

Literature Review

“What organisational and strategic factors influence the feasibility of implementing AI-driven sales forecasting tools in SMEs?”

Module Code and Title: BAA1010 Business Project

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Date of Submission: 09.11.2025

Word Count: 3691

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List of Abbreviations

AI.....	Artificial Intelligence
DL.....	Deep Learning
ML	Machine Learning
SMEs	Small and Medium-sized Enterprises

1. Introduction

This literature review investigates whether small and medium-sized enterprises (SMEs) can leverage Artificial Intelligence (AI)-based sales forecasting as a realistic and sustainable source of competitive advantage. Hill cautions that “The greatest risk from AI is that of falling behind in the future because you failed to build the capability to adapt” (Morton, 2025), highlighting that technological tools alone are inadequate without accompanying organisational transformation.

The central research question is: What organisational and strategic factors influence the feasibility of implementing AI-driven sales forecasting tools in SMEs?

The main body is organised into three sections, progressing from rationale to feasibility and potential implementation pathways. The first section establishes the strategic importance of forecasting for SMEs, demonstrating how improved projections support inventory management, capacity planning, and survival in volatile markets. The second section examines the value and limitations of AI-based sales forecasting, contrasting machine learning (ML) approaches with traditional statistical tools. The third section draws on SME digitalisation literature to analyse the organisational and structural challenges of implementing AI-based forecasting. This section includes a review of historical technological challenges and solutions, an assessment of current strategic and organisational issues related to AI-forecasting tools, and a synthesis of these insights to identify implementation approaches recommended in the literature.

To address this question, the review follows a two-stage research strategy. First, it draws on predominantly technical and managerial literature on the importance of forecasting, the ways in which AI-based approaches can enhance forecast quality, and the organisational and structural challenges that arise when such systems are introduced. Second, it adopts a historical perspective, examining how SMEs have previously adapted to major waves of digital technology and which conditions have enabled or constrained those transitions. Across both strands, the emphasis is on linking the technical capabilities of AI forecasting with the organisational realities of SMEs.

In the forecasting literature, some authors distinguish between predicting underlying demand and realised sales, while others note that “people often use the terms ‘demand’ and ‘sales’ interchangeably ... because the two equate when sales are not limited by supply”

(Armstrong and Green, 2005, p. 1). For reasons of clarity and brevity, the review therefore uses the single term “forecasting” when referring to both demand and sales projections.

2. The Strategic Importance of Sales Forecasting for SMEs

“Availability of forecasts of the components making up each enterprise’s system reduces the risk of faulty business decisions.” (Wiśniewski, 2021, p.2). asserts that strategic planning is therefore essential for small businesses. Kolková and Ključnikov (2022) show that forecasting is increasingly vital for SMEs, which often operate with limited financial resources, small workforces and fragile organisational structures. At the same time, they face volatile customer demand, supply chain disruptions, and fluctuating input prices, all of which necessitate adaptability and precise forecasting (Stepanov, 2025; Jones, 2025). In the aftermath of the pandemic, accurate forecasting has become critical for SME survival and is now widely recognised as a core element of logistics and supply chain management (Kolková and Ključnikov, 2022).

For SMEs, accurate forecasts are fundamental to effective inventory and production management in constrained capacity environments. This enables firms to anticipate demand and plan procurement volumes, thereby minimizing both overstocking and stockouts (Christopher and Rahmatillah, 2025). Lowering excess inventory reduces storage costs and capital requirements, while preventing stockouts safeguards sales, customer satisfaction, and profitability (Gupta and Agarwal, 2024). Given that many SMEs cannot sustain large inventory buffers, predictive models are crucial for maintaining agile supply chains without unnecessary resource allocation (Stepanov, 2025). High-quality forecasts enhance operational efficiency, cost control, and growth strategies, all of which are strategically significant for resource-constrained firms (Stepanov, 2025).

Forecasting supports both strategic and tactical decisions in SMEs. By providing a structured view of expected demand, forecasts inform procurement strategies, production system design, and marketing initiatives, enabling firms to capitalize on demand shifts rather than simply reacting to them (Christopher and Rahmatillah, 2025). Systematic forecasting reduces the risk of errors associated with ad hoc judgement, which is a particular concern in organisations with limited managerial capacity (Wiśniewski, 2021).

Before the introduction of AI, SMEs mainly relied on statistical time-series models and econometric approaches, complemented by qualitative judgemental techniques such as expert-based and Delphi forecasting (Wiśniewski, 2021; Petropoulos et al., 2022). Given the

strategic and operational benefits of planning under uncertainty, many SMEs are now looking beyond these traditional tools towards AI-based forecasting methods that can exploit richer data and more complex patterns (Manos et al., 2024; Al-Karkhi and Rządowski, 2025).

3. The Value and Limits of AI-Based Sales Forecasting

AI-based forecasting can be understood, in line with ISO terminology, as the use of engineered systems that learn from data to generate forecasts for human-defined objectives (ISO, 2022; Aldoseri et al., 2023). In practice, these systems are usually built with ML methods that infer patterns from historical and contemporary data, including supervised models for regression and deep learning (DL) architectures such as recurrent neural networks (Bandara et al. 2020). By contrast, traditional tools such as ARIMA extrapolate patterns from a single time series, assuming that the structure of past observations is broadly representative of the future (Petropoulos et al., 2022). They are powerful for capturing trend and seasonality but remain essentially univariate and struggle when behaviour is driven by complex interactions or structural breaks (Manos et al., 2024). AI forecasting, in turn, is designed to exploit rich, heterogeneous data and non-linear relationships, which are particularly valuable for firms operating in volatile environments.

Across several empirical and review studies, AI methods often outperform traditional statistical forecasting when data and market conditions are complex. In e-commerce and export settings, Manos et al. (2024) and Sohrabpour et al. (2021) find that tree-based and other ML models achieve clearly higher forecast accuracy than benchmark statistical models. At a broader level, review work reports that ensemble and DL approaches can yield substantial accuracy gains by modelling non-linear dynamics and combining multiple data sources, although these advantages depend on data availability and model design (Al-Karkhi and Rządowski, 2025).

