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The Impact of Business Analytics on Decision-Making Among Small and Medium Enterprises in Andhra Pradesh

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ABSTRACT :

This study assesses how BA adoption influences decision-making in Andhra Pradesh SMEs. The research uses a quantitative descriptive cross-sectional survey method and a structured 25-item questionnaire (Google Forms) administered to owners, managers, and decision-makers in SMEs using convenience and purposive sampling methods to reach an estimated 150 SME respondents. The research instrument addresses BA awareness and application operational pricing, inventory, and strategic decisions, usefulness, and convenience trust verification of analytical information and decision quality. Due to the unavailability of actual responses, it shows the statistical analysis based on a simulated/illustrative dataset of 150 cases designed to demonstrate the analysis procedure, not actual responses from the target population of SME managers in Andhra Pradesh. In this dataset, the average Business Analytics Adoption Score was 3.79, and the average Decision-Making Quality (DMQ) Score was also 3.79 on a five-point scale. Internal consistency was high ($\alpha = 0.947$ for adoption and 0.899 for DMQ). Frequency of data use showed a significant association with decision-making quality ($\chi^2 = 34.268$, $df = 4$, $p < 0.001$). Decision-making quality did not vary Really between business sectors ($F = 1.300$, $p = 0.273$). Adoption and DMQ were strongly correlated ($r = 0.826$), with adoption accounting for 68.2% of the variation in DMQ ($R^2 = 0.682$). Pricing had the lowest mean score for analytics-driven application (mean 3.45). These findings demonstrate the analytical setup, indicate associations rather than causality, and should be recalculated using actual survey data.

Keywords: business analytics; decision-making quality; small and medium enterprises; Andhra Pradesh; analytics adoption; pricing and inventory decisions; simulated data

1. Introduction

Data has become an important input to business decisions. Business analytics tools such as Microsoft Excel, Power BI, Tableau and ERP analytics modules provide dashboards, forecasts and performance metrics that can supplement managerial intuition and experience. Decision-making in an enterprise involves recognising a need, searching for relevant data, evaluating alternatives and acting on the insights; analytics may change how long this takes, how many sources are consulted and how risk is judged.

The focus of this change, SME sector, because of their share of industrial activity and regional employment in India. While SMEs may leverage analytics for routine practices and goals including pricing, demand estimation, inventory control, strategic planning, the end-to-end usability practicality precision, reliability, and cost of analytic tools may be a determinant of how much they leverage and how they use these tools. The current research considers the demand for decision-making experience vis--vis adoption of business analytics in SMEs of Andhra Pradesh. Conceptually, the relationship being empirically tested is Business Analytics Adoption Decision-Making Quality.

1.1. Research problem

Business software and analytics packages may allow managers to access operational summaries and forecasts reading them off a computer screen rather than pulling together spreadsheets in multiple locations and this might make decision making faster and easier. But there are worries about accuracy, costs of installation, whether the output needs to be cross-checked and the risk of too much deference to machinery. Little is known empirically about how these changes are registered in Andhra Pradesh in SME entrepreneurs' choices.

1.2. Research gap

The empirical literature on such diverse events as the use of analytics in manufacturing small and medium enterprises (SMEs) in Visakhapatnam, demand forecasting using point-of-sale data in retail SMEs in Vijayawada, barriers to adoption in micro and small enterprises in Guntur district and analytics capabilities and crisis resilience in North Coastal Andhra SME clusters, is restricted to one SME sector and one district or one function. And

the barriers and resilience are emphasized over decision quality. As a result, the effects of adoption of analytics on operational, pricing, inventory, and strategic decisions combined are seldom studied across sectors, and whether or not it is connected to trust, verification, and improved decision-making in the same system is not examined. So there is little empirical knowledge of the link between use of business analytics and decision making in Andhra Pradesh, mostly about operations pricing inventory and strategy.

