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Comparative Evaluation of AI Maturity Frameworks for Predictive Analytics in Food and Beverage Manufacturing SMEs in the UK

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Abstract:
This paper evaluates the suitability of four prominent AI and analytics maturity frameworks- Microsoft, PwC Responsible AI, SAS Business Analytics Maturity, and Domino Data Science Maturity for guiding ERP-enabled predictive analytics in UK food and beverage manufacturing SMEs.
Motivated by the tension between generic, enterprise-oriented frameworks and the resource-constrained, ERP-dependent reality of SMEs, the study develops six context-specific evaluation criteria: Strategic Alignment (ERP-PA), Data Architecture and Governance, Technical Predictive Analytics Capability, SME Context and Scalability, F&B Manufacturing Fit, and a Responsible/Trustworthy AI Lens.
A qualitative documentary design is used, combining PRISMA-style corpus construction, structured data extraction, and multi-criteria scoring to compare the four frameworks systematically. Findings show that no single framework is fully fit-for-purpose. Microsoft and SAS provide relatively strong strategic and technical coverage but embed large-firm assumptions; PwC offers rich governance guidance but limited ERP-centric or sectoral specificity; Domino exemplifies advanced data-science operations yet lacks SME feasibility and food-sector alignment.
The paper contributes a transferable criteria-based lens and a transparent documentary Multi-Criteria Decision Analysis (MCDA) approach for assessing AI maturity frameworks in specific organisational and sectoral contexts. Practical recommendations are offered for SME managers, ERP vendors, and policymakers on selectively combining and adapting existing frameworks rather than creating new ones.

Keywords: SME, Beverage, United Kingdom, Artificial Intelligence, Decision Analysis

CHAPTER ONE: INTRODUCTION

1.1 Background of the Study

Within the broader context of digital transformation, Artificial Intelligence (AI) maturity frameworks have become strategic tools for organisations, guiding them in the appropriate and strategic use of Artificial Intelligence. Frameworks such as Microsoft's AI in European Manufacturing Industries, PwC's Responsible AI Maturity Model, SAS's Business Analytics Maturity Framework and Domino Data Lab's Data Science Maturity Model are designed to help firms assess their readiness for AI, identify development pathways, and guide decisions around governance, investment, resource prioritisation and allocation.
These frameworks and models are widely promoted by consultancies and technology vendors worldwide because they all depict that AI capabilities evolve in stages, typically moving from early experimentation to being the engine room of the entire organisation's operations. In practice, however, these frameworks often assume scalable infrastructure and dedicated specialist expertise. These assumptions do not sit easily

with the realities of Small and Medium- Sized Enterprises (SMEs), where limited resources adapt a necessity rather than a strategic choice, signposting and early misalignment between generalised frameworks and constrained organisational contexts (Ernst & Young LLP, 2020).
Predictive analytics is at the centre of this strategic promise, representing a high impact AI capability that extends beyond technical sophistication to require organisational alignment. In manufacturing settings, predictive analytics supports demand forecasting to reduce stockouts in volatile supply chains, enables predictive maintenance to limit unplanned downtime, and strengths quality assurance by identifying defects earlier in production processes. Its value, however, is not automatic. Benefits depend less on the presence of advanced algorithms and more on effective data integration across fragmented systems, and across functional engagement that allows insights to inform decisions in practice (Department for Business and Trade, 2025).
For UK food and beverage manufacturing SMEs, these dependencies are intensified by sector-specific pressures. The sector comprises roughly 20,000 firms, contributes approximately £37 billion annually, and employs close to 500,000 people. At the same time, it operates under constraints shaped by product perishability, strict compliance with Food Standards Agency regulations, and consistently thin profit margins, often below 5% (Food and Drink Federation, 2025; Department for Business and Trade, 2025).
Focusing specifically on ERP-enabled food and beverage manufacturing SMEs in the UK highlights a critical context. Enterprise Resource Planning (ERP) systems function as the core digital infrastructure for these firms, integrating planning, inventory management, financial reporting and regulatory compliance within environments characterised by production barely meeting demands and deadlines, also ongoing labour shortage (Ernst & Young LLP, 2020). This centrally positions ERP systems as the primary gateway for predictive analytics, bringing together data from shop floor equipment, suppliers and sales channels to support use cases

Figure 1.1 Integration of operational data, ERP and predictive analytics for business outcomes (Authors own illustration)

1.2 Problem Statement

The core research problem is that existing AI maturity frameworks are poorly aligned with the operational realities of UK food and beverage manufacturing SMEs that are attempting to develop predictive analytics capabilities. Most frameworks adopt abstract, capability-centric architectures that assume enterprise-scale conditions, while SMEs operate within tightly constrained, ERP-centred environments.

