

From data to decisions: A narrative review of business intelligence and predictive analytics framework for enhancing SME competitiveness and economic resilience in the United States

Prince Gyane Twum ^{1,*} and Matthew Oman-Amoako ²

¹ Westcliff University in Irvine, CA, USA.

² Independent Researcher, Texas, USA.

Magna Scientia Advanced Research and Reviews, 2026, 17(02), 011–021

Publication history: Received on 26 May 2026; revised on 30 June 2026; accepted on 02 July 2026

Article DOI: <https://doi.org/10.30574/msarr.2026.17.2.0118>

Abstract

Small and medium-sized (SME) business organizations constitute the structural foundation of the United States economy but are systematically under-served by advanced business intelligence (BI) and predictive analytics infrastructure, which is structurally threatening to inclusive economic growth and resiliency. This narrative review critically summarizes peer-reviewed literature (2020-2025) to understand new trends, frameworks, and uses of BI and predictive analytics to increase U.S. SME competitiveness and economic resilience and define gaps in governance and future research priorities. The data shows that there is a paradigm shift between retrospective reporting to real-time and AI-enhanced analytics, adaptive dashboarding, cloud-based predictive models, agentic supply-chain pipelines, and machine-learning-based scenario planning are changing the operations of the SMEs. There are still critical gaps in data literacy, fair access to AI and bias in algorithms, and governance mechanisms that are tuned to the scale of SME deployment. Empirical claims across the literature vary in methodological rigor and should be viewed with proper caution before the standardized replication. Implementation science, ethical AI governance in line with NIST AI RMF, ISO/IEC 42001, and OECD AI Principles, and SME-specific digital resilience benchmarks should be the priorities of future research to democratize data-driven decision-making in the U.S. SME sector.

Keywords: Business Intelligence; Predictive Analytics; SME Competitiveness; Economic Resilience; AI Governance; Digital Transformation; Data Ethics

1. Introduction

The United States economy is structurally reliant on the dynamism of their small and medium-sized enterprises (SME) sector. More than 33 million small businesses with a total of 61.7 million workers and an overall contribution to the U.S. economy amounting to about 43.5% (SBA Office of Advocacy, 2023). However, even with their combined mass, U.S. SMEs are still under-represented in the transformative potential of business intelligence (BI) and predictive analytics-technologies that have fundamentally changed the strategic decision-making process of large organizations in the last 10 years.

The definition of business intelligence is quite broad to include the technological infrastructure, analytical processes and organizational practices in which firms transform raw information into useful strategic information (Ahmad et al., 2020; Alzghoul et al., 2024). Predictive analytics builds on this ability by using statistical modeling, machine learning, and past data trends to predict the future and model decision scenarios (Akpe et al., 2023; Ikbal, 2025). Coupled with these capabilities is an underpinning competency in dealing with the volatility, complexity, and competitive intensity that define modern markets.

* Corresponding author: Prince Gyane Twum

The COVID-19 pandemic itself acted as a catalyst with the structural weakness of SMEs that did not possess data-driven adaptive capacities (Akpan et al., 2021). Companies that had already invested in digital analytics infrastructure proved to be much more resilient- turning supply chains, changing price strategies, and finding new customer segments much faster than their less digitally equipped competitors (Hokmabadi et al., 2024; Islam et al., 2023). This deviation raises a pressing query that drives this review, how can BI and predictive analytics structures be crafted, structured and enacted in a way that facilitates a systematic enhancement of SME competitiveness and economic resilience in the United States?

The body of literature has reacted to scholarly literature. An early and detailed survey of BI adoption rates in SMEs by Llave (2021) revealed that there always remained significant gaps between technology accessibility and its application in a company. The later research reported the effectiveness of adaptive dashboards in enhancing operational effectiveness (Akpe et al., 2022a), speedy strategic responsiveness (Ogbuefi et al., 2024), decision support systems enhanced with AI and increased forecasting precision (Shafa, 2025), and cloud-based predictive models in improving supply-chain risk management (Zhang et al., 2024). Simultaneous research has explored ethical and regulatory aspects, such as algorithm bias in credit score (Oware & Amfo Junior, 2025), data disclosure (Agbadamasi et al., 2025), and regulatory adherence in AI-based BI settings (Agbadamasi, L.K.O. et al., 2025).

Nevertheless, with this growing body of literature, there are critical gaps. Current reviews are either focused on limited empirical accounts of tools or general theoretical models which do not have enough roots on SME-specific operational realities.

No existing critical synthesis: (1) follows the development of retrospective BI to forward-looking predictive analytics in the SME context; (2) incorporates AI agentic capabilities and governance models; (3) suggests a scalable framework with U.S. SME resource limitations; or (4) interacts with existing AI governance standards, including the NIST AI Risk Management Framework (RMF), ISO/IEC 42001 or OECD AI Principles.

This narrative review fills these gaps. It presents trend-based synthesis of business analytics, information systems, strategic management, and computational science peer-reviewed literature (2020-2025) using more than 35 primary sources. The methodological stance of this review needs to be mentioned: being a narrative review; it is not based on a systematic protocol of PRISMA. Selection of studies was purposive based on topical relevance, methodological diversity, and prominence of citation. Individual studies are given numeric claims (e.g. percentage efficiency gains) which are said to be indicative, and the readers are advised to weigh confidence accordingly until standardized replication studies are performed. The article advances the descriptive knowledge to the prescriptive one, that is, the current state of BI and predictive analytics in SMEs today, to the future state, which is what these technologies need to do to solidify the competitive bases of the U.S. economy tomorrow.