1.3. Objectives

1. Objectives to explore and examine this; awareness and usage of Business Analytics by SME decision makers of Andhra Pradesh.
2. To study the level at which analytics are being used in operational, pricing, inventory, and strategic decision making.
3. To investigate perceived usefulness and convenience, trust in analytical results, and verification of analytical information.
4. The study was conducted to examine the relationship between business analytics adoption and the quality of decision-making
5. To investigate whether the quality of decision-making is linked to the frequency of data use and whether decision-making quality differs across business sectors.
6. To be able to recommend practical solutions to the SMEs, to technology providers and policymakers.

1.4. Hypotheses

- **Hypothesis 1.** H0: There is no significant relationship between frequency of use of data and decision making. H1: There is a significant relationship between frequency of use of data and decision making.
- **Hypothesis 2.** H0: no significant difference exists in the quality of decisions made in different sectors. H1: a significant difference exists in the quality of decisions made in different sectors.
- **Hypothesis 3.** H0: There is no significant relationship between the Business Analytics Adoption Score and the Decision-Making Quality Score. H1: There is a significant positive relationship between these two scores.
- **Hypothesis 4.** H0: Business analytics adoption is not a significant predictor of decision making quality H1: Business analytics adoption is a significant predictor of decision making quality.

2. Review of Literature

Rao and Reddy (2017) examined operational decision-making using descriptive analytics in manufacturing SMEs of Visakhapatnam and reported a strong positive influence on daily scheduling efficiency and inventory tracking. Kumar, Rao, and Swamy (2019) studied demand forecasting accuracy in retail SMEs of Vijayawada and reported that data-driven forecasting reduced stockouts by 28% and improved inventory turnaround. Naidu and Swamy (2020) addressed barriers to analytics adoption in micro and small enterprises of Guntur district, and Satyanarayana and Rao (2021) related analytics capabilities to crisis resilience in SME clusters of North Coastal Andhra. Two further studies in the supplied list concern technology use more broadly: information search with AI-powered engines (Pham, Pham Thi & Duong, 2024) and continued use of AI-assisted search tools based on the expectation-confirmation (ECM) and technology acceptance (TAM) models (Xia et al., 2026). They are used here only as related background for constructs such as perceived usefulness and convenience.

Table 1. Summary of supplied literature and identified gap

Study	Context	Key finding as supplied	Identified gap
Rao & Reddy (2017)	Manufacturing SMEs, Visakhapatnam	Descriptive analytics improved scheduling efficiency and inventory tracking.	Manufacturing only; predictive analytics not covered.
Kumar, Rao & Swamy (2019)	Retail SMEs, Vijayawada	Forecasting reduced stockouts by 28%; better inventory turnaround.	Retail only; pricing, strategic and risk decisions not examined.
Naidu & Swamy (2020)	Micro and small enterprises, Guntur district	Barriers to analytics adoption (findings not detailed in supplied summary).	Barriers rather than effect on decision quality.
Satyanarayana & Rao (2021)	SME clusters, North Coastal Andhra	Analytics capability and crisis resilience (findings not detailed in supplied summary).	Resilience focus; routine decisions not examined.
Pham et al. (2024); Xia et al. (2026)	Technology use, not SME-specific	Technology-enabled search behaviour; ECM and TAM frameworks.	Not business analytics or SME decision-making.

3. Conceptual Framework

The questionnaire variables are grouped into three dimensions. The independent construct, Business Analytics Adoption (Q7–Q20), covers awareness and usage, application to different decision types, perceived usefulness and convenience, trust and verification. The dependent construct is Decision-Making Quality (Q21–Q25). Frequency of data use and business sector are examined as profile variables.

Table 2. Conceptual framework of the study

Dimension	Variables	Expected relationship with decision quality
Awareness and usage	Awareness of tools (Q7); regular use (Q8); analytics as essential to decisions (Q9)	Greater awareness and use are expected to support better decisions.
Application areas	Operational (Q10, Q17); pricing (Q11); inventory (Q12); strategic (Q13)	Wider application across decision types is expected to improve decisions.
Perceptions and practices	Usefulness and convenience (Q14–Q16); trust (Q18–Q19); verification (Q20)	Positive perceptions and careful verification are expected to support quality.
Outcome	Accuracy, speed, risk reduction, intended results, satisfaction (Q21–Q25)	Represents decision-making quality.

