grover et al., 2017). The studies are complementary to the present framework and suggest the importance of context-specific investigation in Indian small-scale enterprises.

The conditions of implementation are important, as reinforced by recent research on digital transformation and Industry 4.0. Indian manufacturing research projects indicate that digital technologies can be instrumental in improving operational performance, though factors such as readiness, skills, infrastructure, finance, and the feasibility of integrating technology into current processes hinder implementation. The recent study on Indian manufacturing organisations has shown a positive correlation between the implementation of Industry 4.0 and operational performance benefits. The 2025 study on Indian SMEs highlighted the importance of technological integration, process optimisation, business agility, and workforce readiness. The findings provide a broader context for the digital transformation of the BA implementation factors explored in this study (Wilder et al., 2015).

Contrary to the common belief that TOE constructs are independent in BDA adoption, this study challenges that assertion. Additionally, it indicates that environmental factors moderate the relationship among technology compatibility, organisational readiness, and management support. It implies that the upper echelons encourage business enablers to adopt BDA in response to technological and environmental forces. According to Maroufkhani et al. (2023), pre-existing models may have exaggerated the extent to which these factors are interlocked and daisy-chain-like in determining BDA adoption.

Organisations need management support on a regular basis, which is consistently cited as critical for the successful adoption of analytics and business intelligence. Sustaining management's commitment can enable organisations to allocate resources, connect

analytics to business goals, motivate employee involvement, and incorporate data-driven approaches into the decision-making process. Similarly, Andar and Kasparova (2024) highlight the significance of continuous management participation in the adoption of business intelligence. This support is particularly needed by SMEs that do not have the luxury of large resources, where decisions regarding budgets, technology, training, and organisational change need to be coordinated to implement analytics.

Technological, organisational and environmental factors interact and influence the adoption of business analytics. Horani et al. (2023) have identified key factors driving BA adoption, and Shahadat et al. (2023) demonstrate that organisational, technological, and environmental factors influence the adoption of digital technology in emerging-economy SMEs. Similarly, existing research on Indian manufacturing SMEs indicates that infrastructure, investments, workforce skills, government support, and implementation barriers are key factors influencing digital transformation (Kumar et al., 2024). Taken together, the results from these studies support a study of technical infrastructure capability, management support, talent-related issues, environmental support, and government support in the current study model.

For SMEs, government and institutional support might be particularly valuable as smaller businesses may be less able to access finance, digital infrastructure, skilled staff, training and technical advice. Government support can influence firms' technology-related decisions (Chundakkadan & Sasidharan, 2023), and recent studies on Indian manufacturing SMEs highlight the need for policy and institutional interventions to address barriers to digital transformation (Borana et al., 2026). In the context of Tamil Nadu, this can range from digital skills development initiatives and technology facilitation to financial support, infrastructure facilitation, and access to innovation ecosystems.

The broader literature also indicates that external assistance can influence the organisation's capacity to use digital technologies responsibly. According to Makhloufi et al. (2023), government support can strengthen the link between analytics-related capabilities, green innovation, and organisational performance. This means that these findings have implications for SMEs, as external institutional support can create circumstances in which analytics investments can more easily be made and are strategically important. But this impact can vary across sectors and adoption phases, underscoring the importance of empirical evidence in specific SME contexts.

Research Questions

This research aims to address the following questions:

1. What is the importance of technical infrastructure capacity on the application of Business Analytics (BA) in India's small-scale industries?

2. To what extent is the use of BA (Business Analytics) in small-scale industries in India influenced by the support of management?
3. What are the effects of the complications of talent development on the use of BA (Business Analytics) in small-scale industries in India?
4. What is the extent of the impact of environmental factors on the use of BA (Business Analytics) in SMALL-SCALE INDUSTRIES in India?
5. How much of an impact does government support have on the application of BA (Business Analytics) in India's small-scale industries?

Definition of Terms

Analytics

In analytics, data is processed methodically so that value can be synthesised from it. It is about extracting, interpreting, and communicating meaningful patterns from data to support decision-making. Analytics can include: Descriptive analytics, which is used to understand data and analyse trend Diagnostic analytics, which helps explain why trends are happening; Predictive analytics that makes a calculated guess at what will happen in future based only on the patterns of past behaviour – for example 80% of people who did a snowboard taster session last time there was a lot of snow went on to book another lesson (Waller et al., 2013); Lastly is: Prescriptive analysis where you try to influence any outcome from occurring (Evans, 2017; Provost & Fawcett, 2013)

Big Data

Big data refers to large, complex datasets that cannot be easily managed, processed, or analysed using traditional tools. Such datasets are known as the "3Vs" of data: Volume (amount of information), Variety (range of information types and sources), and Velocity (speed of generation and processing). Big data enables you to generate insights, improve decision-making, and innovate through advanced analytics and machine learning (Chen et al., 2014; Katal et al., 2013).

