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Design, Implementation, and Evaluation of a Business Intelligence Dashboard for Key Performance Indicators in a Portuguese Furniture Manufacturing SME

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Abstract

Purpose: The increasing competitiveness in manufacturing sectors demands efficient performance monitoring systems to support strategic decision-making. This study presents the design, implementation, and evaluation of a business intelligence (BI) dashboard for monitoring key performance indicators (KPIs) in a Portuguese furniture manufacturing SME that previously lacked systematic performance monitoring capabilities.

Methodology: Following an action research approach guided by the Plan-Do-Check-Act (PDCA) cycle, the study developed a dashboard in Microsoft Power BI integrating data from eight product categories over three years (2021–2023). Eight KPIs were monitored: sales volume, average selling price, production costs, profit margins, customer complaints, production defects, average production time, and production line efficiency. A pilot inventory control system was also developed to address the complete absence of stock management capabilities.

Findings: The dashboard centralised fragmented data sources and enabled data-driven identification of bottlenecks, quality issues, and pricing opportunities previously invisible to management. Production efficiency improved from 64.7% in 2022 to 98.8% in 2023. However, the analysis also revealed concerning trends: a cumulative 30.8% decline in sales volume between 2021 and 2023 and eroding profit margins across most product categories. The inventory control pilot reduced average foam stock levels by 22% and cut monthly stockout incidents from 4.3 to 1.1, releasing approximately €15,000 in working capital.

Implications: This research offers practical guidance for SME manufacturers undertaking BI implementations, demonstrating that technical deployment alone is insufficient without sustained investment in change management, data governance, and user capability development. It also contributes empirically to the literature, which is predominantly focused on large enterprises, highlighting how resource constraints and organisational dynamics in smaller firms fundamentally shape implementation success.

Keywords: Business Intelligence; Performance Dashboard; Key Performance Indicators; Manufacturing; PDCA Cycle; Furniture Industry; Data Visualization; Decision Support Systems

1. Introduction

Manufacturing organisations today operate under growing pressure to improve efficiency, contain costs, and sustain competitive positions in markets shaped by rapid technological change and increasingly globalised supply chains (Chaudhuri et al., 2011; Chen et al., 2012). These pressures are particularly acute in production environments that span complex processes, multiple product lines, and demanding quality requirements. The furniture manufacturing sector is an especially instructive context for performance management research: it sits at the intersection of traditional craftsmanship and modern industrial production, catering simultaneously to mass-market buyers and higher-end custom segments, which creates distinctive measurement challenges.

Performance measurement has long been recognised as fundamental to organisational success, with scholars and practitioners advocating for systematic approaches to tracking, analysing, and improving business performance (Kaplan & Norton, 1996). However, the rapid proliferation of data sources, coupled with limitations in traditional performance measurement systems, has created a paradoxical situation where organisations are simultaneously data-rich and information-poor (Few, 2004). Many small and medium-sized enterprises (SMEs) struggle particularly to transform raw operational data into actionable insights that inform strategic and tactical decisions (Hódosi et al., 2023).

Business Intelligence (BI) systems have emerged as critical tools for addressing these challenges, offering integrated platforms for data collection, analysis, visualisation, and dissemination (Elbashir et al., 2008; Watson & Wixom, 2007). Modern BI solutions enable real-time monitoring of key performance indicators (KPIs), predictive analytics, and interactive data exploration capabilities that were previously accessible only to large corporations with substantial IT budgets. The democratisation of BI tools, exemplified by platforms such as Microsoft Power BI, Tableau, and Qlik, has created opportunities for SMEs to implement sophisticated performance management systems at relatively modest costs.

Despite the proliferation of BI technologies and success stories from large enterprises, significant gaps remain in understanding how SMEs can effectively implement and benefit from these systems. Research has identified numerous barriers to BI adoption in smaller organisations, including resource constraints, lack of technical expertise, data quality

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issues, organisational resistance to change, and the absence of data-driven cultures (Olszak & Ziemba, 2012). Moreover, the existing literature tends to focus on technical implementation aspects while giving insufficient attention to organisational change management, user adoption challenges, and the inherently iterative nature of dashboard development.

This study addresses these gaps by presenting a detailed case study of dashboard implementation at Paulo S. Antunes Lda., a Portuguese furniture manufacturing company that previously lacked systematic performance-monitoring capabilities. The company produces a diverse range of upholstered furniture, including sofas, armchairs, chairs, beds, bar stools, pouffes, chaise longues, and miscellaneous furniture items. Despite employing approximately 40 workers and generating annual revenues exceeding €1 million, the company operated without integrated performance monitoring systems, relying instead on fragmented data sources and intuitive decision-making approaches.

The study pursued three objectives. First, to design and implement a BI dashboard consolidating performance data across eight product categories and tracking key metrics over three years (2021–2023). Second, to use the PDCA (Plan-Do-Check-Act) cycle as both an implementation framework and a mechanism for ongoing refinement. Third, to develop a pilot inventory control system addressing the company's complete absence of stock management capabilities, as a first step towards integrated supply chain management. Behind these objectives lies a central research question: How can SME manufacturers in traditional sectors effectively implement BI dashboard systems to support data-driven decision-making, and what organisational and technical factors determine the success of such implementations? This question directly addresses a gap in the existing literature, which predominantly documents BI deployments in large enterprises and gives little attention to the SME context, where resource constraints and organisational characteristics fundamentally shape the implementation dynamics.

This paper makes several contributions to both academic literature and managerial practice. Academically, it provides empirical insights into BI implementation processes within SME manufacturing contexts, addressing the often-neglected 'human' aspects of digital transformation alongside technical considerations. The detailed description of the challenges encountered, the solutions developed, and the lessons learned offers valuable guidance for similar organisations embarking on digital transformation initiatives. In practice, the study demonstrates how relatively modest investments in BI technologies can yield significant improvements in operational visibility and decision-making capabilities, while also highlighting realistic expectations for implementation timelines and organisational change requirements.

The remainder of this paper is structured as follows. Section 2 reviews relevant literature on business intelligence, performance dashboards, KPIs, and continuous improvement methodologies. Section 3 describes the research methodology and organisational context. Section 4 presents the dashboard design and implementation process. Section 5 analyses performance data and insights generated by the system. Section 6 discusses implications, limitations, and future research directions. Section 7 concludes the paper.