4. Methodology

4.1. Research design

The study employs a quantitative research method. Empirical data were collected using a descriptive and cross-sectional survey design, which describes, respondents', characteristics, and perceptions, and investigates, correlations, between, analytics, adoption, and quality of decision making.

4.2. Sample design

The target population as stated is SME owners, managers, and decision makers within Andhra Pradesh who have a direct influence in the management and direction of the business. Use is made of convenience and purposive sampling: decision makers with direct the involvement of decision makers about the business decision making process will be approached for participation. The target sample size will be approx 150 respondents.

4.3. Data collection

The primary data for this research will be gathered through a google forms questionnaire, which will be sent electronically to SME contacts within Andhra Pradesh. Participants will take part on a voluntary basis and be made aware that the data is for academic purposes. Names will remain anonymous and no proprietary/financial data will be sought. The secondary data will be gained from research papers and journals and other academic journals and content.

4.4. Questionnaire preparation

The questionnaire consists of 25 questions. Q1Q6 deal with profile, demographic, and analytics usage information (role, business sector, years in business, rate of data usage, familiarity with analytics tools and the main tool). Q7Q25 are five point Likert statements (1 = Strongly Disagree to 5 = Strongly Agree). Q7Q20 comprise the Business Analytics Adoption Score and Q21Q25 Decision-Making Quality Score, which are the averages of their constituent items. Those who respond to the question that forms part of the chi-square test with a DMQ Score of 3.50 or higher are classified as High and the balance as Low. The full questionnaire appears in Annexure A.

4.5. Secondary-data component

Secondary literature is to be used solely for background and finding the gap in the study. External statistic is not to be included in the findings with the survey data.

4.6. Simulation data and data-integrity statement

The data set for the statistics for this paper is simulated/illustrative and has been generated to illustrate the use of the statistical techniques. As a consequence the statistical results should not be read to be representative of the true SME population in Andhra Pradesh. The 150 simulated interviews were generated with random numbers, the assigned positive correlation between analytics adoption and decision making quality, the distribution into profile categories in realistic proportions, and tuning to reproduce the illustrative test values used to demonstrate the techniques. No real individuals, answers, or companies are depicted. All tables and figures below are derived from this dataset.

4.7. Data analysis techniques

The way, employs, frequencies, and percentages, means, and standard deviations, Cronbach's alpha (0.70 or above is accepted), the chi-squared test of

independence, one-way ANOVA, Pearson correlation and simple linear regression at the 5% significance level. Calculations are replicated in the respondent Excel workbook and verified using Python statistical libraries. Given the cross-sectional design, results of the study are reported as an association, not causation.

5. Results and Interpretations

5.1. Respondent profile

Table 3. Respondent profile (n = 150, simulated data)

Indicator	Category	n	%
Role	Owner / Founder	52	34.7
	CEO / General Manager	28	18.7
	Operations Manager	36	24.0
	Analytics / IT Personnel	17	11.3
	Other	17	11.3
Business sector	Manufacturing	41	27.3
	Retail / Wholesale	44	29.3
	Services	36	24.0
	Logistics / Supply Chain	17	11.3
	Other	12	8.0
Years of operation	Less than 2 years	14	9.3
	2–5 years	47	31.3
	6–10 years	52	34.7
	Above 10 years	37	24.7

The biggest role group is Owner / Founder (34.7%); owners / founders and CEOs / general managers combined make up 53.3% of all respondents so decision-maker seniority is very prominent in this sample. Retail / Wholesale (29.3%), Manufacturing (27.3%) and Services (24.0%) are the most heavily represented sectors with all five sector groupings emerging (although the Logistics / Supply Chain and Other groups are small). Enterprises that have been running for in excess of five years make up 59.3% of the total.