Frameworks such as Microsoft's AI in European Manufacturing Industries, PwC's Responsible AI Maturity Model, SAS's Business Analytics Maturity Framework and Domino Data Lab's Data Science Maturity Model typically present linear maturity pathways grounded in assumptions of extensive data lakes, specialised analytics teams, and iterative governance structures that support progression from descriptive to predictive analytics.

While these models are effective at conceptualising staged advancement, emphasising outcomes such as productivity and return on investment (SAS Institute Inc., 2016), ethical scaling (PricewaterhouseCoopers, 2021), manufacturing integration (Ernst & Young LLP, 2020), and data science workflow maturity (Domino Data Lab, 2020), they embed assumptions of resource availability that contrast sharply with SME conditions. This disconnect is heightened by current economic pressures, with 41% of UK food and beverage SMEs having scaled back digital investment during 2025 (Food and Drink Federation, 2025).

This misalignment is most evident in how frameworks address, or fail to address, ERP integration. ERP systems function as the primary data backbone for over 70% of UK manufacturing SMEs, consolidating shop-floor measurements and activities, inventory movements, compliance records, and transactional data required for predictive analytics. Yet most maturity frameworks treat data infrastructure in largely technology-agnostic terms, paying limited attention to vendor-specific Application Programme Interfaces (APIs), legacy customisations, or persistent data quality challenges. Government evidence suggests that up to 60% of SME ERP deployments suffer from significant data quality gaps, which directly undermine advanced analytics efforts (Department for Business and Trade, 2025). Although Microsoft's manufacturing-oriented framework gestures toward operational AI integration, it largely assumes seamless IoT ERP connectivity, an assumption that rarely holds for SMEs reliant on on-premises SAP systems or fragmented hybrid cloud environments (Ernst & Young LLP, 2020).

Similarly, SAS's analytics maturity metrics prioritise productivity outcomes while overlooking the rigidity of ERP architectures, where real-time predictive use cases often depend on costly middleware solutions that are typically beyond SME budgets (SAS Institute Inc., 2016). PwC and Domino place strong emphasis on governance maturity and cross-functional orchestration, yet these expectations are not necessarily met with SME operating models in which individuals often perform multiple roles and lack the capacity to sustain the level of coordination these frameworks imply (PricewaterhouseCoopers, 2021).

For UK food and beverage manufacturers, these gaps have tangible operational consequences. Predictive analytics is frequently presented as a solution to sector challenges, offering potential reductions in waste of 15- 20% through shelf-life forecasting and downtime reductions of up to 25% through predictive maintenance. However, these benefits are unlikely to materialise without processes that explicitly account for perishability constraints, such as 48-hour dairy shelf lives, mandatory Food Standards Agency traceability requirements, and profit margins compressed to between 3% and 5% by volatile input costs (Food and Drink Federation, 2025).

In practice, managers are often caught between vendor-driven narratives and policy initiatives such as Made Smarter, relying on broad maturity assessments that inflate capability scores and misdirect investment. This has contributed to high failure rates in SME analytics pilots, with over 50% failing due to poor ERP integration and unready data foundations (Make UK, 2025). The result is not only wasted capital but a widening digital divide, where only 12% of food manufacturing SMEs progress beyond basic reporting, increasing their exposure to supply chain shocks and the financial burden of net-zero compliance (Department for Business and Trade, 2025).