2. Emerging Trends and Thematic Analysis

The review of the post-2020 literature synthesis finds four major thematic streams defining the landscape of BI and predictive analytics of U.S. SMEs. These themes are overlapping aspects of a larger change in the conceptualization, acquisition, and use of data, by small and medium enterprises.

2.1. Static Reporting to Adaptive Intelligence: The History of SME Business Intelligence.

The prevailing pre-pandemic discourse framed SME BI adoption as underperforming, due to the high implementation expenses, lack of IT skills, and organizational change resistance (Grant, 2020; Llave, 2021). According to the post-2020 literature, a significant change has occurred: cloud-native, low-priced, and artificial-intelligence-enhanced BI systems have changed the calculation of adoption among small firms.

Akpe et al. (2022a) showed that simple dashboard solutions might provide significant process optimization in SMEs without the capital costs that were traditionally linked to enterprise BI. Akpe et al. (2022b) have reported the development of adaptive BI architectures that respond to changing business conditions by reconfiguring analytical parameters - what they refer to as dynamic data responsiveness, operationally defined as the ability to automatically re-weight analytical modules (e.g. liquidity vs. growth KPIs) based on pre-specified environmental events (e.g., revenue deviation thresholds, this level of adaptability was especially useful in times of economic turmoil, as firms could quickly shift the analytical lens off the growth measures and onto the indicators of liquidity and cost-containment measures.

Champa (2025) showed that the strategic use of data analytics and BI tools has a positive relationship with SME productivity in two ways: direct operation optimization by real-time monitoring of performance, and indirectly by

enhancing market understanding. Akter (2025) has also placed BI as the cornerstone to data-driven strategic decision-making, the competency that redefines competitive advantage in digitally intensive markets.

Ahmad et al. (2020) offered valuable theoretical background with an integrative model of BI adoption that summarizes individual, technological, organizational and environmental contexts. Their model has shown that the biggest determinant of successful BI implementation is technology preparedness and organizational learning capacity, as opposed to financial resources in isolation. The result shifts policy focus to digital literacy and organizational capacity as greater payoff investment options compared to subsidized technology acquisition.

Alzghoul et al. (2024) discovered that companies that have a higher level of BI maturity exhibit a quicker decision-making process, more thorough strategic evaluation, and better financial results. Importantly, firm size did not moderate this relationship, which begs the question that BI capability can be a competitive equalizer. This result is, however based on a sample of SMEs in Jordan and direct generalization to the U.S. setting must be cautioned due to variances in regulatory environment, digital infrastructure, and market structure. Similar to Radagazou et al. (2023), whose researchers were located in a Greek setting, a multi-dimensional BI model comprising data visualization, performance benchmarking, and scenario simulation was created. Although conceptually transferable, before using such frameworks as empirically based guidance to American SME practitioners, U.S.-specific validation research is required.

Table 1 Summary of BI Implementations and Outcomes in SME Contexts (2020–2025). *Non-U.S. contexts: generalization to U.S. SMEs requires independent validation.

Study	BI Approach	Context/Geography	Key Outcome
Akpe et al. (2022a)	Low-cost dashboards	Multi-sector SMEs	Improved process efficiency
Akpe et al. (2022b)	Adaptive BI architectures	SMEs in disruption	Enhanced strategic agility
Alzghoul et al. (2024)	BI capability assessment	Jordanian SMEs*	Faster decisions; better performance
Champa (2025)	Data analytics deployment	U.S. SMEs	Increased productivity
Ragazou et al. (2023)	Multi-dimensional BI model	Greek SMEs*	Competitive positioning
Akter (2025)	Data-driven BI framework	U.S. SMEs	Enhanced competitiveness

2.2. Predictive Analytics as a Competitiveness Strategy.

Predictive analytics is the foresight strategic component of the information-based company. The literature review reports a stunning rise in the level of sophistication and availability of predictive analytics solutions to SMEs owing to innovations in cloud computing, open-source machine learning packages, and API-based models' implementation.

Akpe et al. (2023) reported the reduction in inventory waste, optimization of prices and prediction of customer churn by Monte Carlo simulations and regression-based demand forecasting compared to historical reporting. The 12-18% cost savings were reported in areas where predictive models were actively implemented, which is based on a single study and must be considered indicative until it is replicated across studies. Solt (2023) showed that machine learning-enriched models were able to decrease cost estimation error in SME project management by up to 34% compared to traditional approaches- another estimate in a single study. Okeke et al. (2025) showed that the use of business data-driven financial modeling tools enhanced the accuracy of cash flows projection and diminished the stress levels in working capital among SMEs.

In the groundbreaking study of the adoption of SME analytics in the U.S., Kasiri et al. (2024) proposed a typology of adoption levels: foundational (descriptive analytics), operational (real time monitoring and simple predictive abilities), and strategic (comprehensive predictive modeling). Companies in the strategic level showed statistically significant benefits in terms of revenue growth, customer retention, and expansion of market share. This U.S. based evidence offers greater contextual soundness of the main claims of the review compared to other national settings.