Business Analytics

Business Analytics (BA) is the systematic analysis of organisational data using statistical methods, predictive models, and analytical tools to produce information and insights that inform business decisions (Mikalef et al., 2018). It may consist of descriptive analytics to gain insight into past and current performance, diagnostic analytics to understand why performance is as it is, predictive analytics to assess future performance, and prescriptive analytics to suggest actions to improve future performance (Delen & Zolbanin, 2018;

Power et al., 2018). For the purposes of this study, the capability/application domain that is considered an analytical capability is defined as Business Analytics Implementation.

Business Analytics Implementation

Business Analytics Implementation (BAI) is a framework for measuring how well an organisation has embedded analytics into its normal business activities and decision-making processes. Five indicators from a questionnaire are used to operationalise BAI in this research: historical reporting, diagnosis of underlying problems, performance monitoring, forecasting/future prediction, and strategic planning. Answers to each item were rated on a 5-point Likert scale ranging from strongly disagree to strongly agree. The dependent variable in the regression model is the measured composite construct.

Operational efficiency is how well an organisation produces the desired outputs using time, resources, processes, and costs, while maintaining the required level of quality and responsiveness. For the current study, operational efficiency is merely a practical motivation and a supposed organisational benefit of applying BA, and it is not modelled as an independent variable, since the questionnaire and regression model explicitly measure Business Analytics Implementation (BAI). This explanation does not mix up BA implementation with the downstream performance construct.

Technological Infrastructure Capabilities

Technology Infrastructure Capability (TIC) is the availability and sufficiency of hardware, software, networks, cloud computing resources, data storage, analytics applications, and other digital resources that enable an organisation to collect, process, store, communicate, and analyse data. TIC is assessed in this study using five questionnaire questions related to cloud-based data storage and management, data preparation in Excel, Google Analytics, analytics software and data visualisation tools.

Management Support

Management Support (MS) is the support and involvement of senior management in the development, provision and maintenance of BA initiatives. The five measures of MS include: promotion of BA, use of data in decision-making, clarity of BA goals, budget allocation, and collaboration to improve the use of analytics.

Talent Development Complications

Talent Management Challenges (TMC) are challenges and organisational practices related to attracting, developing, keeping and effectively leveraging staff with analytics expertise. The five items measured in this study include the ability to recruit experts, train employees,

retain employees with this skill, make complex information understandable to decision-makers, and communicate effectively. Higher scores thus indicate greater capacity or practices with the instrument items related to the analytics talent; the word "challenge" is retained to maintain consistency with the original model.

Government Support

Government Support (GS) is financial, regulatory, infrastructure, training, information and other institutional support that can support SME capability building and technology adoption. This study employs five items to measure GS, focusing on government support for managerial tools, employee learning, conservation and pollution prevention, sustainable technology information, and an SME's understanding of sustainability (Dubey et al., 2016).

Hypothesis

The research looks to test the following hypotheses:

1. Technical infrastructure capacity does not significantly affect SME business analytics implementation.
2. Management support has not been significant in SME business analytics implementation.
3. Talent development complications have not been significant in SME business analytics implementation.
4. Environmental support has no significant impact on SME business analytics implementation.
5. Government support has not been significant in SME business analytics implementation.

Diffusion of Innovation Theory

In 1903, Gabriel Tarde introduced the concept of diffusion in his book 'The Laws of Imitation'. He proposed that innovations spread through society in a predictable pattern, from technology adopters to the population. Ryan and Gross conducted an empirical study of diffusion innovation in 1943. The significant development in diffusion theory came from Everett M Rogers in 1962, who published the book Diffusion of Innovations, which became the definitive work on the topic. He categorised adopters into five segments: innovators, early adopters, early majority, late majority, and laggards. Today, his theory is one of the most widely used and influential in sociology, marketing, and technology adoption.

According to this theory, prospective adopters assess innovations based on their impressions and decide whether or not to accept them if they believe the innovation to have one or more of five general characteristics: 1. RA-Relative advantage, 2. CLX-complexity, 3. CLP-compatibility, 4. TRI-trialability, and 5. OBS-observability. It is an explanation of

how, why, and at what speed novel concepts and technological advancements proliferate across societies, affecting both people and businesses (Oliveira & Martins, 2011).