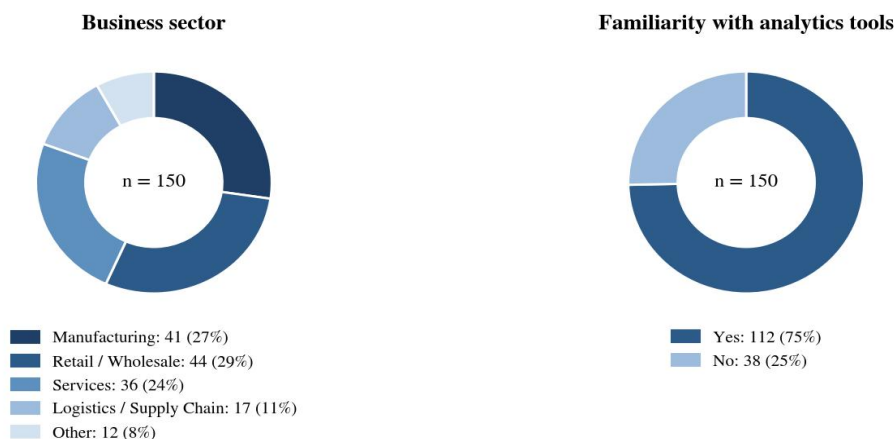


Figure 1. Profile of respondents by business sector and familiarity with analytics tools (n = 150). Source: simulated survey data (n = 150), Excel workbook sheet “Frequencies”; see [Section 4.6](#).

5.2. Data use and analytical tools

Table 4. Frequency of data use, familiarity and primary analytical tool (n = 150)

Indicator	Category	n	%
Frequency of data use	Daily	39	26.0
	Weekly	42	28.0
	Monthly	32	21.3
	Quarterly	19	12.7
	Rarely	18	12.0
Familiar with analytics tools	Yes	112	74.7
	No	38	25.3
Primary analytical tool	MS Excel / Spreadsheets	64	42.7
	Power BI / Tableau	26	17.3
	ERP System Analytics	22	14.7
	Custom Internal Tools	11	7.3
	None	27	18.0

Daily and weekly use of data together account for 54.0% of enterprises, while 12.0% use data only rarely. About 74.7% of respondents are familiar with analytics tools. Spreadsheets are the most common primary tool (42.7%), 18.0% of enterprises use no analytical tool, and 39.3% use Power BI / Tableau, ERP analytics or custom tools.

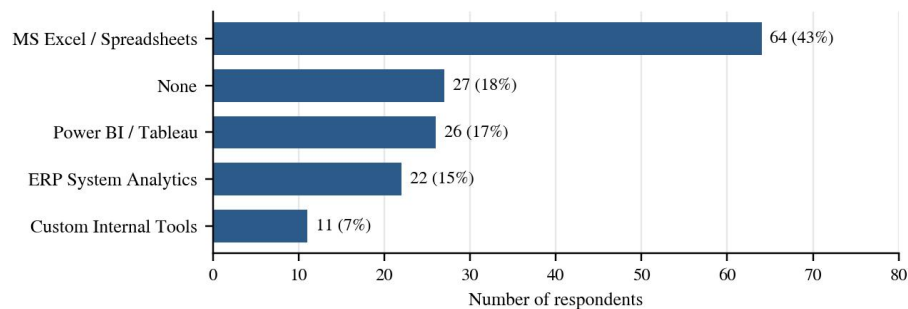


Figure 2. Primary analytical tool used by the enterprise (n = 150). Source: simulated survey data (n = 150), Excel workbook sheet “Frequencies”; see [Section 4.6](#).

