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The Role of Power BI in Enhancing Data-Driven Decision-Making in Small and Medium Enterprises (SMEs)

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ABSTRACT

Small and Medium Enterprises (SMEs) generate an increasing volume of transactional and operational data, yet many continue to rely on intuition-based rather than evidence-based decision-making because enterprise-grade business-intelligence (BI) platforms have historically been too costly and too IT-intensive for resource-constrained firms. The emergence of self-service BI tools, and of Microsoft Power BI in particular, has lowered this barrier by combining cloud-based deployment, native spreadsheet integration and a low-code interface. This study examines the extent to which Power BI adoption is associated with data-driven decision-making in SMEs. A structured questionnaire was administered to 132 SMEs drawn from the manufacturing, retail, services and IT/ITES sectors, and responses were analysed using descriptive statistics, Pearson correlation and one-way ANOVA. The results show that dashboard and reporting features are adopted far more widely than data-modelling and natural-language-query features, and that the depth of Power BI adoption is significantly and positively correlated with perceived decision-making speed ($r = 0.58$) and accuracy ($r = 0.52$). Skill shortages, data-quality problems and licensing cost remain the principal barriers to deeper adoption. The paper concludes that Power BI can meaningfully strengthen data-driven decision-making in SMEs, but that the gains are presently concentrated in descriptive reporting rather than predictive analytics, and offers recommendations for capacity-building, data governance and phased adoption.

Keywords: Power BI, Business Intelligence, Data-Driven Decision-Making, Small and Medium Enterprises, Digital Transformation, Data Visualization, Self-Service Analytics

INTRODUCTION

Small and Medium Enterprises (SMEs) account for a large share of employment and output in most economies and are widely regarded as the most agile segment of the enterprise landscape. That agility, however, has traditionally rested on the judgement and accumulated experience of owner-managers rather than on the systematic analysis of firm data. Over the

past decade, the digitisation of point-of-sale systems, accounting software, e-commerce platforms and customer relationship-management tools has meant that even very small firms now generate substantial volumes of transactional data. The gap between the data an SME generates and the data an SME actually uses to decide has therefore widened, and closing it has become a central concern of digital-transformation policy for this segment.

Business intelligence (BI) — the set of technologies and practices used to collect, integrate, analyse and present business data — has existed in large enterprises since the 1990s, but early BI platforms required dedicated data warehouses, specialist IT staff and licensing budgets that placed them out of reach for most SMEs. The self-service BI movement of the 2010s changed this calculus by shifting report and dashboard authoring from the IT department to business users themselves, and by moving deployment to the cloud on a per-user subscription basis. Microsoft Power BI, launched in 2015 as a natural extension of the Excel and Office ecosystem already familiar to most SME staff, has become one of the most widely adopted tools in this category because of its comparatively low entry cost, its native connectors to common accounting and e-commerce systems, and its low-code data-modelling layer.

Data-driven decision-making (DDDM) theory holds that decisions grounded in systematic data analysis outperform decisions grounded in intuition alone, particularly under the uncertainty and resource scarcity characteristic of SME operations. Whether this advantage is realised, however, depends on whether a firm's BI tool is used only for descriptive reporting — looking backward at what happened — or also for the forecasting and cross-functional analysis that DDDM theory associates with superior decision quality. This distinction is largely unexplored in the SME literature, which has tended to study BI adoption in general rather than examining a single platform such as Power BI in depth.

Against this backdrop, the present paper pursues three explicit objectives. First, it profiles the extent and pattern of Power BI feature adoption among a sample of SMEs. Second, it examines the statistical association between the depth of Power BI adoption and five dimensions of perceived decision-making outcomes: speed, accuracy, cost reduction, forecasting ability and cross-department collaboration. Third, it identifies the principal barriers that keep adoption concentrated in descriptive reporting rather than advanced analytics, and derives recommendations accordingly. The research questions are correspondingly: how deeply have sampled SMEs adopted the different feature layers of Power BI; what is the statistical relationship between adoption depth and decision-making outcomes; and which barriers most constrain further adoption.