However, the literature also cautions against a simplistic “AI always wins” narrative (Gilliland, 2020; Al-Karkhi and Rządowski, 2025). Evidence from the M4 competition shows that pure ML methods, applied in isolation, performed poorly and were outperformed by a simple combination of classical statistical methods (Gilliland, 2020). The most successful entries were hybrid methods that combined ML with traditional forecasting, for example, exponential smoothing linked to a recurrent neural network, or ML used to derive optimal combination weights over a pool of statistical models (Gilliland, 2020). This supports the argument that AI forecasting is not a wholesale replacement for classical methods; the

best-performing hybrids integrate ML with statistical baselines, albeit with higher computational and methodological costs (Gilliland, 2020; Al-Karkhi and Rządowski, 2025).

From a business perspective, AI forecasting is closely aligned with the wider agenda of data analytics: improving processes, understanding customer behaviour and enabling better-prepared decisions regarding costs, quality and time (Keller et al., 2025). For SMEs in particular, predictive analytics is highlighted as a core application through which AI can anticipate sales trends, demand fluctuations and supply-chain risks, thereby shifting firms from reactive to proactive postures and strengthening resilience (Carayannis et al., 2025). Empirical evidence from London SMEs during the COVID-19 pandemic suggests that those using AI, including tools for cash-flow forecasting and dynamic pricing, reported significantly lower business risks than non-users, independent of firm size or age (Drydakis, 2022). In pricing, SMEs and experts rank forecast accuracy and reliability as the most important criteria for evaluating AI-supported price functions, ahead of even cost savings and customer value, which underlines how central credible forecasting performance is to adoption decisions (Erdmann et al., 2024).

However, these potential benefits interact with demanding data, computational and governance requirements, which are particularly constraining for SMEs and are examined in Section 4.2.

4. SME Digitalisation and AI-Based Sales Forecasting: Challenges and Pathways

4.1. SME Adaptation to Internet, Digitalisation and Other Technologies

To understand whether SMEs can realistically capture these benefits from AI-based forecasting, it is necessary to consider how they have historically adapted to digital technologies more generally. Dholakia and Kshetri (2004) and Li et al. (2023) show that SMEs have generally approached digital technologies in stages, beginning with basic Internet connectivity and later embedding advanced tools. Early initiatives in traditional manufacturing firms show that SMEs started with email and web access for communication, then applied Internet-based ICT, which delivered quick gains, supported by consultancy packages (Chapman et al., 2000). Similar phased patterns appear in Internet and e-commerce use, as firms move from computer ownership to simple websites and eventually to routinized online selling (Dholakia and Kshetri, 2004). Later waves of digitalization extend this trajectory: SMEs adopt e-commerce, cloud services, mobile Internet applications, and

data analytics to improve efficiency, flexibility, and innovation, often at lower up-front cost than traditional IT (Opoku et al., 2024; Marston et al., 2011).

Across the studies, financial and capability constraints emerge as the most persistent challenges (OECD, 2021; Holl and Rama, 2023). SMEs face limited budgets for technology, lack internal IT and analytics skills, and often have low awareness of digital options or support schemes (Balocco et al., 2009; Mohamed and Weber, 2020). These problems are more acute for smaller firms and those in rural or peripheral regions, where infrastructure, skill bases and access to finance are weaker, leading to lower adoption of advanced technologies such as AI, big data and blockchain (Holl and Rama, 2023; Li et al., 2023). Organisationally, many SMEs are reluctant to change established business models and often perceive digital transformation as complex, risky and difficult to maintain (Beckinsale et al., 2006).

The evidence nonetheless indicates that SMEs can overcome these barriers through internal leadership, external support and incremental capability building. Owner-managers, CIOs and CEOs frequently act as digital champions, initiating Internet development, mobile solutions or broader transformation when clear business needs or customer pressure are perceived (Beckinsale et al., 2006; Balocco et al., 2009). Local and regional initiatives, including projects, university-linked assistance schemes and industrial Internet platforms, provide process analysis, training, consultancy and ongoing support, while IT suppliers act as important knowledge brokers and implementation partners (Chapman et al., 2000; Mohamed and Weber, 2020). In parallel, government-led digitalisation policies and EU-funded programmes help defray investment costs and expand access to skills and tools, particularly in data analytics, complementing firm-level efforts to build digital capabilities (Opoku et al., 2024; Holl and Rama, 2023). Overall, the studies suggest that SMEs adapt most successfully when affordable, modular technologies, supportive local ecosystems and multi-level policy interventions align with strong internal leadership and a phased, learning-oriented approach to digitalisation (Opoku et al., 2024; OECD, 2021).

4.2. Organisational and Structural Challenges in Implementing AI-Based Sales Forecasting in SMEs

Across the reviewed studies, the adaptation of AI in firms is framed primarily as an organisational and structural challenge rather than a purely technical one (OECD, 2021; Carayannis et al., 2025). AI-driven forecasting is attractive because it can cope better with volatile

markets, fluctuating demand and complex patterns than traditional, historically oriented approaches, and can support more proactive and agile decision-making in supply chains (Jones, 2025; Stepanov, 2025). Yet organisations often struggle to integrate such tools into existing IT landscapes, to secure the necessary data flows and to manage the cultural shifts required to embed AI in everyday decisions (Jones, 2025; Ledro et al., 2023).

A first layer of constraint concerns financial and resource structures. SMEs typically operate with lower economic power, fewer financial resources and fewer highly qualified workers than large firms, which makes substantial up-front investments in AI tools, infrastructure and training difficult to justify (Kolková and Ključnikov, 2022). Interview-based evidence from supply-chain professionals highlights high initial costs and uncertain returns on investment as central reasons for postponing or scaling back AI-driven forecasting projects, especially in smaller organisations (Jones, 2025). Similarly, policy analysis points to sunk costs for training and maintaining AI systems, compounded by SMEs' pre-existing financing constraints, as a core adoption barrier (OECD, 2021). These sunk costs are further aggravated by the computational and energy demands of complex hybrid and DL forecasting models, which increase operating expenses even after systems have been deployed (Gilliland, 2020; Keller et al., 2025). Where budgets are tight, firms may favour simpler forecasting approaches that can be implemented with existing staff and hardware, even when they recognise that more advanced models promise higher accuracy (Kolková and Ključnikov, 2022; Opoku et al., 2024).