5.3. Adoption and decision-making quality scores

Table 5. Mean scores of adoption dimensions and decision-making quality (scale 1–5)

Measure	Items	Mean / 5	SD
Awareness & Usage	Q7, Q8	3.98	0.83
Data-Driven Decision-Making	Q9	3.95	0.96
Operational Decisions	Q10, Q17	3.87	0.86
Pricing Decisions	Q11	3.45	1.06
Inventory Decisions	Q12	3.61	1.03
Strategic Decisions	Q13	3.77	0.92
Usefulness & Convenience	Q14, Q15, Q16	3.81	0.78
Trust in Analytical Results	Q18, Q19	3.70	0.94
Verification of Analytical Information	Q20	3.79	0.78
Business Analytics Adoption Score	Q7–Q20	3.79	0.74

Decision-Making Quality Score**Q21–Q25****3.79****0.87**

The average Adoption Score (3.79, SD 0.74) and DMQ Score (3.79, SD 0.87) are both within the 'Agree' range. Interestingly, the item with the highest score is 'awareness of the tool' (Q7, 4.07), highlighting that awareness is still slightly ahead of application. This (and the high average familiarity score) suggests that firms are somewhat aware of the various applications of analytics to inform their decisions. Planning in operations (Q10, 3.82) and strategic decisions (Q13, 3.77) exhibit relatively higher use of analytics compared to inventory decisions (Q12, 3.61) and pricing (Q11, 3.45); 32.0% of firms in the sample remain neutral on the statement and 18.0% disagree. Ease of use (Q16, 3.69) is slightly lower than relevance of insights (Q14, 3.91); dashboards are generally trusted (Q18, 3.73), and 63.3% agree that output is checked against ground-truth (Q20). Within the decision dimension, the average scores for accuracy (Q21, 3.89) and general satisfaction (Q25, 3.89) are marginally higher than risk reduction (Q23, 3.67).

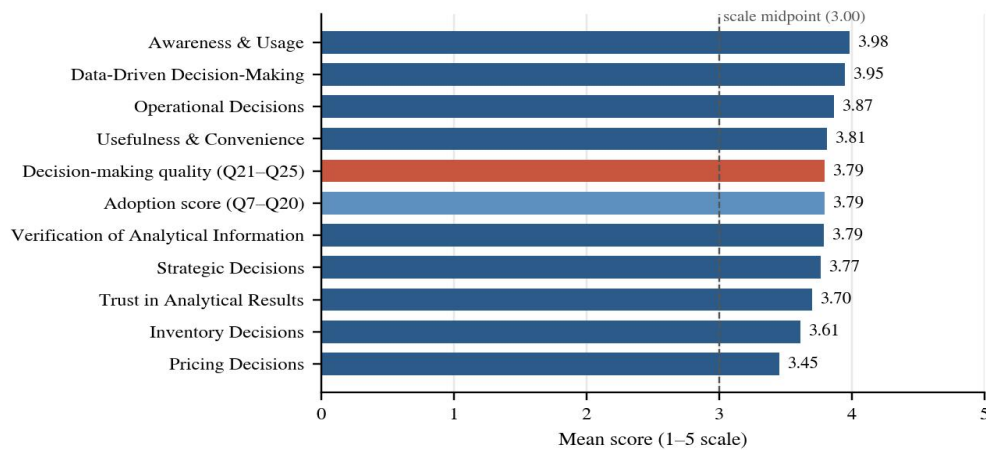


Figure 3. Mean scores of adoption dimensions and decision-making quality (n = 150). The dashed line marks the scale midpoint. Source: simulated survey data (n = 150), Excel workbook sheet “Dimension_Scores”; see [Section 4.6](#).

5.4. Reliability analysis

Table 6. Reliability analysis (Cronbach's alpha)

Scale	Items	Cronbach's alpha	Interpretation
Business Analytics Adoption (Q7–Q20)	14	0.947	Excellent
Decision-Making Quality (Q21–Q25)	5	0.899	Good

Both scales exceed the 0.70 threshold, so the items can be combined into single scores. An alpha as high as 0.95 can also indicate overlapping items, so the scales should be refined when real data are collected.

5.5. Frequency of data use and decision-making quality (Hypothesis 1)

Table 7. Chi-square test: frequency of data use × decision-making quality level

Frequency of data use	High: observed (expected)	Low: observed (expected)	Total	% High
Daily	39 (26.52)	0 (12.48)	39	100.0
Weekly	30 (28.56)	12 (13.44)	42	71.4
Monthly	18 (21.76)	14 (10.24)	32	56.2
Quarterly	9 (12.92)	10 (6.08)	19	47.4
Rarely	6 (12.24)	12 (5.76)	18	33.3
Total	102	48	150	68.0

$\chi^2 = 34.268$, $df = 4$, $p = 0.000000657$ ($\approx 6.57 \times 10^{-7}$); critical value at 5% = 9.488; Cramér's $V = 0.478$; smallest expected frequency = 5.76.