2. Literature review

Business Intelligence (BI) encompasses a broad range of applications, technologies, and processes for gathering, storing, accessing, and analysing data to help enterprise users make better business decisions (Duan & Xu, 2012). The evolution of BI systems has progressed through several distinct phases, from early decision support systems and executive information systems in the 1970s-1980s, through data warehousing and OLAP (Online Analytical Processing) in the 1990s, to modern self-service BI platforms emphasising visualisation, mobility, and predictive analytics (Chaudhuri et al., 2011).

Research has consistently demonstrated positive relationships between BI system quality and organisational performance outcomes. Elbashir et al. (2008) found that effective BI systems improve organisational performance through enhanced process efficiency, customer satisfaction, and strategic decision-making capabilities. Similarly, Hou (2012) demonstrated that BI system usage positively influences individual job performance and organisational productivity in manufacturing contexts. However, these benefits are not automatic; they depend critically on factors including data quality, system functionality, user capabilities, and organisational support for data-driven decision-making.

The transformation from data to actionable intelligence requires multiple processing stages. Raw operational data must be extracted from diverse sources, cleaned and standardised, integrated into consistent formats, analysed using appropriate techniques, and finally presented in accessible, interpretable forms (Watson & Wixom, 2007). Each stage presents potential failure points that organisations may struggle with, particularly SMEs with limited technical resources and expertise. Data quality issues, incomplete data dictionaries, lack of standardised definitions, and fragmented data sources represent common challenges that must be addressed during BI implementation.

Recent trends in BI emphasise self-service analytics, where business users can independently explore data, create visualisations, and generate insights without extensive IT support (Eckerson, 2011). This democratisation of analytics capabilities represents both an opportunity and a challenge for organisations. While it empowers end users and reduces bottlenecks, it also raises concerns about data governance, analysis quality, and the potential for misinterpretation by users lacking statistical literacy.

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Performance dashboards are specialised BI applications that display critical performance metrics in visual, easily digestible formats (Few, 2004; Malik, 2005). Effective dashboards serve as mission control centres for organisations, providing at-a-glance visibility into key performance drivers while enabling drill-down capabilities for detailed analysis. The dashboard metaphor derives from automobile dashboards, which display essential information in standardised, immediately comprehensible formats, allowing drivers to monitor vehicle performance while focusing primarily on driving tasks.

Eckerson (2011) identifies three primary dashboard types: operational dashboards (monitoring real-time operations), tactical dashboards (analysing trends and patterns), and strategic dashboards (tracking progress toward strategic objectives). Operational dashboards typically require high refresh rates and focus on exception detection, while strategic dashboards may be updated monthly and emphasise trend analysis and goal achievement. The furniture manufacturing dashboard developed in this study combines operational and tactical characteristics, monitoring both real-time production metrics and longer-term performance trends.

Dashboard design principles emphasise information density, visual simplicity, and cognitive efficiency (Few, 2004). Effective dashboards maximise data-to-ink ratios, eliminate chartjunk and unnecessary decorative elements, use colour purposefully rather than decoratively, and organise information hierarchically based on importance and usage patterns. Research in data visualisation has established evidence-based guidelines for chart selection, colour usage, labelling practices, and layout strategies (Malik, 2005).

Despite their potential value, dashboards frequently fail to deliver expected benefits due to poor design, inadequate data quality, lack of user training, or misalignment between dashboard content and actual decision-making needs (Dowding et al., 2014). Common pitfalls include displaying too many metrics (creating information overload), using inappropriate visualisations for specific data types, updating data too infrequently to support decisions, and failing to provide the context necessary for interpretation. Successful dashboard implementations require iterative design processes incorporating user feedback, pilot testing, and continuous refinement.

Key Performance Indicators represent quantifiable measures used to evaluate success in achieving business objectives (Indelicato, 2012). Effective KPIs possess several characteristics: they are quantifiable, directly linked to organisational goals, actionable, regularly monitored, and communicated throughout the organisation. The process of selecting appropriate KPIs requires careful consideration of organisational strategy, competitive context, industry norms, and data availability constraints.

Manufacturing organisations typically monitor KPIs across multiple domains, including quality (defect rates, first-pass yield, customer complaints), efficiency (production cycle time, overall equipment effectiveness, labour productivity), financial performance (profit margins, cost of goods sold, revenue per employee), and customer satisfaction (on-time delivery, order accuracy, net promoter score) (DeNisi & Smith, 2014). The specific mix of KPIs should reflect organisational priorities and strategic emphases, while accounting for resource constraints that limit monitoring capabilities.

Research has demonstrated that effective performance measurement systems share several common characteristics: they align with organisational strategy, balance multiple performance dimensions, include both leading and lagging indicators, remain parsimonious rather than exhaustive, and support learning and improvement rather than mere compliance reporting (Kaplan & Norton, 1996). Organisations must resist the temptation to measure everything measurable, instead focusing monitoring efforts on truly critical performance drivers.

The furniture manufacturing context presents unique measurement challenges due to product diversity, customisation requirements, craft elements in production processes, and variability in material and customer specifications. Unlike highly standardised mass-production environments, furniture manufacturers must balance efficiency with flexibility, quality with speed, and standardisation with customisation. These tensions necessitate careful consideration of which metrics truly capture performance rather than merely what is easily measurable.

The Plan-Do-Check-Act cycle, developed by Walter Shewhart and popularised by W. Edwards Deming, represents a fundamental framework for continuous improvement and quality management (Johnson, 2002). The four-phase cycle involves: planning improvements and establishing objectives, implementing planned changes, checking results against objectives, and acting on lessons learned to standardise improvements or revise plans. PDCA provides a structured yet flexible approach to problem-solving, experimentation, and organisational learning.

Contemporary applications of PDCA extend beyond traditional quality management into diverse domains, including project management, strategic planning, product development, and digital transformation initiatives (Jagusiak-Kocik, 2020). The cycle's simplicity and universality have contributed to its enduring relevance, though effective implementation requires genuine organisational commitment to learning and improvement rather than mere ritualistic adherence to procedures.