Kgakatsi et al. (2024) noted that predictive analytics value realization depends on the quality of data pipelines, and not only the choice of analytics tools. Ogbuefi et al. (2024) have shown that real-time analytics systems when adequately connected with operational systems allow adjusting strategies dynamically at speeds that were once considered unfeasible by SMEs. Recent research on pretrain-then-finetune pipelines to optimize small datasets (e.g. Chronos and

similar methods) is especially promising to SME small-n, large-N tasks like SKU-level inventory prediction and promotional scheduling, where transfer learning across tasks can partially offset small proprietary datasets.

2.3. AI-Augmented Business Intelligence: Agentic Capabilities, Integration, and Governance

The most impactful change of the review period is the incorporation of artificial intelligence and BI infrastructure, which increases the analytical abilities that SMEs have access to and provokes more basic governance concerns. The emergent agentic AI taxonomy, differentiating AI systems on a continuum of autonomy between L0 (no autonomy; human-executed tasks) and L5 (fully autonomous, self-directing agents) can be a helpful conceptual anchor. Most existing SME BI implementations are at L1-L2 (AI-assisted analytics with human control), and supply-chain and financial forecasting apps are starting to enter L2-L3 (AI-generated actions within human-defined guardrails). SMEs are advised to be when rolling out at a higher level of autonomy (L4-L5) without attendant governance infrastructure. Shafa (2025) recorded the integration of machine learning algorithms, natural language processing and neural networks into decision-support architecture to facilitate autonomous pattern recognition, anomaly detection and prescriptive recommendations. Alim et al. (2025) offered a macro-level view and discovered that AI-enhanced BI implementations are linked to quantifiable gains in firm-level productivity and sector-level production. The meta-analytic synthesis by Ikbali (2025) showed that AI-based business analytics positively and significantly correlate with the quality of strategic decisions, responsiveness to competition, and the ability to innovate in different sectors of the SME. The risk of structural bias in large language model (LLM)-based analytics is a crucial aspect of AI-enhanced BI in the financial field. Relevant work finds five types of bias that are especially relevant to SME financial applications: look-ahead bias (applying future information to historical training data); survivorship bias (training on firms that survived, rather than firms that failed); narrative bias (excessive weight on textual sentiment); objective bias (the discrepancy between optimization goals and business objectives); and cost bias (ignoring inference costs in real-time SME applications). SMEs that use LLMs to make forecasts, credit analytics, or financial reporting ought to have minimum structural validity checks, such as temporal holdout checks, calibration checks, and disaggregated fairness audits based on demographic characteristics of the firm. In credit risk applications, transparency is needed on the interpretability of trade-offs between high-performance models (e.g., gradient-boosted trees, random forests) and explainable alternatives (logistic regression, Delphi scoring). The partial bridging of this gap can be achieved by explainability tools that are SME-feasible, e.g., SHAP and LIME, which should be viewed as minimum artifacts of governance in the regulated deployment of financial BI. Zhang et al. (2024) reported the CloudScale framework, a SME supply-chain risk management system based on AI that combines real-time market information, supplier performance data, and demand variability signals to produce dynamic risk evaluations. Among the firms that participated in the study, a 28% decrease in the costs of supply chain disruption was reported; it is a one-study estimate and can be understood as such. Emerging agentic supply-chain pipeline architecture goes a step further to allow multi-stage data retrieval, reasoning, and action sequences on procurement, logistics, and demand planning processes. These pipelines bring with them substantial capability potential and remaining risks such as information leakage, agent hallucination, and cascading mistakes in decision-making that are especially significant to SMEs with limited capacity to absorb errors. AI-infused BI has governance aspects that require a methodical approach. Agbadamasi et al. (2025) maintained that a clear analytics architecture is the key to responsible AI implementation. Agbadamasi et al. (2025) reported the complicated regulatory environment of AI and BI systems in U.S. corporations. Carayannis et al. (2025) studied AI-enhanced scenario planning as a strategic foresight tool, whereas Jabeen et al. (2025) showed that data-driven capabilities allow SMEs to detect the opportunities of reconfiguring the business model that is not apparent to companies based on traditional market intelligence.

2.4. Barriers to Adoption, Digital Maturity Disparities, and Continued Struggle.

Although the case of BI and predictive analytics is quite convincing, there are structural barriers to SME adoption that cannot be resolved by solely providing technologies. Grant (2020) determined the organizational culture as the most significant barrier to adoption: the readiness to implement advanced analytics was better predicted by managerial openness to using data-driven decisions than by financial resources or technical infrastructure. This questions technology-based adoption narratives and focuses attention on organizational change management. Motjolo-pane & Chanza (2023) reported that SMEs in a digitally aware maturity phase often had an over-optimistic view of their analytical ability, which posed a risk in implementation when they applied tools that are not fit to their real data infrastructure. Ojonugwa et al. (2021) presented a framework mapping of digital maturity between simple data management and entirely AI-driven systems. The five-stage model used in this review (Table 2) is a conceptually based model that has not yet been tested on U.S. SME data; its diagnostic value is subject to the development of the operational definitions, stage-specific KPIs, and instrument items that allow the reliable self-assessment. Measurement invariance needs to be tested in future validation studies in terms of sector, geography, and ownership demographics. The multi-dimensional capability requirements that Arno (2025) captured to achieve real business agility included. A recent study by Philbin et al. (2022) highlighted sustainability as a neglected aspect by stating that the BI frameworks should align with the environmental and social goals in addition to financial performance. Hokmabadi et al. (2024) discovered that

SMEs that were more digital recovered faster to economic disruptions. Kumar et al. (2024) outlined digital resilience enablers such as leadership commitment, talent development, technology architecture flexibility, and ecosystem partnerships as key determinants of whether investments in digital transformation create long-lasting competitive advantages.