This study contributes to the literature by exploring how knowledge management capabilities affect NPD in an entrepreneurial firm in Jordan. It adds knowledge infrastructure capabilities as a necessity for dynamic knowledge capabilities that directly affect product/ service innovation. The original results elaborate on how these diverse factors affect innovation in Jordanian entrepreneurial firms, providing clear evidence of the relationship between knowledge management capabilities and innovation. The analytical results showed that the cultural and technological knowledge infrastructural capabilities were more influential on knowledge dynamic capabilities than the structural knowledge infrastructural capacities (Qandah et al., 2021).

Malaysia's adoption is lower than others, with cloud computing ng accounting for just 3.63% of overall IT expenditure and a growth rate of merely 13.13%. This study aims to determine the mediating roles of top management support and the innovative characteristics and contexts of the Application of the TOE framework in cloud computing adoption in Malaysian SMEs (Kumar et al., 2020; Oliveira et al., 2014). The present study could more precisely identify the relationship between IV and DV, and the results are essential for understanding how to accelerate cloud computing adoption among Malaysian SMEs (Bakar et. al (2020)), with top management support serving as a mediator. This, in turn, can lead to improved business performance. It was finally deduced and proved that top management support significantly mediates the adoption of cloud computing, and that the innovative characteristics of DOI and the TOE contexts drive cloud computing adoption (Teh et al., 2024).

This study sought to use both the TOE and DOI theories to examine what motivates small businesses in Malaysia to adopt GSCM practices. This study found that technological, organisational, and environmental factors may influence whether small businesses adopt GSCM. The statistically significant factors that affect SMEs' plans to adopt GSCM are perceived cost, perceived relative advantage, perceived compatibility, perceived complexity, support from top management, quality of human resources, firm size, regulatory pressure, customer pressure, and environmental uncertainty (Lin et al., 2020).

This study investigates the drivers of blockchain technology adoption in the supply chains of Indian SMEs using the integrated TAM-TOE-DOI framework (Öberg et al.,2016). Relative advantage, compatibility, technology readiness, top management support, and vendor assistance are considerable antecedents that drive the adoption intention. Complexity and cost are the recognised barriers. (Kumar Bhardwaj et al., 2021).

Maroufkhani et al. (2023) have studied the implementation of Business Analytics in SMEs in Iran. While examining the strong roles in implementing business analytics in Iranian SMEs, he concluded that one of them was management support. Environmental

factors in the study had a positive moderating effect on the implementation of business analytics (Nam et al.,2019). Consequently, government support and Business Analytics Implementation had negative effects on SMEs' performance. Adzandeh et al. (2024) conducted the study in 'Makurdi Metropolis', 'Benue State', 'Nigeria'. He established that 'Talent management challenges', technology capability, management support, and environmental factors were strong influences on the implementation of business analytics in Nigeria. The study examined top management support and organisational readiness for Business Analytics Implementation in SMEs in Malaysia, with statistically significant results. (Atan & Mahmood, 2022)

In recent years, business analytics has become a hot topic for making better business decisions using business data. Many companies have started off, but adoption of BA remains limited; few have yet to realise its potential. The available research spectrum reveals a positive link between the diffusion of enterprise systems (ERP, CRM, SCM) and the degree of BA implementation, as well as the development of technological and management ICT competencies, though the latter carries greater weight (Kyriakou et al., 2020).

Bany Mohammed et al. (2024) examine top management support, environmental factors, and talent management challenges that have influenced the use of business analytics in the Jordanian banking sector. He proved that these are strong influences on Business Analytics Implementation in the banking sector.

There are many variables that could affect how businesses implement business analytics, including Processes or circumstances that help an organisation successfully apply business analytics, which are referred to as organisational factors. These include management support, environmental factors, talent management challenges, and technological infrastructure capabilities (Chen et al., 2014; Goss & Veeramuthu, 2013; Kaisler et al., 2013; Singh & Singh, 2012; Wielki, 2013).

RESEARCH METHODOLOGY

This section outlines the study design, target population, sample size and sampling method, data collection tools, validation and reliability of the instruments, data collection procedures, variable or model specifications, and the techniques used for data analysis.

Study Design

The study employs a quantitative, cross-sectional survey design to quantify perceptions of specific organisational and technological constructs and to determine their statistical relationship with BAI. Survey methods should be used to obtain standardised responses from a large but limited number of SMEs and to translate construct indicators into numerical scales for descriptive and inferential analysis. The study is conducted on small business

units in Madurai district, Tamil Nadu, as the district has a diverse base of small businesses across various industries and sectors, making it an apt location to explore the factors influencing the implementation of analytics in small businesses.