In dashboard implementation contexts, PDCA supports iterative development approaches where initial versions are deployed, evaluated, and refined based on user feedback and changing organisational needs (Alves, 2015). This contrasts with traditional waterfall approaches that attempt to specify all requirements upfront, which often proves impractical when users cannot fully articulate their needs until they experience working systems (Zelles et al., 2024). Agile and iterative development methods align naturally with PDCA philosophy, emphasising rapid prototyping, continuous feedback, and incremental improvement.

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Critical success factors for PDCA implementation include management commitment and involvement, employee participation and empowerment, adequate resource allocation, systematic data collection and analysis, and organisational cultures that support experimentation and learning from failures. Organisations that treat PDCA mechanistically, going through the motions without genuine engagement or follow-through, typically fail to realise benefits while potentially generating cynicism about improvement initiatives.

Small and medium-sized manufacturing enterprises face distinct challenges in digital transformation initiatives compared to larger corporations. Resource constraints limit investments in technology and expertise; organisational structures may lack dedicated IT departments; and smaller production scales can make it difficult to justify automation investments (Müller et al., 2018). However, competitive pressures increasingly require digital capabilities, as customers expect shorter lead times, greater customisation, and transparent communication about order status and delivery schedules. Recent evidence suggests that SMEs that successfully embed data-driven practices—even through relatively modest tools—demonstrate measurably greater supply chain resilience and operational adaptability (Alsakhen et al., 2024; Rejeb et al., 2025). Despite this growing body of evidence, a significant research gap remains: the majority of BI implementation studies focus on large enterprises, leaving the specific barriers, success factors, and implementation dynamics within SME manufacturing contexts underexplored. This study directly addresses that gap through an in-depth action research case study in a small Portuguese furniture manufacturer operating under realistic resource and expertise constraints.

Recent research has identified several critical success factors for BI and digital transformation initiatives in SMEs: top management support and championship, clear strategic alignment between technology investments and business objectives, adequate change management and training programs, realistic expectations regarding implementation timelines and resource requirements, and phased implementation approaches that demonstrate early wins while building toward comprehensive solutions (Olszak & Ziemba, 2012; Ramakrishnan et al., 2020).

The COVID-19 pandemic accelerated digital transformation timelines across industries, forcing the rapid adoption of technologies previously considered nice-to-haves rather than essentials. Organisations that had already begun digital transformation initiatives demonstrated greater resilience and adaptability during disruptions, reinforcing business cases for modernisation investments even in uncertain economic conditions (Alsakhen et al., 2024; Priyono et al., 2020). The period 2021–2023, which constitutes the data collection window for this study, represents precisely the post-acute pandemic phase during which companies were simultaneously managing recovery from supply chain disruptions, volatile demand patterns, and accelerated digitalisation pressures. These pandemic-era conditions are particularly relevant when interpreting the sales volume declines and operational efficiency challenges documented in this case, as they reflect a combination of sector-specific issues and broader macroeconomic disturbances whose effects may be difficult to disentangle fully. This context has made decision-makers in SMEs more receptive to BI and performance monitoring investments, though economic uncertainties simultaneously constrain budgets available for such initiatives.

Successful digital transformation requires more than technology deployment; it demands organisational culture change, new skill sets and capabilities, revised business processes, and different approaches to decision-making (Rejeb et al., 2025; Verhoef et al., 2021). Research consistently shows that technical challenges, while significant, are less formidable than human and organisational obstacles, including resistance to change, a lack of digital literacy, fear of job displacement, and inertia favouring familiar approaches over untested alternatives.

3. Methodology

This study employs an action research methodology, which positions the researcher as an active participant in organisational change processes while simultaneously generating scholarly knowledge applicable beyond the specific case (Cruz, 2021). Action research aligns naturally with PDCA philosophy, emphasising iterative cycles of planning, action, observation, and reflection. The first author's role as an employee of the case company facilitated deep access to organisational contexts, challenges, and stakeholder perspectives while also providing opportunities to influence and support implementation processes.

Paulo S. Antunes Lda. operates in the Portuguese furniture manufacturing sector, specialising in the production of upholstered furniture. The company serves both domestic and international markets through furniture retailers and direct-to-consumer channels. Production processes combine traditional craftsmanship with modern manufacturing technologies, including CNC (Computer Numerical Control) machines for frame fabrication, automated cutting systems for textiles and leather, and manual assembly and upholstery processes requiring skilled labour.

At the project's commencement, the company operated without any systematic performance monitoring. Management decisions rested on intuitive judgements, incomplete financial reports, and anecdotal information from production supervisors. The company used an ERP system (PHC software) for basic transaction processing, but data remained fragmented across multiple modules and file formats, making any cross-functional analysis extremely difficult. This situation, while clearly

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problematic, is far from unusual among SMEs in traditional manufacturing sectors where digital transformation has lagged behind larger corporations and more technology-intensive industries.

The dashboard development process began with comprehensive data inventory activities to identify available data sources, assess data quality, and understand existing data structures. This revealed that relevant data existed in multiple locations: the PHC ERP system contained transactional data on sales, purchases, and production; separate Excel spreadsheets maintained by production supervisors tracked time and defect data; and email communications contained customer complaint information never systematically aggregated.

Data extraction proved challenging due to inconsistent terminology and reference codes across systems. Product categories were not standardised, with the same items variously described as 'armchair,' 'lounge chair,' or model-specific codes, depending on the system and the user who created the entries. Extensive manual review and data cleaning were required to establish consistent product categorisations across three years of historical data (2021–2023). The eight final product categories were: bar stools, chairs, beds, chaise longues, miscellaneous furniture (items not fitting other categories), armchairs, pouffes, and sofas.

For each product category, data collection focused on eight key performance indicators: (1) total sales volume in units, (2) average selling price, (3) average production cost, (4) profit margin ratio, (5) number of customer complaints, (6) number of production defects/non-conformities, (7) average production time, and (8) production line efficiency. Not all metrics were available for all time periods; production efficiency metrics, for example, were only systematically tracked beginning in 2022 as part of concurrent improvement initiatives.

Dashboard development followed an iterative process guided by PDCA principles. The Plan phase involved stakeholder workshops to identify information needs, define KPIs, establish data definitions and calculation methods, and specify preliminary dashboard layouts. Management prioritised visibility into profitability by product category, production efficiency metrics, and quality indicators, as these areas lacked systematic monitoring under existing practices.