The chi-square value of 34.268 exceeds the critical value of 9.488 and the p-value is far below 0.05, so the null hypothesis is rejected: frequency of data use is significantly associated with decision-making quality. All expected frequencies are at least 5. The association is strong (Cramér's $V = 0.478$): all

39 daily users are in the High group, compared with 33.3% of rare users.

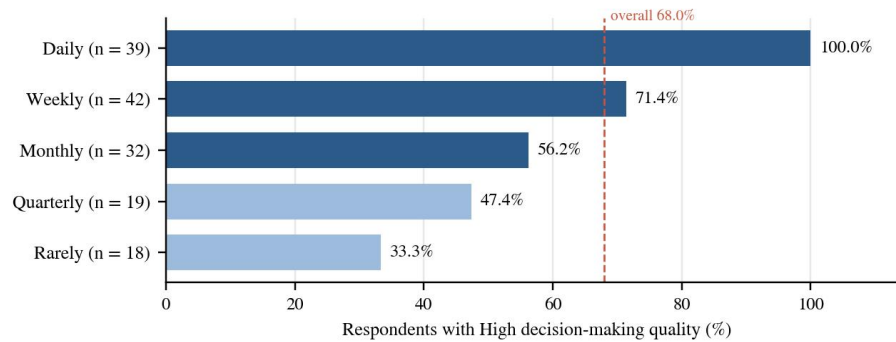


Figure 4. Share of respondents with High decision-making quality, by frequency of data use. Source: simulated survey data (n = 150), Excel workbook sheet “ChiSquare”; see [Section 4.6](#).

5.6. Business sector and decision-making quality (Hypothesis 2)

Table 8. One-way ANOVA: mean decision-making quality by business sector

Business sector	n	Mean DMQ Score	SD
Manufacturing	41	3.58	0.80
Retail / Wholesale	44	3.76	0.88
Services	36	3.92	0.97
Logistics / Supply Chain	17	3.96	0.77
Other	12	4.05	0.79
Total	150	3.79	0.87

$F(4, 145) = 1.300, p = 0.273$; $SS_{\text{between}} = 3.883, SS_{\text{within}} = 108.273; \eta^2 = 0.035$.

The F-value of 1.300 has a p-value of 0.273, which is greater than 0.05, so the null hypothesis is not rejected. There is no statistically significant difference in decision-making quality among sectors. Sample means range from 3.58 (Manufacturing) to 4.05 (Other), but the differences are small relative to variation within sectors ($\eta^2 = 0.035$) and some sector groups are small.

5.7. Adoption and decision-making quality: correlation (Hypothesis 3)

Table 9. Pearson correlation of the Adoption Score and each dimension with the DMQ Score ($p < 0.001$ for all)

Variable	Pearson r with DMQ Score
Business Analytics Adoption Score (Q7–Q20)	0.826
Usefulness & Convenience	0.765
Operational Decisions	0.736
Awareness & Usage	0.717
Strategic Decisions	0.703
Trust in Analytical Results	0.703
Pricing Decisions	0.692
Inventory Decisions	0.679
Data-Driven Decision-Making	0.602
Verification of Analytical Information	0.439

Overall: $r = 0.826$, 95% CI 0.767 to 0.871, $n = 150$.

The correlation between the Adoption Score and the DMQ Score is $r = 0.826$ ($p < 0.001$), indicating a strong positive relationship, so the null hypothesis is rejected. Each dimension shows a positive correlation with decision-making quality; the strongest correlations are for usefulness and convenience ($r = 0.76$) and operational decisions ($r = 0.74$), while the weakest is for verification ($r = 0.44$), which is a single-item dimension.