Table 1
Population of the study

Business Nature	Population
Individual Business Service	157
Manufacturing Services	178
Leather Industries Service	163
Total	498

Study Area

The study was carried out in Madurai district, the southern part of Tamil Nadu, India. Madurai has a highly diversified base of SMEs, including manufacturing and traditional businesses, which provides a relevant context for understanding how resource constraints and digital competencies affect the implementation of BA. The study is a detailed quantitative examination of the small-scale business units prevalent in the district. This study has surveyed the population.

The study was conducted on 498 small-scale enterprises in Madurai district. Table 1 shows that there were 157 individual businesses/service enterprises, 178 manufacturing enterprises and 163 leather-industry enterprises in the population. The target respondents were owners/managers of the identified enterprises. Table 1 thus defines the population base on which to allocate samples. Table 1 presents the study population.

Sample and Sample Techniques

The sample size was determined using the Taro Yamane approach for a finite, known population, with a conventional margin of error. The population size was 498, and the resulting target sample was 221. Bowley's proportional allocation method was then applied to allocate the sample to the three subsectors, resulting in 70, 78, and 72 respondents being allocated to the three subsectors, respectively. To identify the subsectors, a systematic random sampling procedure was used to select the respondents. The method was selected to provide proportional representation of the study population and to ensure a structured procedure for selecting respondents, as shown in Equation 1:

$$n = \frac{N}{1+N(\mathrm{e})^2} \quad [1]$$

where n is the sample size, N is the population size, and e is the margin of error. Because this technique relies on random sampling, all members have an equal chance of being chosen; thus, the sample is valid.

Thus,

$$n = \frac{498}{1 + 498(0.05)^2}$$

$$n = \frac{498}{1 + 1.25}$$

$$n = 221$$

The population allocation formula developed by Bowley (1964) was utilised to establish the sample size for every SME subsector.

$$nh = \frac{n * Nh}{N}$$

is the formula, in which 'nh' is the sample size for each sector, 'N' is the population size, 'n' is the sample size, and 'Nh' is the population size of the sector.

Individual business Sector

$$nh = \frac{221 * 157}{498} = 70$$

Manufacturing Sector

$$nh = \frac{221 * 178}{498} = 78$$

Leather Industries Sector

$$nh = \frac{221 * 163}{498} = 72$$

Total = 70 + 78 + 72 = 221

A systematic random sampling method was used to select SMEs for examination in each sector type. By using this method, the study can be guaranteed to include all members of the population group.

Data Collection Instrument

The primary data were gathered using a structured questionnaire, with responses scored on a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree. The demographic data were collected in Section A, and the construct items related

to Technology infrastructure capability, Management support, Talent management challenges, Environmental support, Government support, and Business Analytics Implementation were included in Section B. The items on the questionnaire are presented in the Appendix, along with the indicators for the constructs.

Table 2
Data reliability test

Construct	Cronbach's Alpha
Business Analytics Implementation	0.806
Technology Infrastructure Capability	0.744
Management Support	0.807
Environmental Support	0.847
Talent Management Challenge	0.794
Governmental Support	0.813

Validity of Data

The content validity of the instrument was determined through its development based on the study constructs, and the preliminary instrument was reviewed by the research supervisor and the subject/analytics specialists. The review evaluated the representation of the conceptual domains and the wording for the research context. The final instrument, then, maps each construct definition to observable indicators in the questionnaire.

Reliability of Data

Internal consistency reliability was calculated in SPSS version 25 using Cronbach's alpha. This reliability was reported as Cronbach's alpha values for the study's constructs ranging from 0.744 to 0.847, with an overall Cronbach's alpha of 0.920 (Table 2). These are indicators of acceptable internal consistency for this instrument. The reliability coefficients for each construct are reported in Table 2 and should be interpreted in conjunction with the measurement definitions above. The data reliability test is shown in Table 2.

Data Collection Method

This study included Primary data from respondents who took part in the survey. A questionnaire was used to collect data. The questionnaire was completed by the respondent with assistance from a research assistant who had the necessary training.