The Do phase encompassed data extraction, transformation, and loading (ETL) processes; dashboard construction in Microsoft Power BI; and iterative refinement based on preliminary reviews. Power BI was selected for several advantages: relatively affordable licensing, strong integration with Microsoft Excel and other data sources, intuitive interface requiring limited training, and robust visualisation capabilities. Initial development utilised Excel as an intermediate platform for data cleaning before importing into Power BI, though plans envision direct integration with the ERP system.

The Check phase involved testing dashboard functionality with representative users, gathering feedback on usability and information relevance, and verifying data accuracy by comparing it with source documents. Multiple review sessions revealed several design improvements: simplifying initial layouts that displayed too many concurrent metrics, reorganising information hierarchies to prioritise most-used analyses, and adding contextual information (historical trends, targets, benchmarks) necessary for meaningful interpretation.

The Act phase focused on finalising dashboard designs, providing user training, establishing update procedures, and planning ongoing refinement processes. Training emphasised not merely technical dashboard operation but also interpretative skills for translating data into insights and analytical thinking to identify actionable opportunities. Management received additional training in facilitating data-driven discussions and decision-making.

A significant discovery during dashboard planning was the complete absence of inventory control systems. The company maintained no systematic records of stock levels, relying instead on visual inspection and subjective judgments about reorder timing. This created obvious inefficiencies through excess inventory, stockouts, and capital tied up in materials. Addressing this deficiency extended beyond the original dashboard scope but represented a critical foundation for comprehensive supply chain management.

A pilot inventory control system was developed, focusing initially on foam materials (a major cost component in upholstered furniture). The system established minimum stock levels for each foam type based on historical usage patterns, implemented simple tracking procedures for receipts and issues, and created alert mechanisms for reorder points. Implementation utilised Excel-based tools that production staff could easily maintain without extensive training. While rudimentary compared to sophisticated inventory management systems, this represented a substantial improvement over previous practices and demonstrated the feasibility of expanding to other material categories in the future.

4. Results: dashboard implementation and key performance indicators analysis

4.1 Sales volume and revenue trends

Analysis of sales data across the three years revealed concerning volume trends. Total units sold decreased from 2,165 in 2021 to 1,666 in 2022 (-23.0%) and further to 1,499 in 2023 (-10.0% year-over-year), representing a cumulative 30.8% decline over the period. Figure 1 illustrates this downward trajectory, which management had not fully recognised due to a lack of systematic tracking. The decline occurred amid a complex post-pandemic macroeconomic environment characterised

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by inflationary pressures, supply chain disruptions, and shifting consumer demand patterns in the furniture sector, which affected the entire industry during 2022–2023. However, while broader market contractions provide a partial explanation, the observed decline exceeded the estimated industry-average contractions for Portuguese furniture manufacturers over the same period, suggesting that company-specific factors—including product mix decisions, pricing strategy, and limited market reach—played a significant role alongside external conditions. Disentangling pandemic-driven effects from structural company challenges thus requires cautious interpretation, and the findings presented here should be understood within this contextual complexity.

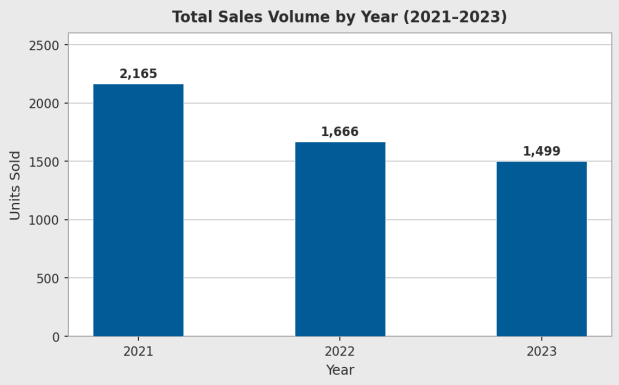

Figure 1. Total Sales Volume by Year (2021–2023)

Product category analysis revealed heterogeneous performance patterns (Figure 2). Chairs consistently accounted for the highest volume across all years (41.9% of 2021 sales, 53.1% in 2022, 40.4% in 2023), though absolute chair sales declined from 906 units (2021) to 606 units (2023). Bar stools demonstrated counter-trend growth, increasing from 162 units (2021) to 257 units (2023), suggesting this category as a potential growth opportunity warranting increased marketing investment. Conversely, chaise longues showed negligible demand (27 units in 2021, declining to 4 units in 2023), raising questions about continued production viability.

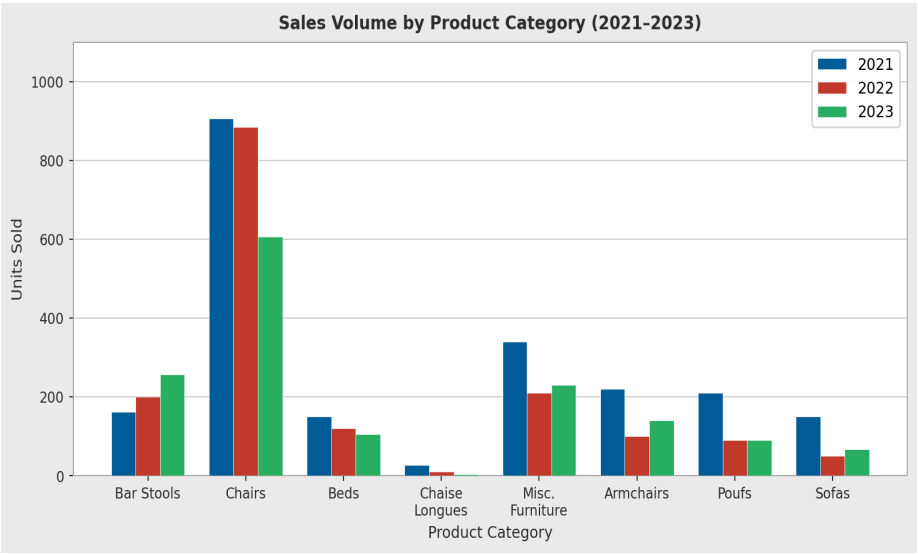

Figure 2. Sales Volume by Product Category (2021–2023)

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Revenue trends presented a more nuanced picture than volume alone. Despite volume declines, total revenue decreased less dramatically: €1,479,257 (2021) to €1,113,403 (2022) to €1,234,125 (2023). The 2023 recovery reflected both mix shifts toward higher-priced items and pricing adjustments. The miscellaneous furniture category consistently generated the highest revenue (€513,348 in 2021, €325,675 in 2022, €351,031 in 2023), despite not being the highest-volume category, indicating that average prices in this category substantially exceed those of other categories (Figure 3).