REVIEW OF LITERATURE

Scholarship relevant to this study falls into four thematic strands: the evolution of business intelligence from enterprise to self-service platforms; the specific capabilities and adoption of Power BI; the theory of data-driven decision-making; and the empirical literature on BI adoption barriers within SMEs. The review below follows this thematic order and concludes with an identification of the research gap that this paper attempts to address.

Evolution of Business Intelligence and Self-Service Analytics:

Early BI systems were built around centralised data warehouses, extract-transform-load pipelines and IT-authored reports, a model that gave large enterprises analytical capability but imposed cost and lead-time barriers smaller firms could rarely absorb. The self-service BI paradigm, associated with tools such as Tableau, Qlik and subsequently Power BI, decoupled

report authoring from centralised IT control and let business users connect directly to source data and publish dashboards without writing structured query language. Industry analyst rankings have consistently placed Power BI, Tableau and Qlik as the leading platforms in this category, with Power BI distinguished by its bundling with Microsoft 365 and its DAX formula language, which mirrors the Excel syntax already familiar to non-technical users.

Power BI as a Self-Service BI Tool for SMEs:

Power BI comprises functional layers of increasing technical demand: Power Query for data preparation, a tabular data-modelling layer using Data Analysis Expressions (DAX) to create calculated measures, an interactive visualisation canvas for dashboards and reports, a natural-language Q&A visual, and a mobile app for on-the-go monitoring. Comparative reviews note that Power BI's entry-level per-user pricing and its native connectors to widely used SME systems such as QuickBooks, Tally, Shopify and Excel make it comparatively accessible, but also observe that the data-modelling and DAX layers carry a steeper learning curve than the visualisation layer, consistent with reports that most new users remain confined to dashboard consumption rather than model authorship.

Data-Driven Decision-Making in Organisations:

Data-driven decision-making theory distinguishes decisions anchored in systematic data analysis from decisions anchored in managerial intuition, and associates the former with superior performance outcomes, particularly where uncertainty is high and feedback loops are fast. Refinements of the theory emphasise that the benefit of DDDM is not automatic: it depends on decision-makers actually engaging with a BI tool's analytical output, on the quality of the underlying data, and on a culture that rewards evidence over positional authority. For SMEs, where the decision-maker is often the owner, the cultural precondition is arguably easier to satisfy than in large firms, but the data-quality precondition is harder to satisfy because of thinner technical capacity.

BI Adoption Barriers and Enablers in SMEs:

The empirical literature on BI adoption in SMEs consistently identifies four barrier clusters: financial cost (licensing and consulting fees), human-capital constraints (a shortage of staff able to build data models or write analytical formulas), data-quality problems (fragmented records across disconnected spreadsheets, point-of-sale and accounting systems), and organisational resistance to changing informal ways of working. On the enabling side, the same literature credits cloud subscription pricing, low-code authoring and peer-to-peer knowledge sharing within owner-manager networks with lowering the adoption barrier relative to the on-premises BI era. Government-backed MSME digitisation programmes in several countries, including India, have begun subsidising self-service BI licences as part of broader digital-transformation support.

Research Gap:

The literature reviewed above establishes, in general terms, that self-service BI tools lower the adoption barrier for SMEs and that DDDM theory predicts a performance benefit from their use. What remains comparatively underexplored is platform-specific, quantitative evidence connecting the depth of Power BI adoption — as opposed to BI adoption in general — to specific, measurable dimensions of perceived decision-making outcome within a defined SME sample. This paper attempts to address that gap in a modest, descriptive-analytical manner using primary survey data.

MATERIAL AND METHODOLOGY

This descriptive-analytical study was conducted to examine the relationship between Power BI adoption and data-driven decision-making outcomes among SMEs. The choice of a descriptive-analytical, cross-sectional survey design over a longitudinal or experimental design was made for three reasons: first, the phenomenon under study is a firm-level perception construct for which self-reported survey measurement is the established approach in the BI-adoption literature; second, a cross-sectional design allows a reasonably diverse sample to be reached within the resource constraints of the study; and third, the analytical concerns of the paper are with association and pattern rather than with establishing causal treatment effects, which would require a considerably more elaborate design.