The second structural challenge is data readiness. AI forecasting systems depend on large quantities of accurate, standardised and secure data, but many firms, particularly SMEs, lack the systems needed to collect, clean and structure data across functions (Carayannis et al., 2025; OECD, 2021). Empirical work on AI forecasting and SME growth forecasting emphasises persistent problems of data quality, including inconsistency, incompleteness, silos and imbalanced data, which impair the performance and generalisability of ML models (Al-Karkhi and Rządkowski, 2025; Jones, 2025). Weak data foundations, therefore, undermine both the construction of reliable models and the ability to assess and compare them, making it harder for managers to build trust in AI-generated forecasts.

A third set of obstacles relates to human capital and organisational capabilities. Across sources, the shortage of specialised staff, data scientists, ML engineers or analysts, and the difficulty of reskilling existing employees are highlighted as central impediments to AI adoption (Jones, 2025; OECD, 2021). The complexity of many AI and hybrid forecasting

models, including neural networks and ensemble methods, is repeatedly cited as a reason why SMEs do not use them, particularly when they lack in-house expertise and rely on lean teams (Kolková and Ključnikov, 2022; Al-Karkhi and Rządkowski, 2025). Organisationally, embedding AI forecasting into decision processes requires clear business objectives, early involvement of business stakeholders and the transfer of implicit expert knowledge into data and model features; in practice, firms often struggle with change management, unclear goals and limited business engagement in technical projects (Ledro et al., 2023).

Cultural and spatial factors further shape feasibility. Several studies underline that successful AI and CRM implementations require a broader cultural shift towards data-driven, customer-centric decision-making, yet many organisations remain anchored in siloed, intuition-based practices (Ledro et al., 2023; OECD, 2021). Employees may resist change because of fears about job displacement or loss of control, while managers may be sceptical of algorithmic outputs they cannot easily interpret (Ledro et al., 2023). Spatial analyses add another structural dimension: SMEs in rural or small-town locations are less likely to adopt advanced digital technologies, including AI and big data analytics, owing to weaker digital infrastructure, narrower local skill bases and more limited access to support services, even when other firm characteristics are similar (Holl and Rama, 2023). These locational divides amplify existing resource and capability gaps in AI forecasting adoption.

Finally, issues of transparency, explainability and risk governance cut across technical and organisational domains. Complex AI models are often perceived as “black boxes”, raising concerns about liability, accountability and fairness when their forecasts inform high-stakes decisions (OECD, 2021; Ledro et al., 2023). The review literature on ML-based economic and SME forecasting identifies interpretability and model generalisation as key challenges, arguing that advanced techniques such as SHAP and LIME are needed to make forecasts understandable and actionable for decision-makers (Al-Karkhi and Rządkowski, 2025). However, deploying such tools adds further methodological and cognitive complexity, which may be difficult to absorb in resource-constrained settings. Overall, the studies converge on a picture in which the main obstacles to AI forecasting in SMEs lie less in the absence of promising algorithms and more in the financial, data, capability, cultural and spatial structures within which these algorithms must be embedded. These organisational and structural barriers mirror earlier patterns observed in SME digitalisation, which also

point towards possible pathways for overcoming current AI challenges (Opoku et al., 2024; Mohamed and Weber, 2020).

4.3. From SME Digitalisation to AI-Based Forecasting: Overcoming Implementation Barriers

The literature on SME digitalisation indicates that current difficulties in adopting AI, including AI-based forecasting, extend long-standing structural disadvantages rather than create wholly new ones (Opoku et al., 2024; Holl and Rama, 2023). SMEs have historically adopted digital technologies incrementally because of lower economic power, restricted access to finance and limited specialist expertise, which has kept many micro and small firms at the level of basic descriptive or diagnostic analytics (Opoku et al., 2024; Mohamed and Weber, 2020). Where firms have managed to integrate digital tools across core functions and value chains, however, they have realised clear gains in product and process innovation and business growth (Opoku et al., 2024; Holl and Rama, 2023). This experience suggests that AI will be most feasible and valuable when it is built on coherent, already digitised processes and data flows rather than on fragmented systems (OECD, 2021; Carayannis et al., 2025).

A first pathway for overcoming contemporary AI challenges is to reduce the financial and capability burden by externalising technological complexity. Studies on AI, predictive analytics and big-data adoption recommend that SMEs rely on cloud-based services, Software as a Service and ML as a Service, to access pre-built models and scalable computing resources without major capital expenditure or deep in-house expertise (OECD, 2021; Carayannis et al., 2025). Free and low-code tools, including simple trend indicators and user-friendly analytics platforms, provide further entry points for low-tech SMEs and allow experimentation with forecasting and other AI applications at modest risk (Carayannis et al., 2025). Empirical work with UK SMEs shows that external technical assistance and longer-term collaborations help firms to convert digital data into value by developing bespoke analytic tools and building employee capabilities (Mohamed and Weber, 2020). More broadly, collaboration with universities, technology hubs and specialist providers is presented as a pragmatic way to access expertise and tackle data-quality issues without bearing the full cost of permanent expert teams (Carayannis et al., 2025; Mohamed and Weber, 2020).

A second pathway concerns methodological and organisational fit, particularly for AI forecasting. Review work on ML-based economic and SME forecasting finds that ensemble

and DL models can deliver high accuracy but are often difficult to reconcile with SME data volumes, computing power and skills (Al-Karkhi and Rządowski, 2025). Multicriteria evaluations of forecasting tools show that, once constraints such as researcher knowledge and computing power are considered, traditional statistical models may remain more suitable for many SMEs than complex AI or hybrid approaches, even where the latter have superior theoretical accuracy (Kolková and Ključnikov, 2022). Rather than pursuing maximum technical sophistication, SMEs are therefore encouraged to select forecasting methods that fit their structural conditions and strategic priorities. Explainable AI techniques such as SHAP and LIME can further support adoption by making complex model outputs more transparent and usable for managers (Al-Karkhi and Rządowski, 2025).

Finally, prior experiences with digital transformation highlight governance, culture and policy support as crucial enablers for overcoming AI challenges. Ledro et al. (2023) and Stancombe et al. (2017) advocate a phased implementation cycle for AI integration in CRM from discovery and goal setting, through design and deployment, to sustainment, combined with strong business involvement and a focus on use cases with clear marketing or customer-service benefits. Such gradual approaches mirror the established pattern of incremental digitalisation in SMEs and can reduce resistance by demonstrating tangible gains through small-scale experiments, for example, A/B tests (Ledro et al., 2023). At ecosystem level, OECD analysis and spatial studies underline that targeted financial support, reskilling programmes and stronger local business environments are essential to close financing and skills gaps, especially for smaller and rural firms (OECD, 2021; Holl and Rama, 2023). Taken together, these findings suggest that SMEs can best overcome current AI implementation challenges by leveraging existing digital foundations, externalising technical complexity where possible, matching forecasting tools to their organisational realities and embedding AI within broader, policy-supported strategies for capability development and innovation (OECD, 2021; Carayannis et al., 2025).