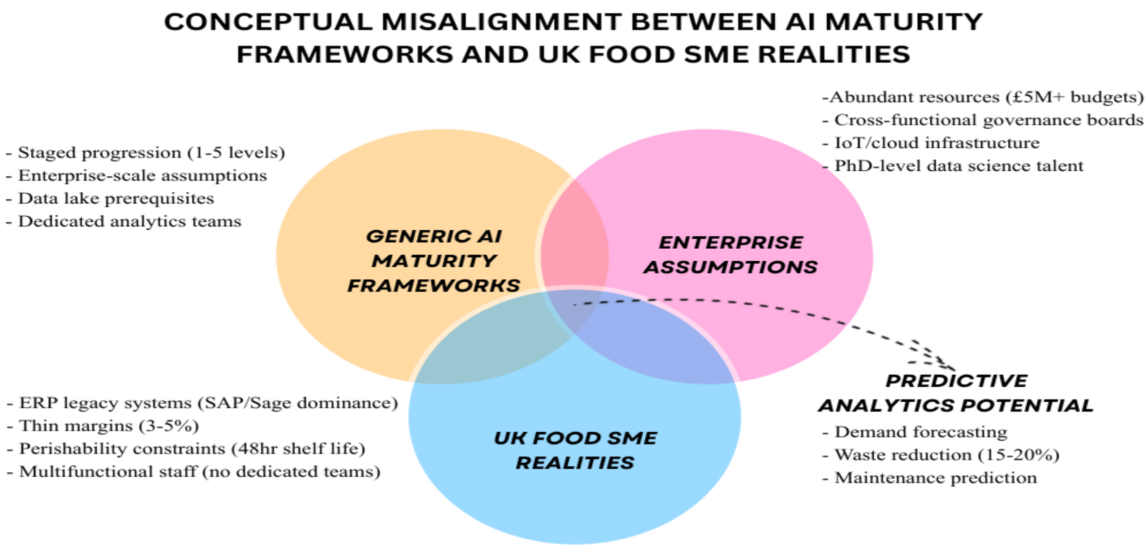

Figure 1.2: Conceptual Misalignment Between AI Maturity Frameworks and UK Food SME Realities

Critically, there is no systematic comparative evaluation of the suitability of these four AI maturity frameworks for ERP-dependent predictive analytics within a highly regulated, low-margin sector. This leaves SME decision-makers without evidence-based guidance for selecting or interpreting maturity models. The issue, therefore, is not simply one of contextual adaptation but of structural incompatibility. Frameworks designed around universal progression encourage over-optimistic roadmaps, while SME environments demand pragmatic, context-sensitive diagnostics capable of bridging the gap between strategic aspiration and operational execution.

1.3 Research Aim and Research Question

This paper aims to conduct a systematic comparative evaluation of four established AI maturity frameworks: Microsoft's AI in European Manufacturing Industries, PwC's Responsible AI Maturity Model, SAS's Business Analytics Maturity Framework and Domino Data Lab's Data Science Maturity Model (Domino Data Lab, 2020). The evaluation seeks to determine how well these frameworks support the adoption of predictive analytics within ERP-enabled food and beverage manufacturing SMEs in the UK.

This aim is addressed through the following research question:

How suitable are the selected AI maturity frameworks for guiding ERP-enabled predictive analytics implementation in UK food and beverage manufacturing SMEs?

A comparative assessment approach is appropriate because it allows for systematic examination of the frameworks' core documentation and stated applications. This enables structured comparison against

SME-relevant criteria, including ERP integration practicality, sector-specific constraints, and the operational realism of proposed maturity roadmaps (Ernst & Young LLP, 2020; PricewaterhouseCoopers, 2021).

This approach aligns with the study's scope by using secondary data and eliminating the need for primary data collection. At the same time, it allows the research to surface the misalignments identified in the problem statement without introducing new constructs or proposing alternative models.

1.4 Research Objectives

To fulfil the research, aim and address the research question, the paper pursues four objectives, moving from descriptive review to evaluative synthesis and applied insight:

1. To systematically review and describe the main characteristics of the four selected AI maturity frameworks, including their design principles, structural components, assessment logic, and documented applications within manufacturing or analytics contexts.
2. To develop an evaluation criteria framework tailored to UK food and beverage manufacturing SMEs, reflecting challenges specific to ERP integration and incorporating dimensions such as strategic fit, data infrastructure feasibility, predictive analytics coverage, SME resource constraints, governance suitability, and empirical grounding.
3. To conduct a comparative documentary analysis of the four AI maturity frameworks against the developed criteria, identifying areas of alignment and misalignment, relative strengths and limitations, and overall suitability for supporting ERP-enabled predictive analytics in the target sector.
4. To synthesise the findings into practical recommendations for UK food and beverage manufacturing SME managers, ERP vendors, and policymakers, focusing on informed framework selection or adaptation to support predictive analytics adoption, without proposing a new maturity model.