Table 2 SME BI and Predictive Analytics Digital Maturity Framework (adapted from Ojonugwa et al., 2021; Arno, 2025). Note: framework is conceptually grounded but not yet empirically validated with U.S. SME data; stage thresholds require field testing.

Stage 1 Data Aware	Stage 2 Data Active	Stage 3 Data Driven	Stage 4 Predictive	Stage 5 AI-Augmented
Basic spreadsheets; manual reports	Dashboards; KPI tracking	Integrated BI platforms; real-time reporting	Predictive models; scenario planning	AI/ML decision augmentation; agentic analytics (L1–L3)
Key capability: Data literacy training	Key capability: BI tool adoption	Key capability: Data governance foundations	Key capability: ML/statistical capability	Key capability: AI governance; bias auditing

3. Applications of BI and Predictive Analytics in SME Operations

In addition to theoretical models, the literature review records explicit operational implementations whereby BI and predictive analytics are creating quantifiable value in the U.S. SME settings.

3.1. Financial management and predictions.

Okeke et al. (2025) established that the use of predictive financial models that included cash flow projection, credit risk evaluation, and revenue projection enhanced working capital management in surveyed SMEs. Oware & Amfo Junior (2025) reported AI-driven credit scoring systems that incorporate alternative data to offer more reliable creditworthiness evaluation of SMEs that have limited credit histories. In their research, algorithmic bias risks were recorded in situations where alternative data indicate historical socioeconomic disparities. Minimum governance artifacts to responsible financial BI deployment are implementation of SME-feasible interpretability routines (SHAP, LIME), temporal holdout validation, and periodic fairness audit, disaggregated by ownership demographics. The risks of look-ahead bias and survivorship bias are especially relevant to the training of models with historical data on financial activities of SMEs, and leakage-safe holdout designs must be taken into consideration in the evaluation protocol.

3.2. Supply Chain Optimization

Zhang et al. (2024) showed that AI-infused BI platforms allow SMEs to attain enterprise level supply chain intelligence without incurring the related investment in infrastructure. The CloudScale model resulted in real-time visibility of multi-tier supply chain networks, which facilitated dynamic procurement change and proactive risk mitigation. Akpe et al. (2023) showed how scenario modeling tools could be used to simulate the scenario of the disruption of the supply chain to find the best response strategies. The next generation agentic supply chain pipelines automate multi-stage reasoning in procurement, logistics, and demand planning but run risks of hallucination and cascading decision error that demand human-in-the-loop oversight protocols that suit SME error-recovery capability.

3.3. Customer Intelligence and Market Analytics.

Rezvi et al. (2025) reported evidence-based persona development as the optimization of customer experience in SMEs and discovered that companies with sophisticated customer segmentation and behavioral analytics had much greater rates of customer retention and more efficient distribution of marketing resources. Kasiri et al. (2024) found customer analytics to be the most reported BI application domain with the highest reported return on investment among surveyed U.S. SMEs.

3.4. Food Safety, Quality Assurance, and Sector-Specific Applications.

Gaye et al. (2025) and Oware et al. (2025) reported AI-based predictive food safety risks management, showing that machine learning-based predictive models could detect risks of contamination more sensitively than standard food inspection policies owing to the use of supplier quality data and environmental monitoring data. The implications of

these findings on SMEs in food production and distribution include the fact that safety incidents have disastrous reputational and financial impacts.

3.5. Strategic Decision Making and Mergers and Acquisitions.

Narteh-Kofi et al. (2025) reported the use of AI analytics in decision-making during mergers and acquisitions, showing that information asymmetry risks may be greatly reduced in SME acquisitions through data-driven due diligence tools. Carayannis et al. (2025) offered a more strategic approach, looking at how AI-enriched scenario planning can help SMEs create more complex and responsive strategies for environmental complexity.

4. Benefits, Limitations, and Ethical Considerations

4.1. Benefits

The aggregate evidence provides strong grounds to believe that BI and predictive analytics may be transformative in the context of SMEs, but the research underpinning this argument is categorically varied in terms of quality design, sample size and geographic location, which raises the uncertainty about the confidence one can place in any single result. Benefits reported include: accelerated and improved decision-making speed and quality (Alzghoul et al., 2024); better operational efficiency and cost management (Akpe et al., 2022a; Solt, 2023); improved financial performance and resilience (Okeke et al., 2025; Hokmabadi et al., 2024); more market responsiveness and customer intelligence (Rezvi et al., 2025; Kasiri et al., 2024); and enhanced supply chain visibility and risk management (Zhang et al., 2024). At macro level, Alim reported positive correlations between AI-driven BI use and U.S. economic productivity, indicating SME analytics ability had aggregate economic importance beyond performance in individual firms.