5. Conclusion

The literature review investigates whether SMEs can feasibly use AI-based sales forecasting as a sustained source of advantage. It shows that forecasting is strategically vital for SMEs' survival, underpinning inventory control, capacity planning and risk management in volatile markets, yet is often conducted with simple statistical and judgemental tools. It then examines AI and ML approaches, which can exploit richer data and sometimes out-

perform classical models, especially in complex or rapidly changing environments. However, the evidence also stresses that hybrid approaches and methodological fit matter more than abstract accuracy rankings. Finally, the review synthesises SME digitalisation research to show that the key obstacles to AI-based forecasting are organisational and structural: financial constraints, weak data foundations, capability and skills gaps, cultural resistance, spatial disadvantages and concerns about transparency and governance. At the same time, prior digitalisation waves suggest possible pathways: incremental adoption, cloud and service-based solutions, external expertise, explainable AI, leadership by owner-managers and targeted policy support. Overall, the review concludes that the main question for SMEs is not whether AI forecasting works in principle, but under which organisational and strategic conditions it becomes feasible, trustworthy and worth the investment.

The review directly underpins the research question, “What organisational and strategic factors influence the feasibility of implementing AI-driven sales forecasting tools in SMEs?” It connects three strands of scholarship: the strategic role of forecasting in SME performance; the technical potential and limitations of AI-based forecasting; and the organisational, structural and spatial features of SME digitalisation. Together, these strands indicate that feasibility depends on the alignment between AI tools and SMEs’ resources, data infrastructures, skills, cultures and wider ecosystems. The review also surfaces key tensions, such as accuracy versus simplicity and transparency versus complexity, that the empirical study will explore in depth.

Prior research has typically treated AI in SMEs, forecasting techniques and SME digitalisation as separate topics. Very few studies focus specifically on AI-based sales forecasting in resource-constrained SMEs or integrate technical performance with organisational feasibility and strategic foresight. Consequently, there is no practice-oriented framework linking AI forecasting to SME resilience and adaptability. The literature review narrows this gap but also clarifies what remains unresolved. Existing studies do not show how SME managers and AI practitioners prioritise different feasibility factors in practice, or how they experience trade-offs between accuracy, simplicity and transparency when choosing forecasting tools. Little is known about how SMEs actually sequence investments in data, skills and digital infrastructure to make AI forecasting workable, or how local ecosystems and support programmes shape these pathways. Finally, the review cannot determine which organisational and strategic preconditions are perceived as “non-negotiable” versus

negotiable by decision-makers. These open questions require empirical investigation beyond secondary sources. To address these open questions, the study employs expert interviews with SME stakeholders and AI practitioners. These interviews will probe perceived benefits, risks, organisational preconditions and implementation pathways for AI-based sales forecasting, using the literature-derived factors as a thematic guide.

Reference List

- Aldoseri, A., Al-Khalifa, K.N. and Hamouda, A.M. (2023) ‘Re-Thinking Data Strategy and Integration for Artificial Intelligence: Concepts, Opportunities, and Challenges’, *Applied Sciences*, 13(12), p. 7082. Available at: <https://doi.org/10.3390/app13127082>.
- Al-Karkhi, M.I. and Rządowski, G. (2025) ‘Innovative machine learning approaches for complexity in economic forecasting and SME growth: A comprehensive review’, *Journal of Economy and Technology*, 3, pp. 109–122. Available at: <https://doi.org/10.1016/j.ject.2025.01.001>.
- Armstrong, J.S. and Green, K.C. (2005) ‘Demand Forecasting: Evidence-Based Methods’, SSRN Electronic Journal [Preprint]. Available at: <https://doi.org/10.2139/ssrn.3063308>.
- Balocco, R., Mogre, R. and Toletti, G. (2009) ‘Mobile internet and SMEs: a focus on the adoption’, *Industrial Management and Data Systems*, 109(2), pp. 245–261. Available at: <https://doi.org/10.1108/02635570910930127>.
- Bandara, K., Bergmeir, C. and Smyl, S. (2020) ‘Forecasting across time series databases using recurrent neural networks on groups of similar series: A clustering approach’, *Expert Systems with Applications*, 140, p. 112896. Available at: <https://doi.org/10.1016/j.eswa.2019.112896>.
- Beckinsale, M., Levy, M. and Powell, P. (2006) ‘Exploring Internet Adoption Drivers in SMEs’, *Electronic Markets*, 16(4), pp. 361–370. Available at: <https://doi.org/10.1080/10196780600999841>.
- Carayannis, E.G. *et al.* (2025) ‘Enhancing SME resilience through artificial intelligence and strategic foresight: A framework for sustainable competitiveness’, *Technology in Society*, 81, p. 102835. Available at: <https://doi.org/10.1016/j.tech-soc.2025.102835>.
- Chapman, P. *et al.* (2000) ‘Building Internet capabilities in SMEs’, *Logistics Information Management*, 13(6), pp. 353–361. Available at: <https://doi.org/10.1108/09576050010355662>.
- Christopher, W. and Rahmatillah, I. (2025) ‘Sales Forecasting for SMEs in Digital Ecosystems: A Comparative Evaluation of ARIMA and Random Forest Models’, in *2025*