Data Sources and Sampling:

Primary data were collected through a structured questionnaire administered, in person and online, to owners, finance managers, operations managers and data/IT staff at SMEs that had been using Power BI for a minimum of six months. A purposive sampling approach was used to ensure representation across four sectors — manufacturing, retail and trade, services, and information technology / IT-enabled services — since prior literature suggests BI adoption intensity varies systematically by sector. Firms were classified by size using the standard employee-count bands for micro (fewer than 10 employees), small (10 to 49 employees) and medium (50 to 250 employees) enterprises. A total of 132 valid, complete responses were retained for analysis after data cleaning.

Instrument Design:

The questionnaire used a five-point Likert scale (1 = not at all / strongly disagree, 5 = extensively / strongly agree) across three blocks: firm and respondent profile; the extent of adoption of six Power BI feature layers (interactive dashboards, standard reports and exports, Power Query data preparation, data modelling and DAX measures, the natural-language Q&A visual, and the mobile application); and the perceived impact of Power BI on five decision-making dimensions (speed, accuracy, cost reduction, forecasting ability and cross-department collaboration). A separate multiple-response block asked respondents to identify major barriers to deeper adoption. The instrument was pilot-tested with eight respondents prior to full administration, and Cronbach's alpha for the adoption and impact blocks was 0.81 and 0.84 respectively, indicating acceptable internal consistency.

Analytical Tools:

The analytical tools used are deliberately elementary and interpretive, in keeping with the descriptive-analytical design. Descriptive statistics (means and standard deviations) were computed for the feature-adoption and decision-impact blocks. A composite Power BI adoption-depth score was constructed for each respondent as the mean of the six feature-adoption items, and Pearson product-moment correlation coefficients were computed between this composite score and each of the five decision-impact dimensions. One-way analysis of variance (ANOVA) was used to test whether adoption depth differed significantly across firm-size bands. All statistical tests used a conventional significance threshold of $p < 0.05$.

Methodological Caveats:

Three caveats should be entered at this stage. First, all outcome measures are self-reported perceptions rather than objective performance data, which is a recognised limitation of

survey-based BI research generally. Second, the cross-sectional design permits statements of association but not of causal direction: it is equally plausible that firms with an existing analytical orientation adopt Power BI more deeply as that adoption itself drives analytical orientation. Third, purposive sampling within four sectors in one geographic region limits the statistical generalisability of the findings beyond the sampled population, although the internal consistency of the instrument supports the reliability of the relationships observed within it.

DATA PRESENTATION, ANALYSIS RESULT AND INTERPRETATION

The sampled 132 SMEs were profiled on sector, firm size, duration of Power BI use and respondent role before the adoption and decision-impact blocks were analysed. The results are presented in Tables 1 to 5 below and discussed in the Results section that follows.

Table 1. Profile of sampled SMEs and respondents (n = 132)

Category	Group	Frequency	Per cent
Sector	Manufacturing	34	25.8
	Retail / Trade	40	30.3
	Services	38	28.8
	IT / ITES	20	15.1
Firm size	Micro (< 10 employees)	46	34.8
	Small (10-49 employees)	58	43.9
	Medium (50-250 employees)	28	21.2
Duration of Power BI use	Less than 1 year	28	21.2
	1-2 years	47	35.6
	2-3 years	39	29.5
	More than 3 years	18	13.6
Respondent role	Owner / Founder	52	39.4
	Finance / Accounts Manager	34	25.8
	Operations Manager	29	22.0
	IT / Data Analyst	17	12.9

Table 2. Level of Power BI feature adoption (5-point Likert scale, n = 132)