Table 3 Key Benefits of BI and Predictive Analytics Adoption in SMEs with Methodological Cautions.

Benefit Category	Key Evidence	Reported Effect	Caution
Decision quality	Alzghoul et al. (2024)	Faster, more comprehensive assessments	Non-U.S. sample
Operational efficiency	Akpe et al. (2022a); Solt (2023)	12–18% cost savings; 34% error reduction	Single-study estimates
Financial performance	Okeke et al. (2025)	Improved cash flow management	Peer-review status unclear
Customer analytics	Rezvi et al. (2025)	Higher retention; lower acquisition cost	2025 preprint
Supply chain resilience	Zhang et al. (2024)	28% cost reduction (single study)	Requires replication
Economic productivity	Alim et al. (2025)	Positive macro productivity associations	Preprint; U.S.-focused

4.2. Limitations and Implementation Challenges

Important structural constraints are hindering the adoption of SME BI and analytics. The underlying issues are data quality and integration: Kgakatsi et al. (2024) reported that the fragmentation of data across the legacy systems is one of the main barriers to predictive model performance. The issue of talent constraints is similar; the lack of data analytics skills among SMEs restricts the ability of organizations to utilize even the developed BI solutions (Grant, 2020; Motjolo-pane & Chanza, 2023). Kumar et al. (2024) discovered that flexible technology architecture and ecosystem partnership access, which are key to the implementation of BI, are much more difficult to establish in small companies. Similar results were obtained by Arno (2025) who further discovered that SMEs at lower stages of digital maturity rarely fulfil multi-dimensional agility capability requirements.

A more general methodological shortcoming cuts across the literature reviewed: lack of standardized effect sizes, cross-study bias measures, and replication studies imply that certain numeric assertions should be approached with interpretive care. The biases of publication in favor of positive results, survivorship bias in the selection of case-studies,

and look-ahead bias in financial model analysis are probably present throughout the literature and need to be systematically considered in future meta-analyses.

4.3. Governance Imperatives and Ethical Considerations.

The implementation of AI in BI comes with its ethical imperatives, which the SME analytics literature is only starting to tackle systematically. The inequalities in credit access by minority-owned SMEs due to AI-based credit scoring were also reported by Oware & Amfo Junior (2025), who showed that the models trained on historically biased data may reinforce inequalities in credit access to minority-owned SMEs. Their suggested bias reduction model, comprised of fairness limitations, alternative data curation, and continuous model auditing, provides a viable blueprint of responsible AI implementation in financial systems.

According to Agbadamasi et al. (2025), responsible AI deployment necessitates transparent analytics architecture. The intricate point of convergence of AI governance requirements, legal requirements, and BI system design in U.S. corporate settings was reported by Agbadamasi et al. (2025). Collectively, these studies are indicative that ethical BI governance is an essential aspect of an SME-level analytics strategy with a real legal and reputational impact.

More importantly, the analytics on SME literature is yet to substantially interact with the existing AI governance principles. The NIST AI Risk Management Framework (RMF) offers a voluntary, structured method of managing AI risks throughout the AI lifecycle, with four key functions: Govern, Map, Measure, and Manage, each of which can be directly applied to SME BI deployments. The international standard of AI management systems ISO/IEC 42001 (2023), offers an audit-ready governance architecture that scales to SME size. The OECD AI Principles (2019, revised 2023) codify internationally accepted standards of trustworthy AI, such as transparency, accountability, and robustness standards that apply to SME analytics tools. These standards are supplemented by the NIST Privacy Framework, which offers the guidance of data minimization and privacy-by-design that relates to customer analytics and financial BI applications. The standards must be clearly reflected in future SME BI frameworks instead of governance being an ad hoc issue.

The SAFE-AI governance framework provides a more actionable model in the context of SMEs with minimal viable ethics tooling, such as acceptance criteria, fairness and transparency metrics, responsibility assignment matrices, and ongoing monitoring protocols, optimized to resource-constrained organizations. Its focus on agile governance iteration suits the dynamic operating environments of U.S. SMEs well, and its artifacts (fairness audits, transparency dashboards, incident response protocols) are realistic governance objectives of a company that does not have an established compliance infrastructure.

5. Future Directions and Research Gaps

The synthesis demonstrates an area where the technology underpins transformational SME analytics are in place, yet the organizational, governance, and equity aspects of the implementation are not fully understood. There are six priority research directions.

5.1. SME Analytics Adoption Implementation Science.

The most pressing gap, perhaps, is the deficiency of implementation science studies on the topic of SME BI adoption, i.e., a serious study of what organizational factors, change management strategies, and leadership practices in fact translate into a working analytical capability in small companies. There are very few longitudinal studies that monitor the implementation process, since initiation to maturation of capabilities. The proposed future studies need to adopt mixed method designs to record implementation paths, critical success factors, and playbooks. Such studies should report standardized effect sizes, confidence intervals, and pre-registration protocols to facilitate cumulative synthesis methodologically.