Model/variable Specification

The conceptual model presented in Figure 1 indicates that the dependent variable is Business Analytics Implementation (BAI), while the independent variables are Technology Infrastructure Capability (TIC), Management Support (MS), Talent Management Challenges (TMC), Environmental Support (ES) and Government Support (GS). This is the visualisation of the hypotheses for the regression analysis in Figure 1. The general multiple linear regression model used is $BAI = \beta0 + \beta1TIC + \beta2MS + \beta3TMC + \beta4ES +$

β5GS + ε, where β0 is the intercept, β1, β2, β3, β4, and β5 are the regression coefficients, and ε is the error term. This model was chosen because the study estimates the concurrent association between several predictors and a single continuous composite outcome.

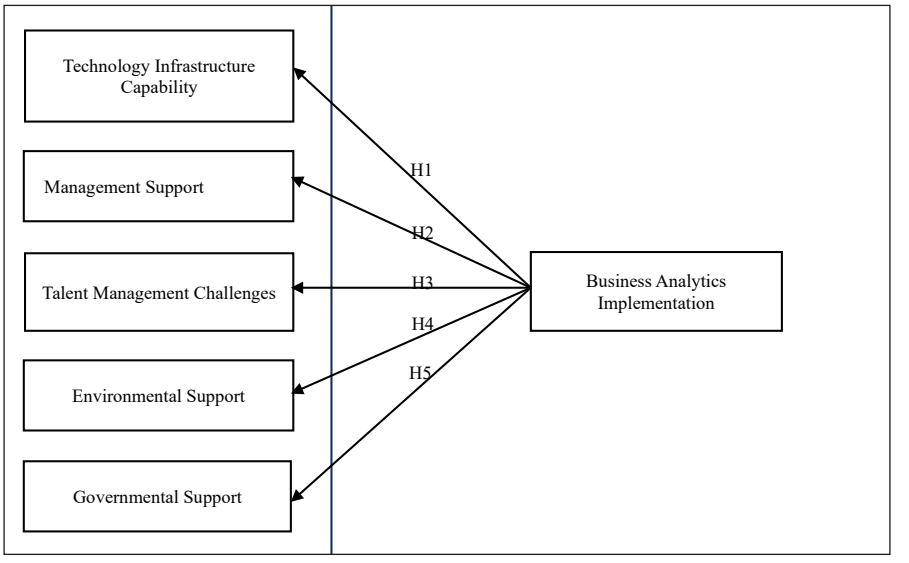


Figure 1. Proposed model

Analysis Techniques

SPSS version 25 was used for data analysis. Descriptive statistics (frequencies, percentages, means, and standard deviations) were used to summarise the characteristics of respondents and their responses at the construct level. Cronbach's alpha was used to assess internal consistency reliability. Multiple linear regression was then used to estimate the joint relationship between the five independent variables (TIC, MS, TMC, ES and GS) and the dependent variable, namely BAI. This is where regression is the appropriate analysis, as there is more than one predictor variable and one dependent variable (a composite construct), enabling it to estimate the unique contribution of each predictor variable while controlling for the others. Model fit was assessed using R, R^2, adjusted R^2, and the ANOVA F-test, while regression coefficients, t-values, and significance levels were used to assess the individual predictors. Statistically significant results at the 5% level ($p<0.05$).

RESULT AND DISCUSSIONS

The targeted sample of 221 respondents was surveyed using a Google Form. Of these, 200 questionnaires were complete and usable (90.5% response/usable data), and 21 were incomplete. The demographic profile of the 200 valid respondents is presented by age, gender and years of experience in Table 3.

Table 3
Demographic attributes of participants

Attribute	Frequency	Percentage (%)
Age: 18–24 years	74	37
Age: 25–34 years	52	26
Age: 35–44 years	38	19
Age: 45–54 years	26	13
Age: Above 55 years	10	5
Age: Total	200	100
Gender: Male	94	47
Gender: Female	97	48.5
Gender: Others	9	4.5
Gender: Total	200	100
Years of Experience: 0–5 years	42	21
Years of Experience: 6–10 years	76	38
Years of Experience: 11–15 years	44	22
Years of Experience: 16–20 years	20	10
Years of Experience: Above 21 years	18	9
Experience: Total	200	100

There is an even gender distribution, with 47.0% of respondents identifying as male, 48.5% as female, and 4.5% as other. According to the experience distribution, the largest percentage of respondents (38%) have 6-10 years of experience, while 22% have 11-15 years of experience. The description results complement the construct-level analysis presented in Tables 4-9.

The entrepreneurs vary in age working years. The largest group (38% of respondents) has between 6 and 10 years' experience. Close behind is 22% with 11 to 15 years of experience. 21% of respondents have worked in their discipline for 0–5 years, and 10% have worked for 16–20 years. A small minority, 9%, have over 21 years of experience.