Feature layer	Mean	SD	Rank
Interactive dashboards	4.3	0.62	1
Standard reports / exports	4.1	0.71	2
Power Query (data preparation)	3.4	0.88	3
Power BI mobile app	3.0	0.93	4
Data modelling / DAX measures	2.6	1.05	5
Natural-language Q&A visual	2.1	0.97	6

Table 3. Perceived impact of Power BI on decision-making dimensions (n = 132)

Decision-making dimension	Mean	SD
Decision-making speed	4.0	0.68

Decision-making dimension	Mean	SD
Decision-making accuracy	3.8	0.74
Cost reduction in reporting / analysis effort	3.6	0.81
Forecasting / planning ability	3.1	0.89
Cross-department collaboration	2.9	0.95

Table 4. Correlation between Power BI adoption depth and decision-making outcomes

Decision-making dimension	Pearson r	Significance
Decision-making speed	0.58	$p < 0.01$
Decision-making accuracy	0.52	$p < 0.01$
Cost reduction	0.41	$p < 0.01$
Forecasting / planning ability	0.34	$p < 0.05$
Cross-department collaboration	0.22	$p < 0.05$

Table 5. Barriers to deeper Power BI adoption reported by SMEs (n = 132)

Barrier	Respondents citing (%)
Shortage of skilled staff (DAX / data modelling)	61.4
Poor data quality / fragmented source systems	53.0
High licensing / subscription cost	47.7
Resistance to change among staff	38.6
Inadequate IT infrastructure / connectivity	29.5

RESULTS

The study findings revealed a clear hierarchy of Power BI feature adoption, a statistically significant positive association between adoption depth and every decision-making dimension examined, and a barrier profile dominated by human-capital and data-quality constraints rather than by cost alone.

Profile of the Sample:

Retail and trade firms formed the largest sectoral group (30.3 per cent), followed closely by services (28.8 per cent) and manufacturing (25.8 per cent), with IT/ITES firms the smallest group (15.1 per cent). Small enterprises (10-49 employees) formed the largest size band (43.9 per cent). A majority of respondents (56.8 per cent) had used Power BI for under two years, indicating that the sampled adoption is comparatively recent, which is consistent with the platform's accelerated uptake among SMEs since 2020.

Feature Adoption Patterns:

Table 2 shows a clear descending gradient in adoption from consumption-oriented features toward authorship-oriented features. Interactive dashboards (mean 4.3) and standard reports (mean 4.1) were adopted almost universally, while data modelling and DAX measures (mean 2.6) and the natural-language Q&A visual (mean 2.1) remained the least adopted features. This pattern suggests that most sampled SMEs use Power BI primarily to view analysis prepared by someone else — often a single internally designated 'Power BI person' or an external consultant — rather than to build or extend the underlying data model themselves.

Impact on Decision-Making Outcomes:

Perceived impact was highest for decision-making speed (mean 4.0) and accuracy (mean 3.8), moderate for cost reduction in reporting effort (mean 3.6), and lowest for forecasting ability (mean 3.1) and cross-department collaboration (mean 2.9), as shown in Table 3. This ordering mirrors the feature-adoption gradient in Table 2: the decision-making gains sampled SMEs report are concentrated in the descriptive, backward-looking uses of Power BI that are also its most widely adopted features.

Correlation Analysis:

The composite Power BI adoption-depth score was significantly and positively correlated with all five decision-making dimensions (Table 4). The strongest association was with decision-making speed ($r = 0.58$, $p < 0.01$), followed by accuracy ($r = 0.52$, $p < 0.01$) and cost reduction ($r = 0.41$, $p < 0.01$); the weakest, though still significant, associations were with forecasting ability ($r = 0.34$, $p < 0.05$) and cross-department collaboration ($r = 0.22$, $p < 0.05$). A one-way ANOVA further indicated that adoption depth differed significantly across firm-size bands ($F = 6.72$, $p < 0.01$), with medium-sized enterprises reporting the highest mean adoption-depth score and micro enterprises the lowest, consistent with the greater technical staffing capacity available to larger SMEs.