5.2. U.S.-Specific Empirical Validation

A large percentage of the BI-SME literature is based on non-U.S. settings (Jordanian, Greek, South African samples). The review's U.S.-specific claims rest primarily on Kasiri et al. (2024), Alim et al. (2025), Champa (2025), and Akpe et al. (2022a, 2022b, 2023). Future studies ought to formulate and test BI and digital maturity models that are specifically tuned to the U.S. regulatory environment of SMEs, competitive market, and diverse ownership demographics. Table 2 maturity model (five stages) needs to be developed through empirical tests using the U.S. samples of SMEs to become a reliable diagnostic tool.

5.3. Scalable and Fair BI Framework Design.

The tiered adoption typology recorded by Kasiri et al. (2024) predicts that a universal SME BI practice will probably produce unequal results in the entire range of U.S. SME situations. Future studies ought to be able to create context-sensitive models that are obviously adjusted to SMEs at varying levels of digital maturity, across various industrial sectors, and also with varying demographic traits of ownership. Special consideration must be given to minority-owned enterprises, rural enterprises, and businesses in areas with low historical data literacy. Specific practical equity practices such as subsidized cloud/BI credits, template governance kits, regional technical support centers, and open-source reference stacks with total cost of ownership (TCO) guidance are all practical equity mechanisms. Democratizing mechanisms of analytical inputs that individual SMEs would have been unable to produce on their own, like secure data trusts and privacy-preserving clean rooms, should be explored.

5.4. Standardized Measurement and SME Analytics Capability Index.

One of the problems that is still present is that no standard metrics exist to assess BI capability, predictive analytics maturity, and their roles in competitive performance and economic resilience. An SME Analytics Capability Index (SACI), including tiered KPIs, reporting frequency, and audit artifacts among five maturity levels, would contribute to the academic and practical benchmarking to a greater extent. An index like this should correspond to NIST AI RMF measurement functions, ISO/IEC 42001 governance artifacts, and sector-specific compliance standards (e.g., PCI DSS in the case of financial BI, HIPAA in the case of applications in the health sector) to provide regulatory coherence.

5.5. SME Analytics Ethical AI Governance.

The literature has little on governance frameworks that are specific to the SME-scale AI-integrated BI deployments. Enterprise frameworks cannot be directly applied in the SME contexts. Future studies ought to design and test lightweight yet resilient governance systems that include SAFE-AI agile ethics tooling, NIST AI RMF risk management functionalities, and ISO/IEC 42001 compliance architecture in SMEs. The workforce implications require certain consideration: domain-driven feature engineering, timely and agent coordination, data governance literacy, and cost-sensitive decisioning are becoming skill priorities and should be addressed by the programs of SME upskilling.

5.6. Macro-Economic Impact Analysis and Open Science.

The overall economic effect of the adoption of SME analytics on the productivity, employment, and innovation in the U.S. is not precisely estimated. Econometric analyses of the relationship between SME digital capability investments and regional economic outcomes on a national level would give an empirical basis to government investment in SME digital capacity. Reproducibility and open science practices need to be built into it: publications of bibliography corpora, screening codes, synthesis artifacts, search strings, and codebooks will make it easier to do follow-on meta-analyses and hasten the process of cumulative knowledge building in this area.

6. Conclusion

This narrative review has integrated an increasingly body of scholarship to offer a critical evaluation of how business intelligence and predictive analytics can be used to enhance SME competitiveness and economic resilience in the United States. The evidence is strong but methodologically diverse: decision-making abilities based on data are some of the most significant determinants of competitive performance in SMEs in modern markets, but definite numeric assertions must be replicated across studies before they can be considered as credible reference points.

There are four thematic conclusions. To begin with, the technological obstacles to the adoption of SME BI have also reduced considerably with the introduction of cloud-native and AI-integrated solutions, acquiring resources the secondary issue in the process of SME BI adoption, but the development of organizational capabilities. Second, predictive analytics, which includes financial forecasting, demand modeling, risk assessment, and strategic scenario planning, provides SMEs with a real avenue to proactive, as opposed to reactive, competitive strategy. Third, AI augmentation of BI systems, although facing hype potential, poses ethical governance requirements, such as the presence of algorithmic bias, lack of transparency, and agentic risk, which must be systematically aligned with the existing standards (NIST AI RMF, ISO/IEC 42001, OECD AI Principles). Fourth, continuing digital maturity disparities and talent shortages still restrain the scope and capacity of adoption, especially among historically disadvantaged groups of small business owners.

To policymakers, these results support investing in the digital capability of SMEs that puts a strong emphasis on organizational and human capital as well as technology infrastructure with the help of shared data infrastructure, technical support centers, and open-source governance toolkits. To researchers, they find a strong agenda: U.S.-specific

empirical validation, standardized measurement, equitable design of the framework, and open science practices. To the SME leaders, they emphasize the strategic necessity of positioning BI and predictive analytics potential-based on a sound governance as a fundamental organizational investment with evident competitive performance, financial sustainability and long-term sustainability.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