Descriptive Statistics of Research Attributes

Technology Infrastructure Capability

The responses gathered from the participants for questions 1, 2, 3, 4, and 5 were analysed using means and standard deviations. Table 4 shows that the participants agreed with all statements regarding the impact of technological infrastructure capabilities on BAI (business analytics) implementation in Tamil Nadu State. The means ranged from 3.72 to 4.08, with 2.50 set as the cut-off point.

Table 4
Participants' views on TIC (Technology Infrastructure Capability)

Items	Mean	SD	Results
We utilise cloud-based tools for data storage and management within our organisation.	3.72	1.921	Significant
We use Excel for data entry and cleaning to prepare the information for analysis within our organisation.	3.86	1.753	Significant
We utilise Google Analytics to monitor and gain insights into visitors' behaviour on our websites.	4.08	1.736	Significant
Our organisation employs analytics software to examine our data.	3.86	1.739	Significant
The organisation uses tables, charts, and maps to visualise data when presenting and sharing reports.	3.98	1.733	Significant

Management Support

Means and standard deviations were used to analyse participants' responses to questions 1, 2, 3, 4, and 5. As shown in Table 5, the participants agreed with all statements regarding the impact of MS-Management Support on BA (Business Analytics) implementation in Tamil Nadu State. The means ranged from 3.47 to 4.52, with 2.50 as the cut-off.

Table 5
Participants' views on MS (Management Support)

Items	Mean	SD	Results
The organisation promotes the implementation of a business analytics system within our constituent business units.	3.5	1.868	Significant
Our organisation uses data for decision-making.	4.42	1.753	Significant
Our organisation has a specific and defined objective for the business analytics system.	3.47	1.891	Significant
Our company has a budget set aside for business analytics systems.	4.52	1.716	Significant
Our organisation collaborates with various industries to enhance our utilisation of analytics.	4.51	1.802	Significant

Talent Management Challenges

The responses gathered from the participants for questions 1, 2, 3, 4, and 5 were analysed using means and standard deviations. Table 6 shows that the participants agreed with all statements regarding the impact of talent management challenges on BA (business analytics) implementation in Tamil Nadu State. The means ranged from 4.17 to 4.53, with 2.50 set as the cut-off point.

Environmental Support

Means and standard deviations were used to analyse the responses to questions 1, 2, 3, 4, and 5. As shown in Table 7, most participants agreed with most statements regarding the

Table 6
Participants' views on TMC (Talent Management Challenges)

Items	Mean	SD	Results
Our company hires highly qualified professionals (experts) in data analytics.	4.17	1.656	Significant
We integrate and train new data analytics employees within our company.	4.29	1.66	Significant
We keep current employees to achieve the organisation's business analytics goal.	4.53	1.715	Significant
Our analytics team helps decision-makers understand complex concepts by simplifying them.	4.2	1.716	Significant
Our analytical team possesses excellent communication skills.	4.49	1.709	Significant

Table 7
Participants' view on ES (Environmental Support)

Items	Mean	SD	Results
We communicate with our clients through ICT platforms like social media.	4.54	1.7	Significant
The ethical use of analytics and data protection laws guide our analytical team.	4.55	1.707	Significant
Our organisation safeguards the privacy of our stakeholders.	4.2	1.634	Significant
Our suppliers use data to inform their decisions.	4.57	1.691	Significant
Our company helps build an analytical team in partnership with data analytics vendors.	4.34	1.712	Significant

Table 8
Participants' views on GS (Government Support)

Items	Mean	SD	Results
Government support can equip managers with the tools they need to achieve sustainability.	3.91	1.724	Significant
With government support, workers can learn to be environmentally friendly.	3.72	1.779	Significant
Government support can encourage conservation and pollution prevention efforts.	3.71	1.848	Significant
Government support can provide information on sustainable technology.	3.88	1.731	Significant
Government assistance can help SMEs understand sustainability.	3.81	1.876	Significant

impact of Environmental Support on the implementation of BA (Business Analytics) in Tamil Nadu State. The means ranged from 4.20 to 4.57; the cut-off was set at 2.50.

Government Support

Means and standard deviations were used to analyse the responses to questions 1, 2, 3, 4, and 5. Table 8 reveals that participants have commented positively on most statements

regarding the effect of Government support on the implementation of BA in Tamil Nadu State. Means varied from 3.71 to 3.91, and 2.50 was used as the cutoff point.