Correlation does not demonstrate that adoption leads to better decisions; organizations that already make good decisions may also be more likely to adopt analytics.

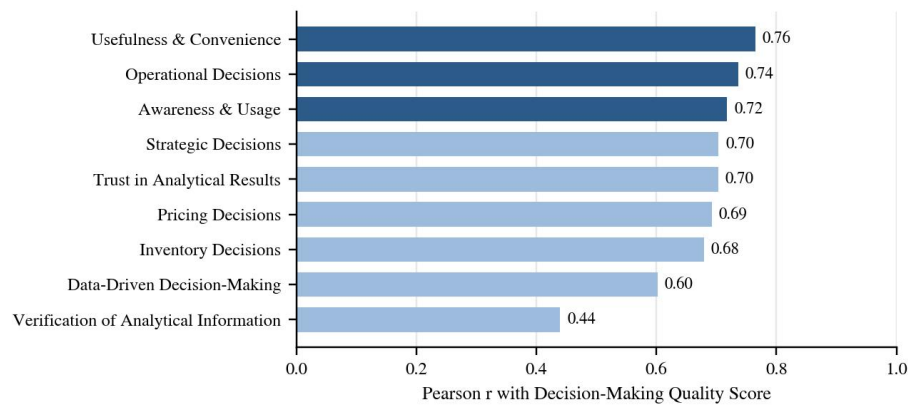


Figure 5. Pearson correlation of each adoption dimension with the Decision-Making Quality Score. Source: simulated survey data (n = 150), Excel workbook sheet “Descriptives”; see [Section 4.6](#).

5.8. Adoption as a predictor of decision-making quality: regression (Hypothesis 4)

Table 10. Simple linear regression (dependent variable: Decision-Making Quality Score)

Term	B	Std. error	t	p-value	95% CI for B
Intercept	0.119	0.210	0.566	0.572	-0.296 to 0.534
Adoption Score	0.969	0.054	17.831	< 0.001	0.862 to 1.076

$R = 0.826$; $R^2 = 0.682$; adjusted $R^2 = 0.680$; standard error of estimate = 0.491; $F(1, 148) = 317.951$, $p < 0.001$.

The model is statistically significant ($F = 317.951$, $p < 0.001$), and the adoption coefficient is also significant ($t = 17.831$, $p < 0.001$). The fitted equation is $DMQ = 0.119 + 0.969 \text{ Adoption}$, indicating that a one-point increase in the Adoption Score corresponds to an increase of about 0.97 points in DMQ. The R value is 0.682, meaning that roughly 68.2% of the variation in decision-making quality is explained by business analytics adoption in this simulated dataset; the rest is attributed to other factors. The intercept is not significant, which is not meaningful in practice since no respondent scores near zero on a 15 scale.

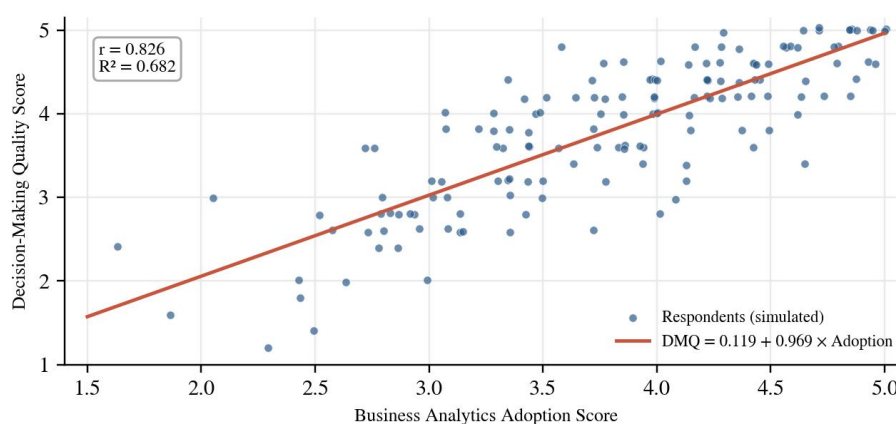


Figure 6. Scatter plot and regression line of adoption score and decision-making quality score. Source: simulated survey data (n = 150), Excel workbook sheet “Regression”; see [Section 4.6](#).