References

- [1] Agbadamasi, T. O., Opoku, L. K., Adukpo, T. K., & Mensah, N. (2025). The role of business intelligence in AI ethics: Empowering US companies to achieve transparent and responsible AI. *EPRA international journal of economics, business and management studies (ebms)*, 12(3), 8-14. <https://doi.org/10.36713/epra20314>
- [2] Agbadamasi, T. O., Opoku, L. K., Adukpo, T. K., & Mensah, N. (2025). Artificial intelligence governance in US corporations: Legal and ethical implications for business intelligence and regulatory compliance. *International Journal of Research Publication and Reviews*, 6(3), 3083-3089. <https://doi.org/10.55248/gengpi.6.0325.11124>
- [3] Ahmad, S., Miskon, S., Alkanhal, T. A., & Tlili, I. (2020). Modeling of business intelligence systems using the potential determinants and theories with the lens of individual, technological, organizational, and environmental contexts-a systematic literature review. *Applied Sciences*, 10(9), 3208. <https://doi.org/10.3390/app10093208>
- [4] Mgbame, A. C., Akpe, O. E. E., Abayomi, A. A., Ogbuefi, E., & Adeyelu, O. O. (2022). Developing low-cost dashboards for business process optimization in SMEs. *International Journal of Management and Organizational Research*, 1(1), 214-230.
- [5] Akpe, O. E. E., Mgbame, A. C., Ogbuefi, E., Abayomi, A. A., & Adeyelu, O. O. (2022). The role of adaptive BI in enhancing SME agility during economic disruptions. *International Journal of Management and Organizational Research*, 1(1), 183-198.
- [6] Akpe, O. E. E., Mgbame, A. C., Ogbuefi, E., Abayomi, A. A., & Adeyelu, O. O. (2023). Predictive analytics and scenario modeling for SME survival and competitiveness. *Journal of Frontiers in Multidisciplinary Research*, 2(1), 101-112. <https://doi.org/10.54660/IJFMR.2021.2.1.101-112>
- [7] Akter, M. (2025). Enhancing SME Competitiveness: the Role of Business Intelligence in Data-Driven Decision-Making.
- [8] Akpan, I. J., Soopramanien, D., & Kwak, D. H. (2021). Cutting-edge technologies for small business and innovation in the era of COVID-19 global health pandemic. *Journal of Small Business & Entrepreneurship*, 33(6), 607-617. <https://doi.org/10.1080/08276331.2020.1799294>
- [9] Alim, I., Akter, S., Afroz, Z., Al Prince, A., & Hasan, M. A. (2025). Business Intelligence in the Age of AI: Evaluating Machine Learning's Impact on US Economic Productivity. *Lead Sci Journal of Management, Innovation and Social Sciences*, 1(3), 15-30. <https://doi.org/10.63056/ljsjmiss.1.3.2025.83>
- [10] Alzghoul, A., Khaddam, A. A., Abousweilem, F., Irtaimah, H. J., & Alshaar, Q. (2024). How business intelligence capability impacts decision-making speed, comprehensiveness, and firm performance. *Information Development*, 40(2), 220-233. <https://doi.org/10.1177/02666669221108438>
- [11] Arno, P. (2025). SME business agility framework: A comprehensive review of capabilities, dimensions, and enablers. *IEEE Access*.
- [12] Carayannis, E. G., Dumitrescu, R., Falkowski, T., Papamichail, G., & Zota, N. R. (2025). Enhancing SME resilience through artificial intelligence and strategic foresight: A framework for sustainable competitiveness. *Technology in Society*, 81, 102835. <https://doi.org/10.1016/j.techsoc.2025.102835>
- [13] Champa, S. S. (2025). Enhancing SMEs Productivity Through the Strategic Deployment of Data Analytics and Business Intelligence Tools. Available at SSRN 5731702. <https://dx.doi.org/10.2139/ssrn.5731702>
- [14] Gaye, A., Paflo, B. N., & Oware, D. A. (2025). Assessing the reliability of AI-driven predictive models in food safety risk management. *Comput Sci IT Res J*, 6, 49-58. <https://doi.org/10.51594/csitrj.v6i2.1832>