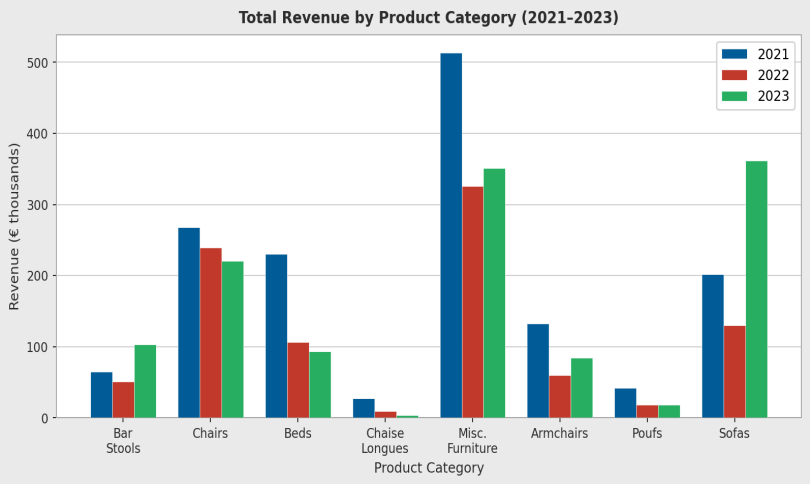

Figure 3. Total Revenue by Product Category (2021–2023)

4.2 Pricing analysis and margin pressures

Average selling prices varied dramatically across categories (Figure 4). Sofas commanded the highest prices (€3,121 in 2021, €2,539 in 2022, €3,259 in 2023), while chairs commanded the lowest (€296 in 2021, €271 in 2022, €363 in 2023). These price differentials reflect differences in complexity, materials costs, and production time requirements. However, price volatility within categories raised concerns about pricing consistency and strategy coherence. For example, average bed prices declined from €1,533 (2021) to €885 (2023), suggesting either a shift in the mix toward lower-end models or pricing pressure from competition.

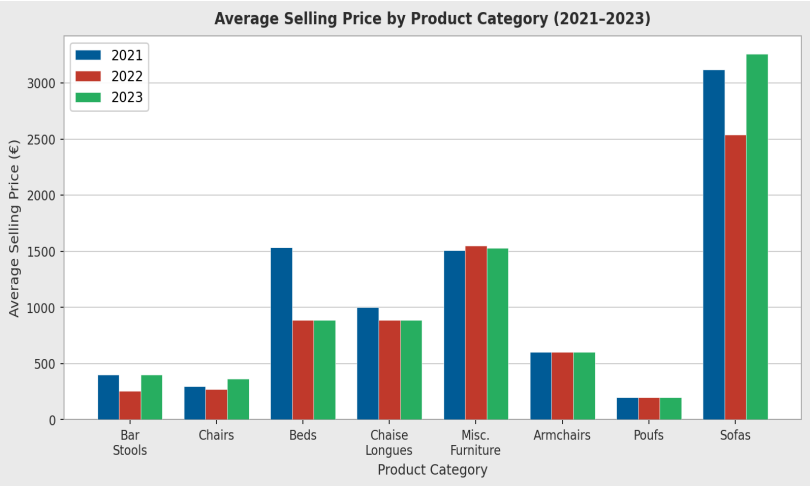

Figure 4. Average Selling Price by Product Category (2021–2023)

Profit margin analysis revealed problematic trends (Figure 5). The company set a target markup ratio of 2.1× (selling price to production cost) across all categories. In 2022, only beds achieved this target (2.84× ratio). By 2023, no categories met the target, and several experienced substantial margin compression. Bar stools declined from 1.94× (2022) to 1.21× (2023), while beds fell from 2.84× to 1.11×. Only miscellaneous furniture approached target levels (2.02× in 2023), though still falling short.

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These margin pressures stemmed from multiple sources. Production costs increased due to materials inflation and labour cost escalations. However, competitive pressures limited pricing flexibility, particularly in high-volume categories like chairs, where price sensitivity appears greatest. The dashboard enabled identification of categories where pricing adjustments might be feasible without excessive volume impacts, though implementation requires careful market testing to avoid accelerating volume declines.

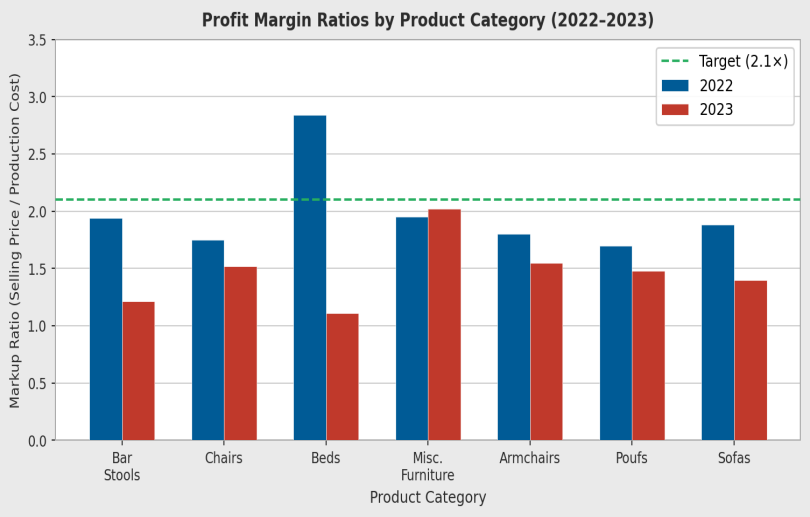

Figure 5. Profit Margin Ratios by Product Category (2022–2023)

4.3 Production efficiency improvements

Production efficiency metrics, first systematically tracked in 2022, showed remarkable improvement trajectories (Figure 6). The efficiency metric compared actual production time allocation against standard times established through work studies. Initial 2022 performance of 64.7% (against a 75% target) reflected both genuine inefficiencies and data-quality issues as workers adapted to systematic time-tracking. Contributing factors included high workforce turnover in 2022, inadequate training of new employees, and incomplete time reporting.