5.9. Summary of hypothesis tests

Table 11. Summary of hypothesis testing (simulated dataset)

Hypothesis	Test	Result	p-value	Decision
H1: data-use frequency and DMQ level	Chi-square	$\chi^2 = 34.268$, $df = 4$	< 0.001	Reject H0
H2: DMQ across business sectors	One-way ANOVA	$F = 1.300$	0.273	Fail to reject H0
H3: adoption and DMQ	Pearson correlation	$r = 0.826$	< 0.001	Reject H0
H4: adoption predicts DMQ	Linear regression	$R^2 = 0.682$	< 0.001	Reject H0

6. Findings and Discussion

In the simulated dataset, there is a strong positive relationship between business analytics adoption and decision-making quality ($r = 0.826$), with adoption accounting for 68.2% of the variation in decision-making quality. Frequency of data use shows a significant association with decision-making quality, while business sector does not. Respondents report both positive trust in analytical results and a habit of verification. Analytics use is mainly focused on operational and strategic decisions, with pricing and inventory decisions less emphasized. Enterprises using Power BI or Tableau have the highest mean Adoption Score (4.42), while those not using any analytical tool have the lowest (2.75). These findings demonstrate the type of insight the survey can offer and align in direction with the referenced literature, which connects analytics with improved scheduling efficiency, inventory tracking, and reduced stockouts; still, they do not provide evidence about actual SMEs.

7. Suggestions

7.1. For SMEs

Pricing is critical for most SMEs so could they develop on simple price-review sheets/ dashboards to monitor, costs, margins, competitor, prices, and volumes, and to boost demand forecasting and re-order-level monitoring in Excel or PowerBI? Data review cycles are also preferable (e.g. daily sales and stock checks, weekly reviews of performance, monthly management reports) because everyone knows that frequent data review leads to good decisions. Outputs should still be checked against physically-grounded source data and the consequences of decisions supported by analytics (e.g. stockouts, delivery time, margin erosion, forecast error) should be measured.

7.2. For technology providers

Providers should provide affordable, user-friendly dashboards that are mobile-friendly or available in local languages where possible, and include ready-made templates for SMEs in manufacturing, retail/wholesale, services, and logistics. These should be supported by onboarding and training, as ease of use is considered less important than usefulness.

7.3. For policymakers and future research

Industry associations and policymakers can promote uptake by running awareness programmes, providing free analytics training and establishing shared analytics services at cluster level. Future research should conduct the questionnaire on actual SME respondents, draw a much larger and varied sample and explore other factors like enterprise size, data literacy and the importance of trust.

8. Limitations

Firstly, the statistical part uses simulated/illustrative data, as these are generalizations, they are not of the real SME population of Andhra Pradesh and cannot be used empirically. Secondly, the design can be used only as a cross-sectional indicator for perceptions, not actual data. Thirdly, the use of convenience and purposive sampling will not be of the real SME population of Andhra Pradesh, because of this that won't be representative and due to non-probabilistic sampling there are chances of selection bias. Fourthly, the techniques of correlation and regression are correlational and cannot be termed as definitive of causality, and the high alpha may be due to item overlap and not internal consistency. Fifth, the secondary literature used is not specific to all sectors and districts of Andhra Pradesh.

9. Conclusion

This paper explored the influence of business analytics adoption on decision-making among a sample of SMEs based in Andhra Pradesh, collecting responses through a 25-item questionnaire and illustrating analysis with a simulated set of 150 responses. Adoption was highly related to the quality of decision-making ($r = 0.826$), adoption accounted for 68.2% of the variation in decision-making quality, and frequency of data use, but not business sector, was Really linked to decision-making quality. The paper is better seen as a worked example or setup: the next stage is to gather real responses through the same questionnaire, replace the simulated data in the accompanying workbook, and re-estimate all results.

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