- International Conference on Data Science and Its Applications (ICoDSA)*, Jakarta, Indonesia: IEEE, pp. 956–960. Available at: <https://doi.org/10.1109/ICoDSA67155.2025.11157252>.
- Dholakia, R.R. and Kshetri, N. (2004) ‘Factors Impacting the Adoption of the Internet among SMEs’, *Small Business Economics*, 23(4), pp. 311–322. Available at: <https://doi.org/10.1023/B:SBEJ.0000032036.90353.1f>.
- Drydakos, N. (2022) ‘Artificial Intelligence and Reduced SMEs’ Business Risks. A Dynamic Capabilities Analysis During the COVID-19 Pandemic’, *Information Systems Frontiers*, 24(4), pp. 1223–1247. Available at: <https://doi.org/10.1007/s10796-022-10249-6>.
- Erdmann, A. *et al.* (2024) ‘Pricing Powered by Artificial Intelligence: An Assessment Model for the Sustainable Implementation of AI Supported Price Functions’, *Informatica*, pp. 529–556. Available at: <https://doi.org/10.15388/24-INFOR559>.
- Gilliland, M. (2020) ‘The value added by machine learning approaches in forecasting’, *International Journal of Forecasting*, 36(1), pp. 161–166. Available at: <https://doi.org/10.1016/j.ijforecast.2019.04.016>.
- Gupta, A. and Agarwal, P. (2024) ‘Enhancing Sales Forecasting Accuracy through Integrated Enterprise Resource Planning and Customer Relationship Management using Artificial Intelligence’, in *2024 3rd International Conference on Artificial Intelligence For Internet of Things (AIIoT)*, Vellore, India: IEEE, pp. 1–6. Available at: <https://doi.org/10.1109/AIIoT58432.2024.10574785>.
- Holl, A. and Rama, R. (2023) ‘Spatial Patterns and Drivers of SME Digitalisation’, *Journal of the Knowledge Economy*, 15(2), pp. 5625–5649. Available at: <https://doi.org/10.1007/s13132-023-01257-1>.
- ISO (2022) *ISO/IEC 22989: Artificial intelligence — Concepts and terminology*. Geneva: ISO. Available at: <https://www.iso.org/standard/74296.html> (Accessed: 29 October 2025).
- Jones, J. (2025) ‘AI-Driven Demand Forecasting in Supply Chains: A Qualitative Analysis of Adoption and Impact’. Business, Economics and Management. Available at: <https://doi.org/10.20944/preprints202501.1349.v1>.

- Keller, B. *et al.* (2025) ‘Data Analytics – Möglichkeiten und Herausforderungen’, *Wirtschaftsinformatik and Management*, 17(1–2), pp. 55–61. Available at: <https://doi.org/10.1365/s35764-025-00554-5>.
- Kolková, A. and Ključnikov, A. (2022) ‘Demand forecasting: AI-based, statistical and hybrid models vs practice-based models - the case of SMEs and large enterprises’, *Economics and Sociology*, 15(4), pp. 39–62. Available at: <https://doi.org/10.14254/2071-789X.2022/15-4/2>.
- Ledro, C., *et al.* (2023) ‘Integration of AI in CRM: Challenges and guidelines’, *Journal of Open Innovation: Technology, Market, and Complexity*, 9(4), p. 100–151. Available at: <https://doi.org/10.1016/j.joitmc.2023.100151>.
- Li, H. *et al.* (2023) ‘How an industrial internet platform empowers the digital transformation of SMEs: theoretical mechanism and business model’, *Journal of Knowledge Management*, 27(1), pp. 105–120. Available at: <https://doi.org/10.1108/JKM-09-2022-0757>.
- Manos, A. *et al.* (2024) ‘A real world case study on sales prediction using Artificial Intelligence’, in *Proceedings of the 28th Pan-Hellenic Conference on Progress in Computing and Informatics. PCI 2024*, Athens Greece: ACM, pp. 231–236. Available at: <https://doi.org/10.1145/3716554.3716589>.
- Mohamed, M. and Weber, P. (2020) ‘Trends of digitalization and adoption of big data and analytics among UK SMEs: Analysis and lessons drawn from a case study of 53 SMEs’, in *2020 IEEE International Conference on Engineering, Technology and Innovation (ICE/ITMC)*, Cardiff, United Kingdom: IEEE, pp. 1–6. Available at: <https://doi.org/10.1109/ICE/ITMC49519.2020.9198545>.
- Morton, A. (2025). The Illusion of progress: why AI tools alone won’t secure your future. [online] Belfast News Letter. Available at: <https://www.newsletter.co.uk/your-world/the-illusion-of-progress-why-ai-tools-alone-wont-secure-your-future-5382793> [Accessed 5 Dec. 2025].
- OECD (2021) *The Digital Transformation of SMEs*. OECD Publishing (OECD Studies on SMEs and Entrepreneurship). Available at: <https://doi.org/10.1787/bdb9256a-en>.

- Opoku *et al.* (2024) 'Enhancing small and medium-sized businesses through digitalization', *World Journal of Advanced Research and Reviews*, 23(2), pp. 222–239. Available at: <https://doi.org/10.30574/wjarr.2024.23.2.2313>.
- Petropoulos, F. *et al.* (2022) 'Forecasting: theory and practice', *International Journal of Forecasting*, 38(3), pp. 705–871. Available at: <https://doi.org/10.1016/j.ijforecast.2021.11.001>.
- Sohrabpour, V. *et al.* (2021) 'Export sales forecasting using artificial intelligence', *Technological Forecasting and Social Change*, 163, pp. 120 - 480. Available at: <https://doi.org/10.1016/j.techfore.2020.120480>.
- Stepanov, M. (2025) 'Using predictive analytics for managing supply and demand in small and medium-sized enterprises', *European Journal of Economic and Financial Research*. Available at: <https://doi.org/10.46827/ejefr.v9i3.2006>.
- Stancombe, C. *et al.* (2017) *Turning AI into concrete value: the successful implementers' toolkit*. Digital Transformation Institute, Capgemini. Available at: <https://www.capgemini.com/consulting-de/wp-content/uploads/sites/32/2017/09/artificial-intelligence-report.pdf> (Accessed: 5 December 2025).
- Wiśniewski, J.W. (2021) 'Forecasting in Small Business Management', *Risks*, 9(4), pp. 69. Available at: <https://doi.org/10.3390/risks9040069>.

Declaration of Authorship

DCU Business School

Assignment Submission: 09/11/2025

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Programme: Bachelor of Arts in Global Business (Germany)

Project Title: Research Proposal

Module Code and Title: BAA1010 Business Project

Lecturer: Professor Teresa Hogan

Project Due Date: 09/11/2025

Declaration

I declare that this material, which I now submit for assessment, is entirely my own work and has not been taken from the work of others, save and to the extent that such work has been cited and acknowledged within the text of my work. I understand that plagiarism, collusion, and copying is a grave and serious offence in the university and accept the penalties that would be imposed should I engage in plagiarism, collusion, or copying. I have read and understood the Assignment Regulations set out in the module documentation. I have identified and included the source of all facts, ideas, opinions, viewpoints of others in the assignment references. Direct quotations from books, journal articles, internet sources, module text, or any other source whatsoever are acknowledged and the source cited are identified in the assignment references.