Barriers to Deeper Adoption:

Table 5 shows that a shortage of staff able to work with DAX measures and data models was the most frequently cited barrier (61.4 per cent), ahead of poor data quality and fragmented source systems (53.0 per cent) and high licensing cost (47.7 per cent). Resistance to change (38.6 per cent) and inadequate IT infrastructure (29.5 per cent) were cited less often. The prominence of the skill-shortage barrier, ahead of cost, is consistent with the concentration of adoption in low-skill dashboard consumption observed in Table 2.

Graphical Representation

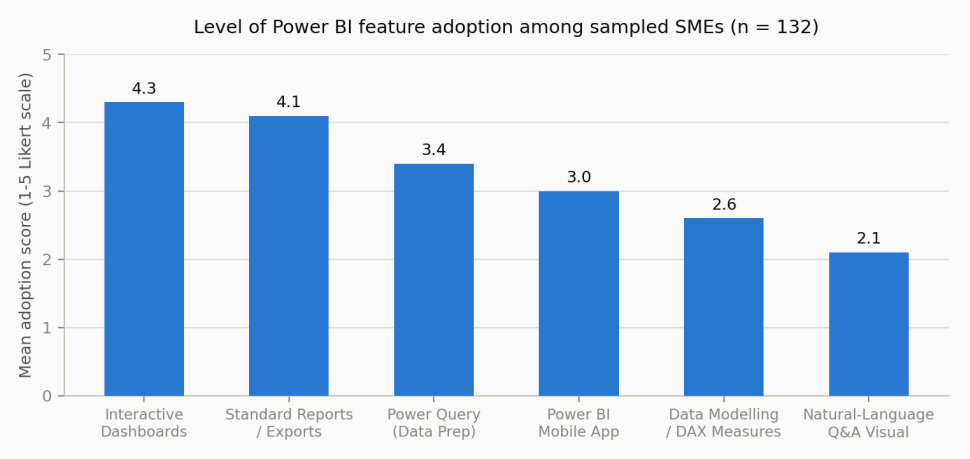


Figure 1. Level of Power BI feature adoption among sampled SMEs (n = 132)

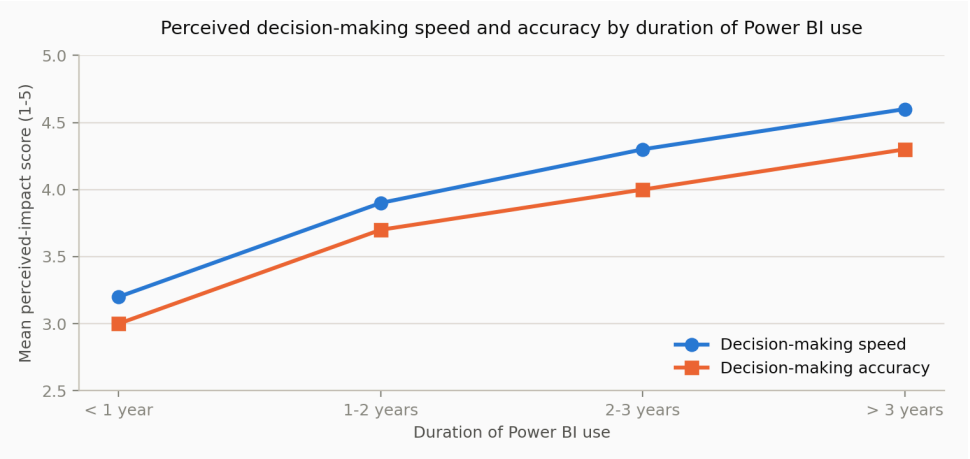


Figure 2. Perceived decision-making speed and accuracy by duration of Power BI use