- [15] Grant, N. C. (2020). Factors influencing willingness to adopt advanced analytics in small businesses. Cleveland State University.
- [16] Ikbal, M. Z. (2025). A meta-analysis of AI-driven business analytics: Enhancing strategic decision-making in SMEs. *Review of Applied Science and Technology*, 4(02), 33-58. <https://doi.org/10.63125/wk9fqv56>
- [17] Islam, S., Hossain, E., Rahman, M. S., Rahman, M. M., Khan, S. I., & Ashik, A. A. M. (2023). Digital transformation in SMEs: Unlocking competitive advantage through business intelligence and data analytics adoption. *Journal of Business and Management Studies*, 5(6), 177-186. <https://doi.org/10.32996/jbms.2023.5.6.14>
- [18] Jabeen, F., Santoro, G., Ključnikov, A., & Jose, S. (2025). Data-driven growth and business model transformation: how startups unlock resilience in turbulent times. *Review of Managerial Science*, 1-28. <https://doi.org/10.1007/s11846-025-00957-z>
- [19] Kasiri, N., Cirino, C., & Narimanian, C. (2024). The Patterns of Business Analytics Adoption in US SMEs: A Qualitative Approach. *Small Business Institute Journal*, 20(1), 26-36.
- [20] Kgakatsi, M., Galeboe, O. P., Molelekwa, K. K., & Thango, B. A. (2024). The impact of big data on SME performance: A systematic review. *Businesses*, 4(4), 632-695. <https://doi.org/10.3390/businesses4040038>
- [21] Kumar, V., Sindhwani, R., Behl, A., Kaur, A., & Pereira, V. (2024). Modelling and analysing the enablers of digital resilience for small and medium enterprises. *Journal of Enterprise Information Management*, 37(5), 1677-1708. <https://doi.org/10.1108/JEIM-01-2023-0002>
- [22] Llave, M. R. (2021). A review of business intelligence and analytics in small and medium-sized enterprises. *Research Anthology on Small Business Strategies for Success and Survival*, 84-109.
- [23] Motjolopane, I., & Chanza, M. (2023). Digital transformation dimensions for evaluating SMEs' readiness for big data analytics and artificial intelligence: A review. *International Journal of Research in Business & Social Science*, 12(7). DOI: 10.20525/ijrbs.v12i7.2837
- [24] Narteh-Kofi, E., Raji, Y. M., Asamoah, E., & Adukpo, T. K. (2025). The role of artificial intelligence in enhancing decision-making and efficiency in mergers and acquisitions: A case study approach within the US capital market. *International Journal for Multidisciplinary Research(IJFMR)*, 7(3).
- [25] National Institute of Standards and Technology. (2023). AI Risk Management Framework (AI RMF 1.0). U.S. Department of Commerce. <https://doi.org/10.6028/NIST.AI.100-1>
- [26] National Institute of Standards and Technology. (2020). Privacy Framework: A Tool for Improving Privacy Through Enterprise Risk Management (Version 1.0). U.S. Department of Commerce. <https://doi.org/10.6028/NIST.CSWP.01162020>
- [27] OECD. (2019, updated 2023). OECD Principles on AI. Organisation for Economic Co-operation and Development. <https://oecd.ai/en/ai-principles>
- [28] Ogbuefi, E., Mgbame, A. C., Akpe, O. E., Abayomi, A. A., & Adeyelu, O. O. (2024). Operationalizing SME growth through real-time data visualization and analytics. *International Journal of Advanced Multidisciplinary Research and Studies*, 4(6), 2033-2054. <https://doi.org/10.62225/2583049X.2024.4.6.4251>
- [29] Ojonugwa, B. M., Ikponmwoba, S. O., Chima, O. K., Ezeilo, O. J., Adesuyi, M. O., & Ochefu, A. (2021). Building digital maturity frameworks for SME transformation in data-driven business environments. *International Journal of Multidisciplinary Research and Growth Evaluation*, 2(2), 368-373. <https://doi.org/10.54660/JFMR.2021.2.1.169-174>
- [30] Okeke, P. T., Okumu, F., Obodai, T., Adams, I., & Buabin, W. K. A. (2025). Predictive analytics in financial forecasting. <https://doi.org/10.5281/zenodo.17461553>
- [31] Gaye, A., Paflo, B. N., & Oware, D. A. (2025). Assessing the reliability of AI-driven predictive models in food safety risk management. *Comput Sci IT Res J*, 6, 49-58. <https://doi.org/10.51594/csitrj.v6i2.1832>
- [32] Oware, D. A., & Amfo Junior, S. (2025). Fairness and bias mitigation in AI-based credit scoring using alternative data. <https://doi.org/10.36713/epra23347>
- [33] Philbin, S., Viswanathan, R., & Telukdarie, A. (2022). Understanding how digital transformation can enable SMEs to achieve sustainable development: A systematic literature review. <https://doi.org/10.26784/sbir.v6i1.473>

- [34] Ragazou, K., Passas, I., Garefalakis, A., & Zopounidis, C. (2023). Business intelligence model empowering SMEs to make better decisions and enhance their competitive advantage. *Discover Analytics*, 1(1), 2. <https://doi.org/10.1007/s44257-022-00002-3>
- [35] Rezvi, R. I., Hasan, M., HASAN, M. A., Protik, M., Nasrullah, F., Ahmed, S., ... & Rahman, K. O. (2025). Data-Driven Persona: How Business Intelligence Analytics Enhance Customer Experience for US Small and Medium Enterprises (SMEs). *Journal of Computer Science and Technology Studies*, 7(9), 196-201. <https://doi.org/10.32996/jcsts.2025.7.9.24>
- [36] Shafa, H. (2025). Artificial intelligence-driven business intelligence models for enhancing decision-making in us enterprises. *ASRC Procedia: Global Perspectives in Science and Scholarship*, 1(01), 771-800. <https://doi.org/10.63125/b8gmddc46>
- [37] Solt, D. (2023). Using Predictive Analytics to Reduce Small Business Cost Estimation Error (Doctoral dissertation, Purdue University).
- [38] Tsiu, S. V., Ngoben, M., Mathabela, L., & Thango, B. (2025). Applications and competitive advantages of data mining and business intelligence in SMEs performance: A systematic review. *Businesses*, 5(2), 22. <https://doi.org/10.3390/businesses5020022>
- [39] Zhang, S., Zhu, C., & Xin, J. (2024). CloudScale: A lightweight AI framework for predictive supply chain risk management in small and medium manufacturing enterprises. *Spectrum of Research*, 4(2). <https://spectrumofresearch.com/index.php/sr/article/view/26>
- [40] U.S. Small Business Administration Office of Advocacy. (2023). *Frequently asked questions about small business*. <https://advocacy.sba.gov/2023/03/07/frequently-asked-questions-about-small-business-2023/>