Business Analytics Implementation

The means and standard deviations of the responses obtained from the subjects to questions 1, 2, 3, 4 and 5 were computed in the analysis. From Table 9, it is observed that all statements have been accepted by the respondents, thereby making each statement a BA (Business Analytics) implementation indicator in Tamil Nadu State. The range of means was 3.73 to 4.17, and 2.50 was chosen as the cut-off point.

Table 9
Participant's view on BAI (Business Analytics Implementation)

Items	Mean	SD	Results
The adoption of business analytics facilitates organisations in the reporting of historical information.	4.17	1.671	Significant
The utilisation of business analytics by organisations facilitates the examination of the underlying causes of problems.	3.77	1.849	Significant
The implementation of business analytics helps performance monitoring.	3.73	1.819	Significant
The application of business analytics aids organisations in forecasting and developing future predictions.	3.76	1.999	Significant
The implementation of business analytics aids organisations in developing strategic ideas and planning.	3.76	1.822	Significant

Results of Regression Analysis

The model summary, ANOVA table and regression coefficients were reported for results of the regression analysis.

Model Summary

Table 10 presents the model summary. The reported R value of 0.863 indicates a strong positive association between the combined predictors and Business Analytics Implementation. The reported R^2 value of 0.842 indicates that, according to the manuscript's current regression output, the five predictors explain 84.2% of the variance in BAI. Because the numerical regression values are central to the conclusions, the authors should verify Table 10 against the original SPSS output before final submission.

Table 10
Model summary

R	R^2	Adjusted R^2	Standard Error of the Estimate
.863a	0.842	0.83	0.3634

ANOVA (Analysis of Variance):

Table 11 presents the ANOVA results for the regression model. The reported F statistic of 45.914 with $p < 0.001$ indicates that the overall regression model is statistically significant under the reported output. This supports evaluating the five predictors jointly rather than relying only on individual coefficient tests.

Table 11
Analysis of Variance

Source	Sum of Squares	df	Mean Square	F	Sig.
Regression	42.712	5	8.542	45.914	.000b
Residual	36.094	194	0.186		
Total	78.806	199			

Coefficients

Table 12 reports the regression coefficients for the five predictors. Technology Infrastructure Capability has the largest reported standardised beta ($\beta = 0.849$), followed by Government Support ($\beta = 0.205$), Management Support ($\beta = 0.201$), Environmental Support ($\beta = 0.067$), and Talent Management Challenges ($\beta = 0.013$). The direction and significance of each coefficient should be interpreted directly from the verified SPSS output. In particular, the environmental-support and talent-management p-values reported in the table should be checked against their corresponding t-values before publication to ensure exact statistical consistency.

Table 12
Regression coefficients

Predictor	B	Std. Error	Beta	t	Sig.
Constant	0.022	0.31		0.073	0.042
Technology Infrastructure Capability	1.053	0.099	0.849	8.668	0.005
Management Support	0.34	0.103	0.201	2.33	0.008
Talent Management Challenges	0.016	0.097	0.013	2.169	0.004
Environmental Support	0.008	0.109	0.067	1.635	0.032
Government Support	0.048	0.113	0.205	2.553	0.011

Note. DV: Business Analytics Implementation

Hypothesis Test

$H0_1$: Technological infrastructure capabilities do not significantly affect SME business analytics implementation.

The Technology Infrastructure Capability coefficient was used to evaluate the first null hypothesis in Table 12. Based on the reported output, the significance value is less

than 0.05 and thus the null hypothesis is rejected, implying that there is a statistically significant association between Technology Infrastructure Capability and Business Analytics Implementation in the sample of the study.

$H0_2$: Management support has not significant in SME business analytics implementation.

The second null hypothesis was tested with the Management Support coefficient in Table 12. The output reported is less than 0.05 so the null hypothesis is rejected. This indicates that there is a significant relationship between Management Support and Business Analytics Implementation of the SMEs surveyed.

$H0_3$: The challenges encountered with talent management are not substantial in implementing SME business analytics.

The third null hypothesis was tested using the Talent Management Challenges (TMC) coefficient in Table 12. The significance value reported in the manuscript is less than 0.05, which means that the Null Hypothesis is rejected based on the reported regression output. The result shows that the construct of talent is related to BAI in the sample of the study, as verified by the actual p-value in the original SPSS output.

$H0_4$: The environmental factor is not significant in influencing SMEs' adoption of BA.

To test the fourth null hypothesis, the Environmental Support coefficient in Table 12 was used. The reported output shows that the p-value is less than 0.05, which means the null hypothesis is rejected in the current manuscript. However, the t-values and significance value displayed should be numerically consistent, and the exact value p should be rechecked in the SPSS coefficient table prior to submission of the final product.