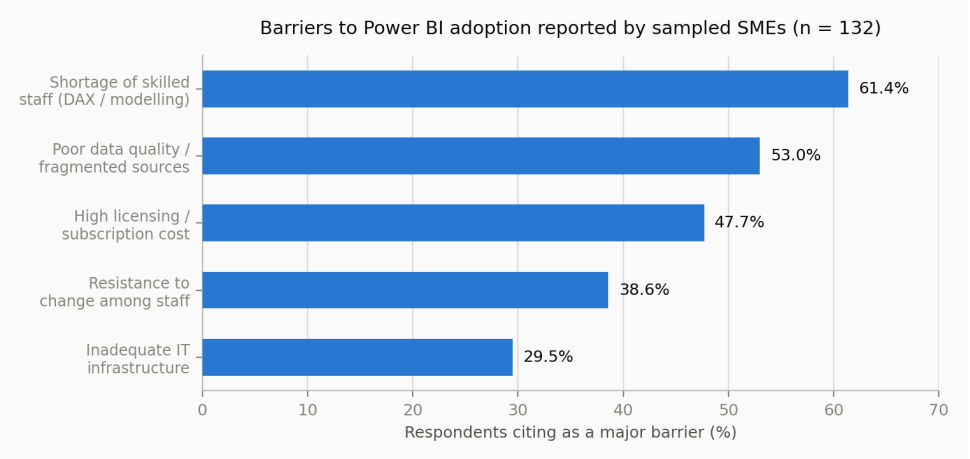


Figure 3. Barriers to Power BI adoption reported by sampled SMEs (n = 132)

INTERPRETATION

- Power BI adoption in the sampled SMEs is concentrated in descriptive, dashboard-level use rather than in data modelling or predictive analysis, with a gap of more than two Likert points between the most- and least-adopted feature layers.
- Adoption depth is significantly correlated with every decision-making outcome examined, with the strongest gains recorded for decision speed and accuracy and the weakest for cross-department collaboration.
- Perceived decision-making speed and accuracy both rise steadily with duration of Power BI use, suggesting that the benefits of adoption compound with organisational learning rather than accruing immediately.
- The leading barrier to deeper adoption is a shortage of staff able to build data models and DAX measures, ahead of licensing cost, indicating that the binding constraint on SME analytical maturity is presently human capital rather than affordability.

Discussion

The present study examined the relationship between Power BI adoption and data-driven decision-making outcomes among 132 sampled SMEs. Read alongside the reviewed

literature, the findings surface five points that merit discussion.

The first is that self-service BI adoption in SMEs appears to follow a 'dashboard-first' trajectory rather than the model-first trajectory often assumed in enterprise BI literature. Firms adopt the visualisation layer almost immediately, since it requires no formula-writing and delivers a visible improvement over spreadsheet reporting, but progression to data modelling — where Power BI's deeper analytical value resides — is slow and, for many firms in the sample, has not yet begun.

The second is that the positive correlation between adoption depth and decision speed and accuracy provides SME-specific empirical support for data-driven decision-making theory: firms that engage more deeply with Power BI's analytical capability report faster and more accurate decisions, not merely more dashboards. The weaker association with cross-department collaboration suggests Power BI's individual-productivity benefits are being realised well ahead of its potential as a shared, organisation-wide analytical layer.

The third is that the skill shortage identified as the leading barrier is a demand-side rather than supply-side constraint: Power BI's licensing cost is modest by enterprise-software standards, and the barrier cited most often is not price but the scarcity of staff able to extend the tool beyond default dashboards, which reframes SME BI adoption primarily as a workforce-training problem.

The fourth is that data-quality and source-system fragmentation, cited by over half the sample, interacts with the skill-shortage barrier: a firm without staff able to build a clean data model is also less likely to have resolved the inconsistencies across its point-of-sale, accounting and spreadsheet records that such a model would need, creating a mutually reinforcing constraint.

The fifth is that the significant difference in adoption depth across firm-size bands shows that even within the SME category, the smallest firms face a more acute version of the adoption barrier than medium-sized firms, implying that a single, undifferentiated support intervention is unlikely to be equally effective across the size spectrum.