By 2023, efficiency improved to 98.8% against a revised target of 98.5%, representing a 34.1 percentage-point improvement. This dramatic enhancement resulted from multiple interventions informed by dashboard insights: targeted training programs to address identified skill gaps, revised workflow layouts to reduce material handling, investments in specialised tooling for high-volume items, and strengthened accountability for time-reporting accuracy. The efficiency gains translated into tangible cost reductions, though precise quantification proved difficult due to simultaneous changes in product mix and materials costs.

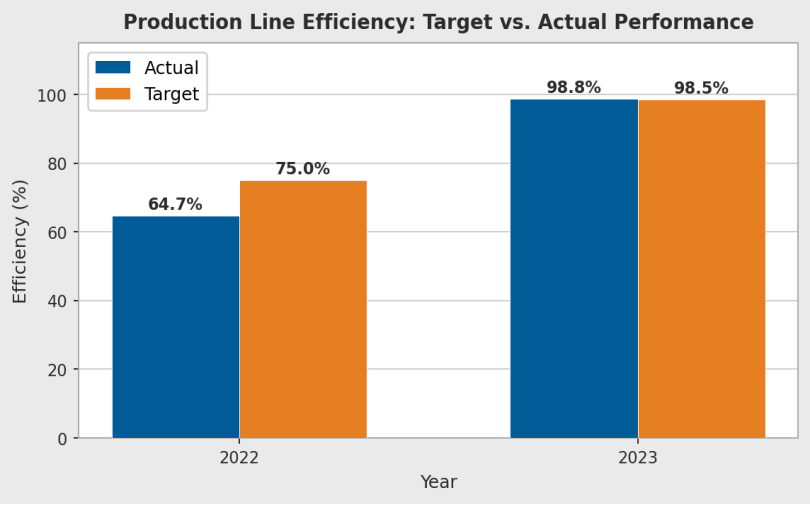

Figure 6. Production Line Efficiency: Target vs Actual Performance

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Analysis of production time by category revealed significant variation and opportunities for improvement. Sofas required the longest average production time (3,503 minutes in 2021, increasing to 3,852 minutes in 2023), reflecting their size, complexity, and customisation options. Some categories demonstrated improved times (pouffes declined from 882 minutes in 2022 to 561 minutes in 2023), while others worsened (miscellaneous furniture increased from 1,170 minutes in 2021 to 1,561 minutes in 2023). These patterns suggested opportunities for process standardisation, improved component prefabrication, and the potential outsourcing of complex frames to specialised suppliers with CNC capabilities.

4.4 Quality metrics and customer satisfaction

Non-conformity tracking revealed quality challenges concentrated in specific categories (Figure 7). In 2021, miscellaneous furniture accounted for 58 of 65 total non-conformities (89%), suggesting systematic issues in this heterogeneous category. By 2022–2023, quality issues became more widespread, with chairs (27 and 17 non-conformities, respectively) and miscellaneous furniture (17 and 21, respectively) representing the primary problem areas. Root cause investigations revealed that chair quality issues stemmed from a specific fabric supplier whose materials failed to meet specifications. At the same time, miscellaneous furniture problems reflected the category's inherent variety and less standardised production processes.

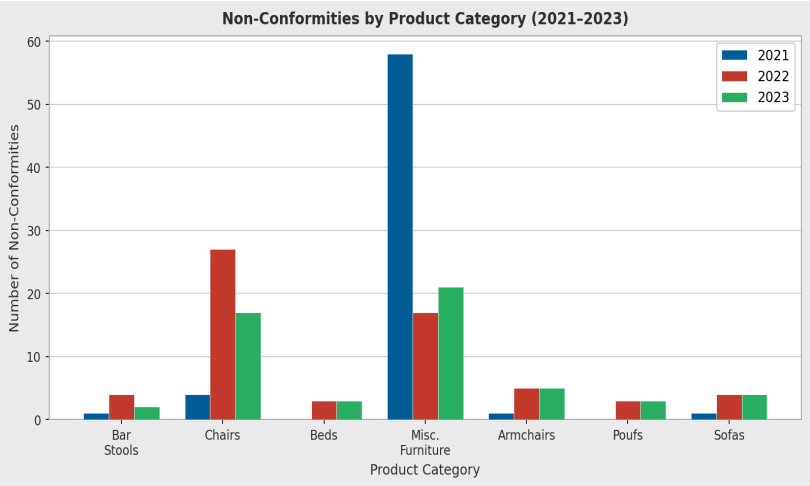

Figure 7. Non-Conformities by Product Category (2021–2023)

Customer complaint trends showed initial increases followed by stabilisation (Figure 8). Complaints rose from 23 (2021) to 66 (2022) before declining to 53 (2023). The 2022 spike coincided with workforce turnover and training challenges, production efficiency struggles, and supply chain disruptions affecting materials quality. Approximately 60% of complaints related to delivery delays, 25% to quality defects, and 15% to order errors or miscommunications. The dashboard enabled tracking complaint resolution times and identifying patterns (e.g., specific delivery routes with persistent delays), facilitating targeted interventions.

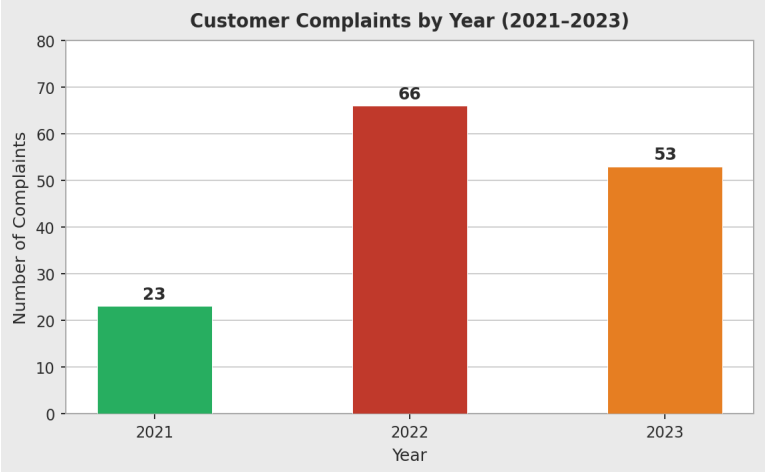

Figure 8. Customer Complaints by Year (2021–2023)

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4.5 Inventory control pilot results

The pilot inventory control system for foam materials demonstrated the feasibility and benefits of systematic stock management. Before implementation, foam inventory values fluctuated unpredictably, leading to periodic stockouts that caused production delays and excessive quantities of slow-moving types tying up capital. The simple tracking system established minimum and maximum levels for each foam density and thickness combination, with reorder points triggering at 125% of the minimum levels to account for lead times.