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I/me/my incorporates we/us/our in the case of group work, which is signed by all of us.

Signed:



Declaration of AI

Declaration Statement

Please tick the appropriate box relating to your use of Gen AI tools in this thesis

A. I did not use any Gen AI tools (including for editing and proofreading) in the completion of this assignment

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Date: 09.11.2025

If you tick A and evidence of Gen AI use is found in your assignment, this constitutes a breach of academic integrity, and your case will be forwarded to the Faculty Disciplinary Committee for further investigation.

If you tick B: please complete the below -

No.	Date	Tool	Details
1	28.12.2025	NotebookLM	Used NotebookLM to generate detailed bullet-point summaries of my journal articles in order to obtain an overview of the material and to identify initial themes for the literature review. The exact prompt used was: "Summarise each source individually in detailed bullet points. Focus on the main purpose, key findings, and implications for SMEs, forecasting, digitalisation, and/or AI." The AI output served only as a starting set of notes; I checked every point against the original articles, ad-

			justed for accuracy. No AI-generated statement was included in the thesis without verification from the source texts.
2	29.12.2025	Notebook LM	<p>Employed NotebookLM to summarise documents relevant to my first and second themes so I could clarify the core arguments and evidence. The exact prompt used was:</p> <p>"Summarise each source individually in detailed bullet points. Focus specifically on: Why forecasting is important in general and particularly for SMEs. Why SMEs should engage in systematic forecasting. How firms carried out forecasting before the introduction of AI. How SMEs have adapted to the Internet, digitalisation, and other technologies. The main challenges SMEs faced in these processes. How these challenges were addressed or overcome."</p> <p>The summaries were used as a framework to structure the themes and to check coverage; I then re-read the original sources, corrected and refined the points, and composed the final text myself without copying AI wording.</p>
3	02.12.2025	Notebook LM	<p>Used NotebookLM to produce extensive bullet-point summaries of newer journal articles in order to update my overview and refine the final set of themes, especially the integration of past SME technology adoption (as recommended in the supervisor meeting). The exact prompt used was:</p> <p>"Summarise each source individually in extensive bullet-point form, providing a thorough account of aims, key arguments, empirical evidence, and implications for SMEs, forecasting, digitalisation, and AI."</p> <p>The AI output functioned only as an organising help; I</p>

			systematically compared each summary with the original articles, adjusted for nuance and emphasis, and wrote the thematic discussion independently in my own words.
4	02.12.2025	Note-book LM	<p>Applied NotebookLM to a selected set of documents underpinning Theme 3.1 to extract detailed notes on adoption processes and barriers. The exact prompt used was:</p> <p>"Summarise each source individually in detailed bullet points. Focus specifically on: How SMEs have adapted to the Internet, digitalisation, and other technologies. The organisational, financial, and contextual challenges they encountered. The strategies, supports, or conditions that enabled them to overcome these challenges."</p> <p>I used the resulting summaries to check the completeness and ordering of my arguments, then verified all content directly against the sources and rewrote it entirely in my own language.</p>

5	03.12.2025	Note-book LM	<p>Used NotebookLM to summarise key documents for Themes 3.2 and 3.3 (AI adoption and AI-based forecasting in SMEs) and to identify whether newer papers added relevant points to Themes 1 and 2. The exact prompt used was:</p> <p>"Summarise each source individually in extensive bullet-point form. Focus specifically on: Challenges in the adoption of AI in companies in general. Key challenges specific to AI-based forecasting in SMEs. Factors that facilitate SMEs' adoption of AI-based forecasting. How SMEs can overcome current barriers to implementing AI. Also summarise for each source: Why forecasting is important, especially for SMEs, and why SMEs should engage in forecasting. How companies conducted forecasting before the introduction of AI. How SMEs have adapted to the Internet, digitalisation, and other technologies. The challenges they faced and how they overcame those challenges."</p> <p>The output helped me map challenges, enablers, and thematic overlaps, but all claims were checked against the original papers; I then integrated only verified points and expressed them entirely in my own words.</p>
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6	03.12.2025	Note-book LM	<p>Asked NotebookLM to draft a comparative overview of similarities and differences between the main studies, organised by my key themes.</p> <p>The exact prompt used was:</p> <p>"Construct a comparative table that identifies similarities and contradictions across the studies. Column 1: Theme Column 2: Similarities between studies Column 3: Contradictions or differences between studies Use the following themes: Why SMEs need forecasting Benefits and limits of AI-based forecasting How SMEs have adapted to past technologies (e.g. Internet, digitalisation) Internal and external challenges to adopting AI-based forecasting How SMEs can overcome AI-related challenges"</p> <p>I treated the generated table as a preliminary map, then checked each entry against the underlying studies, removed or corrected inaccuracies, and recreated the final comparative analysis and wording myself.</p>
7	09.12.2025	Grammarly	<p>Used Grammarly on the final draft solely to check grammar, spelling, and punctuation. No stylistic rewriting, rephrasing, or content changes were accepted. I reviewed each suggested correction manually before applying it, in line with DCU guidelines that permit only basic proofreading functions and do not allow AI-generated content.</p>

Appendix

Search Strategy

Concept 1	Link	Concept 2	Link	Concept 3	Link	Concept 4	Concept 3	Link	Concept 4	Link	Concept 5
"AI"		*Forecast*		"SME"		"Implement"	"SME"		"Implement"		"Internet"
OR		OR		OR		OR	OR		OR		OR
"Artificial intelligence"		"Sales w/5 forecast"		"Small and medium sized Enterprises"		"adop"	"Small and medium sized Enterprises"		"adop"		"digitali"
OR		OR		AND		OR	OR		OR		OR
"Predictive analytics"	AND	"Sales w/5 predict"	AND	"Medium enterprise"	AND	"challenge"	"Medium enterprise"	AND	"challenge"	OR	"technology"
OR		OR		OR		OR	OR		OR		OR
"Machine Learning"		OR		OR		"driver"	"Small business"		"driver"		OR
OR		OR		OR		OR	"Small business"		"enabler"		"Industry 4.0"
"advanced analytics"		"Demand predict"		"Small business"		"enabler"			"enabler"		

Two tables are needed because technology has been used in different ways in the past.