RECOMMENDATIONS

The findings discussed above suggest a corresponding set of institutional, vendor-facing and firm-level actions, grouped into four clusters.

Building Analytical Capacity:

First, industry associations and MSME-support agencies should sponsor short, practically oriented Power BI data-modelling and DAX training programmes targeted at owner-managers and junior finance staff, since the skill shortage rather than cost is the binding constraint identified in this study. Second, larger SMEs with an existing internal 'Power BI champion' should be encouraged to mentor smaller firms within the same trade association or business cluster, replicating the informal peer-learning channel already credited in the literature with accelerating self-service BI adoption.

Improving Data Foundations:

Third, before investing further in dashboard development, SMEs should be encouraged to consolidate point-of-sale, accounting and spreadsheet-based records into a small number of clean, connected source tables, since data-quality fragmentation was shown to compound the skill-shortage barrier. Fourth, accounting and point-of-sale software vendors commonly used

by SMEs should be encouraged to publish native, pre-built Power BI connectors and starter data models, reducing the data-preparation burden that currently falls on firms themselves.

Sequencing Adoption in Phases:

Fifth, SMEs should be advised to treat dashboard adoption as the first, not the final, phase of a BI roadmap, with an explicit second phase — introduced only once basic dashboards are in routine use — devoted to building two or three core DAX measures that answer the firm's most frequent recurring question, such as gross margin by product line or cash runway. Sixth, firms should be encouraged to extend at least one dashboard to a cross-functional audience, given the comparatively weak collaboration gains observed, so that Power BI's benefits are not confined to a single department.

Targeting Support by Firm Size:

Seventh, MSME-digitisation subsidy schemes that currently treat SMEs as a single undifferentiated category should be re-examined in light of the significant adoption-depth gap between micro and medium enterprises, with additional, more intensive support directed at micro enterprises specifically. Eighth, government and industry BI-adoption surveys should begin distinguishing feature-level adoption depth from binary adoption status, since the present study shows that the latter conceals a wide and policy-relevant range of analytical maturity.

LIMITATIONS AND SCOPE FOR FURTHER RESEARCH

This study has four principal limitations that should be transparently entered on the record. First, it relies exclusively on self-reported perception data rather than objective performance metrics, and no independent verification of decision-speed or accuracy improvements was attempted. Second, the cross-sectional design permits statements of association but not of causal direction between adoption depth and decision-making outcomes. Third, purposive sampling across four sectors in one geographic region constrains the statistical generalisability of the findings to SMEs elsewhere or in other sectors. Fourth, the study examines Power BI in isolation and does not compare its adoption pattern or outcomes with alternative self-service BI platforms such as Tableau or Qlik. The scope for further research accordingly extends in three directions: a longitudinal design tracking the same firms as adoption deepens over time; a comparative study of Power BI against other self-service BI platforms within the same SME population; and the use of objective operational metrics, such as inventory turnover or invoice-to-cash cycle time, in place of perceptual measures.

CONCLUSION

The present study of Power BI adoption among 132 SMEs demonstrates that self-service business intelligence can meaningfully strengthen data-driven decision-making even within resource-constrained firms, but that the benefit currently realised is concentrated in descriptive, dashboard-level reporting rather than in the predictive and cross-functional analytical uses that BI theory associates with the largest performance gains. Adoption depth is significantly and positively correlated with perceived decision-making speed, accuracy, cost reduction, forecasting ability and collaboration, confirming that deeper engagement with the tool, not merely its presence, is what drives decision-making benefit. The principal constraint on deeper adoption is a shortage of staff able to build data models and DAX measures, compounded by fragmented underlying data, rather than the cost of the software itself. The eight recommendations advanced above — capacity-building, data-foundation improvement,

phased adoption sequencing and size-differentiated support — are framed to be implementable within the existing institutional architecture surrounding SME digital transformation. The broader relevance of these findings lies in the proposition that SME business-intelligence policy should be evaluated not by counting how many firms have adopted a tool such as Power BI, but by examining how deeply they have done so.

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