After six months, average foam inventory levels decreased by 22%, while stockout incidents declined from an average of 4.3 per month to 1.1 per month. Capital released from excess inventory approximated €15,000, which management could redirect toward faster-moving materials or other business needs. Production planning improved as staff gained visibility into material availability, reducing last-minute sourcing at premium prices. These results provided compelling evidence in support of expanding to other material categories and of eventual integration with the ERP system.

5. Discussion

5.1 Summary of key performance findings

Table 1 provides a consolidated overview of the key performance indicators tracked across the three-year study period, facilitating comparison of trends across the eight product categories and performance dimensions analysed in sections 4.1–4.5.

Table 1. *Summary of key performance indicators across the study period (2021–2023). ↑ denotes an increase; ↓ denotes a decrease relative to the prior year.*

KPI / Dimension	2021	2022	2023
Total units sold	2,165	1,666 (−23.0%)	1,499 (−10.0%)
Total revenue (€)	1,479,257	1,113,403 (−24.7%)	1,234,125 (+10.8%)
Highest-volume category	Chairs (41.9%)	Chairs (53.1%)	Chairs (40.4%)
Counter-trend growth	Bar stools: 162 units	–	Bar stools: 257 units (+58.6%)
Production efficiency	Not tracked	64.7% (target 75%)	98.8% (target 98.5%) ↑
Profit margin ratio (markup)	Not tracked	Only beds met the target (2.84x vs 2.1x target)	No category met the target ↓
Customer complaints	23	66 (+187%) ↑	53 (−19.7%) ↓
Non-conformities (total)	65 (89% misc. furniture)	Distributed across categories	Distributed across categories
Foam stock reduction	No system	No system	−22% inventory; €15k capital released

5.2 Strategic implications and decision support

The dashboard changed how decisions were made at Paulo S. Antunes Lda., going beyond simply making data available. Previously, strategic discussions took place largely in an information vacuum, with participants drawing on selective anecdotes, incomplete financial summaries, and subjective impressions. Disagreements over product portfolio strategy, pricing, and resource allocation often became unproductive, with positions reflecting departmental loyalties rather than shared evidence. By giving those conversations a common factual footing, the dashboard shifted attention from arguing about basic facts to interpreting and responding to them.

Several specific strategic insights emerged from dashboard analysis. First, the concentration of revenues in miscellaneous furniture (despite lower sales volumes) suggested opportunities to emphasise this category in marketing and expand customisation capabilities that command premium prices. Second, the consistent growth in bar stool sales, counter to overall declining trends, indicated potential market opportunities possibly linked to hospitality sector recovery post-pandemic. Third, the negligible and declining demand for chaise longues raised questions about the continued viability of production, prompting an evaluation of whether resources devoted to this category might yield better returns elsewhere.

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The margin pressure analysis facilitated difficult but necessary conversations about pricing strategy. Management recognised that their intuitive pricing approaches had failed to keep pace with cost increases, gradually eroding profitability. The dashboard enabled simulation of pricing adjustments' impacts on revenue and margin scenarios, supporting data-driven experimentation with targeted price increases in categories where demand appeared less price-sensitive. Additionally, the cost breakdown visibility highlighted opportunities to reduce costs through supplier negotiations, process improvements, or strategic outsourcing decisions.

The quality metrics also gave weight to investment decisions that had previously been treated as discretionary. Making non-conformity costs visible (materials waste, rework labour, customer goodwill losses, and complaint handling time) quantified the real business impact of quality problems, providing a concrete basis for investing in enhanced training programmes, improved quality control procedures, and supplier audits. In practical terms, this shifted the conversation from quality as a production department concern to quality as an issue requiring coordinated attention across functions.

5.3 Organisational change management lessons

While the technical challenges were considerable, organisational and human factors ultimately proved more consequential for success. Several lessons about change management stood out. First, visible top management support was essential. When the managing director regularly drew on dashboard data in meetings, framed questions around metrics, and acknowledged data-driven decision-making, middle managers and frontline staff followed suit. Departments whose supervisors rarely consulted the dashboard showed minimal team-level usage. This aligns with the literature's consistent identification of the single most decisive factor in BI adoption within SMEs (Olszak & Ziemba, 2012; Ramakrishnan et al., 2020). This case adds some clarity about the mechanism: leadership attention legitimises the tool, reduces anxieties around performance visibility, and creates the organisational conditions under which data-based reasoning gradually replaces opinion-based debate. This cascading effect from executive to operational levels goes beyond simply confirming that top management support matters; it begins to explain how that support actually translates into changed behaviour on the ground.

Second, training requirements exceeded initial estimates by a considerable margin. While the dashboard interface proved relatively intuitive after a brief introduction, developing genuine analytical skills (interpreting trends, identifying patterns, formulating hypotheses, and translating insights into action) required sustained effort. One-time training sessions proved insufficient; ongoing coaching, group discussions of dashboard findings, and facilitated problem-solving exercises were needed to build these capabilities progressively. Organisations undertaking similar projects should therefore budget substantially more for capability development than for the technical implementation itself.

Third, resistance stemmed less from aversion to technology than from anxiety about accountability and transparency. Some managers worried that making performance visible might expose their departments unfavourably, leading to blame or closer scrutiny. Production supervisors were initially concerned that efficiency metrics would create unrealistic productivity pressure without accounting for differences in task difficulty. Addressing these concerns required explicit conversations about the purpose of measurement (learning and improvement rather than punitive judgment), involving affected parties in defining the metrics, and demonstrating that management was not using the data to assign blame.

Fourth, data quality issues generated initial scepticism, threatening the dashboard's credibility. When early versions contained obvious errors (e.g., impossible efficiency figures due to data-entry mistakes), users questioned the reliability of all dashboard outputs. Addressing this required transparent acknowledgement of data limitations, visible correction of identified errors, and gradual quality improvements over time. Perfection proved unnecessary and unattainable, but consistent reliability in core metrics proved essential for sustained usage and trust.