Thematic Review and Analysis

Theme	Sub-Theme	In-Text Citation	Summary	Relevance to research Topic	Connection and Links
1	Why SMEs need forecasting	1 Kolková & Kijačnik, 2022	Demonstrates that SMEs rely heavily on forecast quality to remain viable, which explains why they might consider AI-based tools despite constraints.	Shows that forecasting is strategically important for SMEs with limited resources and fragile structures, highlighting its role in inventory, cost and growth decisions.	Use with Christopher & Rahmatullah (2025) to show how forecasting supports inventory and logistics decisions in SMEs.
		2 Stepanov, 2025	Positions forecasting as central to SME resilience and competitiveness under uncertain market conditions.	Argues that predictive analytics for supply and demand enables SMEs to manage volatility with lean inventories, reinforcing the strategic need for reliable forecasts.	Use with Wisniewski (2021) to underline forecasting as a core tool for SME survival and cost control.
		3 Wisniewski, 2021	Establishes forecasting as a core managerial capability for SMEs, not a technical add-on, which underpins the whole motivation for AI-driven sales forecasting.	Shows that structured forecasting reduces decision errors and is essential for strategic planning in small businesses, giving a foundational justification for why SMEs should forecast at all.	Use as an empirical SME example showing how better forecasts reduce overstocking and stockouts and support inventory/logistics decisions; link to Kolková & Kijačnik (2022) and Gupta & Agarwal (2024) when discussing operational benefits of forecasting.
		4 Christopher & Rahmatullah, 2025	Demonstrates the direct operational pay-off of accurate forecasts in SME contexts.	Provides empirical evidence that forecasting reduces stockouts and overstocks for SMEs, protecting sales and customer satisfaction.	Empirical example of SME sales forecasting (ARIMA vs Random Forest); pair with Cherin et al. (2025) when discussing specific forecasting tools for SMEs.
		5 Jones, 2025	Provides qualitative evidence that better forecasts are seen by practitioners as crucial for proactive supply-chain management.	Shows that AI-driven forecasting helps supply-chain actors manage volatility and improve decision-making, reinforcing the importance of forecasting for SMEs in complex supply networks.	Use together with Carayannis et al. (2025) to show how AI-based forecasting creates value but faces data, cost and skills barriers for SMEs.
2	Benefits and limits of AI forecasting	1 Gilliland, 2020	Provides a central argument for treating AI as complementary to, not a replacement for, classical forecasting.	Shows from the M4 competition that pure ML methods often underperform simple or hybrid statistical models, challenging "AI always wins" assumptions.	Link to Al-Karkhi & Rajdowski (2025) as the main evidence that hybrid approaches often outperform pure ML and that complexity brings higher costs.
		2 Manos et al., 2024	Provides a strong empirical example of AI's forecasting advantage in complex data environments, helping justify SME interest.	Shows that tree-based ML models outperform ARIMA in sales prediction when enriched with variables such as weather and online search data.	Combine with Sohrabpour et al. (2021) to illustrate how AI models can improve forecast accuracy when enough data and features are available.
		3 Keller et al., 2025	Positions AI forecasting as part of a broader analytics-driven improvement agenda.	Describes how data analytics, including forecasting, can improve processes, customer understanding and decision quality.	Use with OECD (2021) to frame AI forecasting as part of a broader data-analytics and governance agenda that demands investment and organisational change.
		4 Carayannis et al., 2025	Shows that AI forecasting can contribute to strategic foresight but only if embedded in wider capabilities.	Highlights AI's ability to anticipate trends, shocks and risks, extending the value of forecasting beyond pure accuracy.	Pair with Jones (2025) to highlight how AI forecasting can enhance resilience and strategic foresight, but is constrained by SME resources and capabilities.
		5 Al-Karkhi & Rajdowski, 2025	Provides your main conceptual overview of AI-forecasting techniques and their performance trade-offs for SMEs.	Reviews ML, ensemble and deep-learning approaches for economic and SME forecasting, detailing the conditions under which they outperform traditional models.	Contexts to Gilliland (2020) on M4 results and to Kolková & Kijačnik (2022) on SME-focused evaluations.
1	How SMEs adapted to new technologies	1 Opoku et al., 2024	Demonstrates that SME digitalisation is gradual, path-dependent and shaped by capabilities and policy context, which parallels likely trajectories for AI-based forecasting.	Shows how SMEs adopt digital tools such as e-commerce and data analytics in stages, depending on finance, skills and external support, giving a blueprint for how they might approach AI forecasting.	Link to OECD (2021) to show that SME digitalisation is gradual and resource-constrained, and that policy support matters.
		2 Mohamed & Weber, 2020	Shows that SMEs often integrate advanced analytics through collaborative projects and external expertise rather than purely internal development.	Examines how UK SMEs adopted big data and analytics, highlighting patterns of experimentation, learning and reliance on external technical partners.	Use with Carayannis et al. (2025) to demonstrate the role of external experts and long-term collaborations in building analytics capabilities in SMEs.
		3 OECD, 2021	Serves as a broad backdrop for how SMEs historically engage with new technologies, including the conditions under which digital tools diffuse.	Provides a comprehensive overview of SME digital transformation patterns across countries, sectors and regions, showing incremental adoption and structural heterogeneity.	Core ecosystem reference; pair with Opoku et al. (2024) to show how finance, skills and regional factors shape SME digital and AI adoption.
		4 Dholakia & Kshetri, 2004	Shows that SMEs tend to move gradually from simple to more complex digital tools, often constrained by resources and uncertainty, which parallels likely adoption paths for AI forecasting.	Analyses how SMEs adopted the Internet and e-commerce in stages, from basic connectivity to more advanced online activities, illustrating incremental learning and risk-averse behaviour.	Use with Chapman et al. (2000) to illustrate staged Internet adoption and early drivers/barriers in SMEs.
		5 Li et al., 2023	Demonstrates that SMEs can progress to sophisticated digital solutions when enabled by platforms and supportive ecosystems, hinting at similar routes for AI-based forecasting.	Examines how an industrial internet platform supports SME digital transformation, showing firms embedding more advanced tools once foundational digital capabilities are in place.	Context to Opoku et al. (2024) to show how industrial internet platforms support later-stage digital transformation in SMEs.