$H0_5$: Government support does not influence the Business Analytics Implementation in SMEs.

The Government Support coefficient was used to evaluate the fifth null hypothesis, which is presented in Table 12. The reported output shows that the p-value is less than 0.05, so the null hypothesis is rejected. This indicates a significant relationship between Government Support and Business Analytics Implementation among the sampled SMEs.

IMPLICATION AND FUTURE WORK

The findings have implications for practice for managers of SMEs and policymakers. The infrastructure aspect of technology seems to be the key to implementing the BA, suggesting the need for data storage, analytics software, connectivity, and visualisation

tools. Additionally, management support is crucial, as analytics implementation requires strategic alignment, budget allocation, and management encouragement. The talent-related findings emphasise the importance of recruiting, training, retaining, and sharing analytical skills within SME teams. External digital ecosystems, data governance, vendors, training institutions and public programmes are identified as factors that can influence the implementation of BA. From an operations perspective, the practical way forward is to improve the availability, quality, quantity, and accessibility of data to support the five dimensions of operations that are the focus of this study: historical reporting, problem diagnosis, performance monitoring, forecasting, and planning.

In addition, the model highlights the importance of government support in promoting Business Analytics Implementation and could assist policymakers in formulating a large-scale supportive strategy and infrastructure. Therefore, future studies can expand this model to other, larger companies or compare it across regions to validate whether these variables are significant in other regions. The elements proposed in this study could help the government of Tamil Nadu gain insights into the factors that hinder and facilitate BA adoption, as well as devise policies to promote its wider use.

Support mechanisms for policymakers may include programmes for developing digital skills, orientation and technology facilitation programmes, easily accessible infrastructure, advisory support, and incentives to reduce the barriers smaller firms face. Management commitment and development of staff capability should not be viewed as isolated investments for organisations. The evidence from India also suggests that SMEs' investment, infrastructure, skills, and digital readiness pose challenges in the current context, highlighting the need for coordinated organisational and institutional support (Borana et al., 2026; Dwivedy et al., 2025).

For organisations, securing support from leaders and developing talented staff are essential preconditions for successful BA implementation. BA implementation will encounter substantial challenges if it lacks strong managerial support and capable staff, leading to wasted resources and opportunities. Organisations can create internal awareness and training initiatives that promote the value of BA, thereby instigating a culture of data-driven decision-making.

If BA adoption is promoted so that employees engage and are encouraged to see the usefulness of BAs as a tool for improving efficiency and keeping up with competitive pressures, higher acceptance is expected. There’s likely to be a growing push to deploy business analytics across organisations in Tamil Nadu, as businesses are more aware than ever that analytical insights provide a competitive advantage. Both the government and business organisations should develop strategies to describe the benefits of BA in a way that is understood by the organisation and to show support to facilitate implementation. By guiding and working with the organisations, governments and industry, we can create

an ecosystem that enables expansion and sharing of business analytics to drive sustained economic development for Tamil Nadu.

However, the study has certain limitations, such as relying on self-administered questionnaire data, a cross-sectional survey design, and the limited number of small-scale enterprises studied in one District of Tamil Nadu. The conclusions should be applied in the context of the study and not generalised to all Indian SMEs. A series of future studies might expand sampling to other districts and states, compare manufacturing subsectors, employ longitudinal designs, and integrate operational measures such as productivity, lead time, quality, cost, and delivery performance to directly test measurable operational-efficiency gains from the implementation of BA.

CONCLUSION

The study results indicate that Business Analytics Implementation with small-scale enterprises in Tamil Nadu is related to a mix of technological, organisational, environmental and governmental conditions. As per the study objectives, the five constructs, namely, Technology Infrastructure Capability, Management Support, Talent Management Challenges, Environmental Support, and Government Support, were explored as the predictor variables for explaining the BAI, and the regression results reported showed a significant association of the five constructs. The results corroborate the idea that implementing BA need more than just the software - it requires the infrastructure, managerial support, human resources related to the analysis, favourable external conditions, and institutional support. In this study, operational efficiency is understood as a potential downstream effect of BA in addition to being a practical motivation for the adoption of BA.

The study underscores the need for government policy intervention to build technological infrastructure and promote the use of BA amongst SMEs. By eliminating talent management barriers and securing necessary government support, companies will gain more experience applying BA to enhance operational efficiency, innovation, and competitiveness. The report further highlights that the key to creating an environment conducive to business analytics in which it thrives and is widely applied across industries would be the collaboration of businesses with government organisations for greater economic gain for Tamil Nadu.

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