5.4 Limitations and challenges

Several limitations constrain the generalisability and sustainability of results. First, data quality and completeness issues persist despite improvement efforts. Historical data frequently contained inconsistencies requiring manual review and correction, limiting scalability and automation. The company's limited investment in data governance infrastructure means that maintaining data quality requires ongoing vigilance and periodic cleanup rather than systematic prevention of issues at data entry points.

Second, the dashboard currently relies on manual data updates rather than automated feeds from source systems. Integrating Power BI directly with the PHC ERP system would eliminate manual steps, ensure currency, and reduce the potential for errors. However, this requires technical capabilities and cooperation with the ERP vendor that are currently unavailable. The manual process creates ongoing maintenance burdens that could threaten sustainability if key personnel depart or priorities shift.

Third, the relatively short evaluation period (effectively 1 year of systematic use) limits evidence on long-term impacts and

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sustainability. Initial enthusiasm often fades as novelty wears off and competing priorities reassert themselves. Whether the dashboard becomes institutionalised as a permanent management practice or gradually falls into disuse depends on factors such as continued management attention, the ongoing relevance of the metrics, and integration into formal planning and review processes.

Fourth, attributing performance improvements solely to dashboard implementation is challenging given simultaneous changes in market conditions, organisational practices, and personnel. While production efficiency gains occurred concurrently with dashboard deployment, multiple concurrent initiatives (training programmes, process improvements, equipment investments) also contributed to these gains. Isolating dashboard impacts would require controlled comparisons, which are impractical in applied organisational settings.

5.5 Implications for research and practice

This research contributes to business intelligence and performance management literature in several ways. Empirically, it provides detailed documentation of BI implementation processes in an SME manufacturing context, addressing the relative scarcity of research on smaller organisations where resource constraints and organisational characteristics differ substantially from those of large corporations commonly studied. The description of challenges encountered, solutions developed, and lessons learned offers valuable guidance to practitioners and researchers working in similar contexts.

Theoretically, the study reinforces the argument that successful BI implementation requires treating technology as an enabler rather than a solution in itself. Technical systems need to be embedded within appropriate organisational structures, cultures, and capabilities to generate real value. A dashboard deployed without accompanying change management, capability development, and process integration would likely have delivered few benefits regardless of its technical quality.

Methodologically, the action research approach enabled depth of insight and practical relevance, potentially sacrificed in more detached research designs. The first author's organisational insider status facilitated access to sensitive information, candid discussions of challenges, and the ability to influence implementation processes toward successful outcomes. However, this positioning also raises questions about objectivity and generalisability that more traditional research designs might address differently.

For practitioners, several concrete recommendations emerge. First, start with a limited, clearly valuable scope rather than attempting to build a comprehensive system from the outset; early wins matter for building organisational confidence and buy-in. Second, invest substantially in change management, capability development, and stakeholder engagement, well beyond what the technical implementation alone requires. Third, favour iterative development that incorporates user feedback and adapts to needs discovered during deployment, rather than specifying all requirements upfront. Fourth, set realistic expectations about data quality, implementation timelines, and the pace of organisational change.

6. Conclusions

This study documented the design, implementation, and evaluation of a comprehensive performance dashboard in a Portuguese furniture manufacturing SME. The project successfully addressed the company's lack of systematic performance monitoring capabilities, consolidated fragmented data sources into coherent visualisations, and enabled data-driven decision-making processes previously impossible. The dashboard monitored eight product categories across multiple performance dimensions, providing management with visibility into sales trends, profitability patterns, production efficiency, and quality metrics spanning three years of operations.

Implementation followed PDCA continuous improvement principles, treating dashboard development as an iterative learning process rather than a one-time project. This approach proved essential for addressing identified needs, improving data quality, and gradually building organisational capabilities. Improvements in production efficiency from 64.7% to 98.8% demonstrated tangible operational benefits, though attributing these specifically to dashboard availability versus concurrent initiatives remains challenging. The parallel development of a pilot inventory control system addressed critical gaps in supply chain visibility while demonstrating the feasibility of an expanded scope.

Analysis of performance data revealed concerning trends, including a 30.8% decline in sales volume over the study period and eroding profit margins across multiple product categories. Crucially, however, the dashboard allowed these challenges to be identified early and discussed systematically, enabling data-driven responses that would have been difficult under the company's previous practices. Management gained concrete insights to inform decisions on product portfolio emphasis, pricing adjustments, production process improvements, and quality initiatives.

This research contributes to academic literature and managerial practice by providing detailed empirical documentation of BI implementation in an SME context, emphasising organisational change management alongside technical considerations, demonstrating practical application of continuous improvement methodologies, and offering realistic assessments of

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challenges, limitations, and success factors. For similar organisations considering digital transformation initiatives, key recommendations include maintaining modest initial scope, investing substantially in change management and capability development, embracing iterative implementation approaches, and maintaining realistic expectations regarding timelines and challenges.

Future research should examine the long-term sustainability of BI implementations in SMEs, the factors influencing continued use versus abandonment after initial enthusiasm, optimal approaches for capability development in organisations with limited analytical expertise, and integration strategies linking performance dashboards to strategic planning and operational decision-making processes. Comparative studies across different organisational sizes, industries, and national contexts would enhance understanding of how contextual factors moderate BI implementation success and impact. Longitudinal investigations are particularly warranted to determine whether the pandemic-related distortions visible in the 2021–2023 data window persist, dissipate, or interact with structural company-level factors in the medium term. Additionally, future work should explore how advances in AI-assisted analytics and automated reporting (Rejeb et al., 2025) can lower implementation barriers for SMEs with limited technical capacity, and how supply-chain-facing BI tools may complement internal performance monitoring to build broader organisational resilience (Alsakhen et al., 2024).

The pressure on manufacturing SMEs to modernise will only grow as competitive demands increase, customer expectations shift, and digital tools become more accessible. Organisations that build solid performance management capabilities will be better placed to respond quickly to changing conditions than those still relying on intuition and fragmented data. But achieving that requires more than deploying technology: it demands genuine changes in how organisations collect, interpret, and act on information, changes that are harder to make than they might appear, yet increasingly necessary for long-term competitiveness.

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