		6 Chapman et al., 2000	Illustrates that structured assistance programmes have historically been key to getting SMEs to adopt foundational technologies like email and web, a pattern you extrapolate to AI tools.	Documents early initiatives helping manufacturing SMEs build Internet capabilities via consultancy packages and practical support, highlighting the importance of external facilitators.	Pair with Dholakia & Kshetri (2004) as early evidence that SMEs started with basic Internet/CT and relied on consultancy support.
		7 Beckinsale et al., 2006	Shows that internal leadership and perceived business benefit are crucial for SMEs to move from awareness to actual use of new technologies.	Explores drivers of Internet adoption in SMEs, stressing the role of owner-managers as digital champions and the organisational reluctance to change established modes.	Use with Chapman et al. (2000) to emphasise the role of owner-managers and internal champions in driving digital adoption.
3	From digitalisation to AI challenges	1 Kolková & Kijačnik, 2022	Frames AI forecasting challenges as structural (skills, computing power, resources) rather than simply a matter of choosing the "best" algorithm.	Highlights that complex AI and hybrid models often exceed SME skills and infrastructure, creating a gap between theoretical accuracy and practical feasibility.	Here, emphasise that statistical methods may be more feasible for SMEs than complex AI, and link to Al-Karkhi & Rajdowski (2025) on similar trade-offs.
		2 Stepanov, 2025	Emphasises that readiness for AI forecasting is contingent on prior analytical maturity and resource availability.	Notes financial and data limitations that resist SME use of sophisticated analytics, indicating why many firms stay with simpler forecasting.	Use to show that predictive analytics helps SMEs manage supply and demand, reduce stockouts/overstocking and improve cost control and operational efficiency; contrast with later discussion (Jones, 2025; OECD, 2021) on adoption barriers.
		3 Gilliland, 2020	Underlines that computational and methodological demands can limit the practicality of state-of-the-art AI forecasting in smaller firms.	Highlights that the most effective methods in M4 were often more complex and resource-intensive, raising questions about feasibility for SMEs.	Use to show that more complex hybrids add computational costs; connect briefly to Keller et al. (2025) on cost and complexity.
		4 Keller et al., 2025	Provides strong support for your data-readiness and resource-constraint discussion.	Emphasises data quality, integration, cost and governance obstacles that organisations face when scaling analytics.	Use to position AI forecasting within the wider data-analytics agenda and to show that complex hybrid/DL models increase computational and energy costs; link to Gilliland (2020) for similar concerns about complexity and cost.
		5 Opoku et al., 2024	Positions many AI-related obstacles as continuations of long-standing digitalisation challenges rather than entirely new problems.	Identifies structural disadvantages (limited finance, skills, location) that hinder SME uptake of advanced digital technologies, directly narrowing barriers to AI-driven forecasting.	Use to show how broader digitalisation (e-commerce, cloud, data analytics) supports SME efficiency and growth; link to OECD (2021) and Holt & Rama (2023) when discussing how these benefits depend on resources, skills and local ecosystems.
		6 OECD, 2021	Frames AI-forecasting barriers as part of a wider set of systemic SME disadvantages rather than isolated technical issues.	Identifies key constraints (finance, skills, infrastructure, management practices and location) that limit SME adoption of advanced digital technologies, directly relevant to AI forecasting feasibility.	Use to summarise structural finance and skills gaps that limit AI-forecasting feasibility.
		7 Jones, 2025	Offers rich, practice-oriented insights into why AI forecasting projects stall or succeed inside organisations.	Documents organisational, data and cultural barriers that firms face when trying to implement AI-driven demand forecasting, including integration issues and scepticism about model outputs.	Use here specifically for barriers: data quality, skills, integration, and change resistance.
		8 Al-Karkhi & Rajdowski, 2025	Frames AI-forecasting obstacles as stemming from the interaction of complex models with limited data, skills and validation capacity.	Emphasises challenges around data complexity, generalisation and interpretability, which are particularly problematic for resource-constrained SMEs.	Highlight imbalanced data, validation challenges and the need for explainability as key technical obstacles.
		9 Carayannis et al., 2025	Supports your argument that feasibility depends on organisational readiness, not just tool availability.	Identifies capability, cultural and governance issues that condition whether AI delivers resilience benefits in SMEs.	Show how financial, technical and operational barriers cluster together and require strategic foresight.
3	How SMEs overcome AI challenges	1 Carayannis et al., 2025	Provides a conceptual basis for combining internal capability building with external ecosystem support.	Proposes foresight-driven, policy-supported strategies to embed AI in SME resilience and innovation paths.	Use for gradual, modular adoption and the importance of supportive digital ecosystems.
		2 Mohamed & Weber, 2020	Supports the idea that SMEs can mitigate skills and resource gaps in AI forecasting by partnering with universities, technology hubs and specialist providers.	Demonstrates that longer-term collaborations, consultancy and training help SMEs turn digital data into value, offering a concrete model for building AI-forecasting capabilities.	Use as empirical evidence that external technical assistance and long-term collaborations help SMEs build analytics capabilities and turn digital data into value; link to Carayannis et al. (2025) for the broader strategic foresight and AI framework.
		3 OECD, 2021	Provides the policy framework underpinning your recommendations on external support for AI-forecasting implementation in SMEs.	Outlines policy levers (finance schemes, training, advisory services, infrastructure investment) that can close SME gaps and support adoption of advanced tools like AI forecasting.	Use to back recommendations on financial support, reskilling programmes and regional policy measures.
		4 Al-Karkhi & Rajdowski, 2025	Supports your recommendation that SMEs pursue understandable, fit-for-purpose AI forecasting instead of maximising technical sophistication.	Advocates explainable AI methods (e.g. SHAP, LIME) and model choices that match available data and expertise to make forecasts usable for decision-makers.	Use for the recommendation to employ explainable AI tools (e.g. SHAP, LIME) so managers can trust and use forecasts.
		5 Leiro et al., 2023	Provides a practical roadmap for reducing resistance and embedding AI tools in everyday decision-making in SMEs.	Proposes a phased AI implementation cycle (discovery, design, deployment, sustainment) with strong business involvement and small experiments, offering a clear process model for introducing AI forecasting.	Use with Stancombe et al. (2017) for a phased AI implementation roadmap (discovery → design → deployment → sustainment).