Objective	Description	Linked Chapter(s)	Primary Deliverable
Objective 1	Systematically review and document the core characteristics of the four selected AI maturity frameworks (Microsoft, PwC, SAS, Domino), including structure, dimensions, assessment logic, and documented applications	Chapters 2 & 4	Structured framework profiles with documentary evidence

Objective 2	Develop a tailored evaluation criteria framework informed by UK food and beverage SME realities, ERP integration challenges, and predictive analytics requirements (6 dimensions: strategic alignment, ERP/data integration, predictive coverage, SME feasibility, governance, empirical validation)	Chapters 2.11 & 3	6-criteria evaluation matrix with ERP contingency weighting
Objective 3	Conduct comparative documentary analysis of the four frameworks against evaluation criteria, identifying strengths, limitations, patterns of misalignment, and relative suitability	Chapter 4	Weighted MCDA suitability rankings and comparative patterns
Objective 4	Synthesise findings into practical recommendations for UK food and beverage manufacturing SME managers, ERP vendors, and policymakers, highlighting optimal framework selection/adaptation strategies	Chapter 5	Decision-support artefacts and adaptation guidelines

Table 1.1: Hierarchical Structure of Research Objectives and Methodological Linkages

These objectives follow a deliberate sequence. The study begins with a structured examination of existing frameworks (Objective 1), progresses to the development of context-sensitive evaluation criteria (Objective 2), applies these criteria through systematic comparison (Objective 3), and concludes with actionable insights grounded in empirical and contextual analysis (Objective 4). This progression ensures methodological rigour while directly addressing the misalignment between generic AI maturity frameworks and the operational realities of ERP-dependent SMEs.

1.5 Research Significance and Expected Contribution

This paper makes a clear academic and practical contribution by addressing a gap in the AI maturity literature; the limited attention paid to context-specific assessment in ERP-constrained manufacturing SMEs. Much of the existing literature treats AI maturity frameworks as broadly transferable, yet offers little scrutiny of how their underlying assumptions hold in sectors characterised by resource scarcity and operational rigidity.

From an academic perspective, this study contributes to debates on the transferability and contingency of maturity frameworks by demonstrating how differing levels of abstraction across enterprise-oriented models affect their applicability in SME environments. In particular, it shows that Microsoft's manufacturing pathway, PwC's emphasis on ethical scaling, SAS's metrics-driven assessment logic and Domino's data science progression model embody distinct assumptions about organisational scale, governance capacity, and data infrastructure. These assumptions materially shape their usefulness in resource-constrained settings.

Methodologically, the study departs from generic benchmarking approaches by applying a criteria-based comparative analysis grounded in sector-specific operational realities. This shift enables a more critical and contextual evaluation of maturity frameworks, strengthening the rigour of digital transformation research focused on SMEs (Department for Business and Trade, 2025). In doing so, the research extends theoretical discussions on framework contingency by positioning ERP integration and predictive analytics capability as central mediating factors that are largely absent from dominant maturity typologies.

The practical significance of the study is equally pronounced. For UK food and beverage manufacturing SMEs operating amid reduced investment capacity, with 41% scaling back digital spending and business confidence falling to -43% in 2025 (Food and Drink Federation, 2025), the findings offer evidence-informed guidance on selecting or adapting AI maturity frameworks. This is particularly relevant given the high failure rates in SME analytics pilots, which exceed 50% and are frequently linked to misaligned roadmaps and weak ERP integration (Make UK, 2025). By clarifying where and why specific frameworks fall short, the research supports more realistic decision-making and reduces the risk of misdirected investment.

The study also has implications for ERP vendors and policymakers. For ERP providers, the findings highlight recurring SME pain points that constrain predictive analytics adoption, enabling more targeted integration strategies aligned with sector-specific use cases such as perishability forecasting. For policymakers, particularly those involved in initiatives such as Made Smarter and the UK Industrial Strategy, the analysis provides empirical support for more focused digital uplift programmes aimed at addressing the persistent gap in advanced analytics adoption, currently limited to around 12% of food manufacturing SMEs (Department for Business and Trade, 2025).

The outputs of the research include:

1. A validated evaluation criteria matrix for assessing AI maturity frameworks in ERP-dependent SME contexts.
2. A comparative mapping of framework strengths, limitations, and sectoral suitability.
3. Practical adaptation guidelines to support managerial, vendor, and policy decision-making.

No new AI maturity framework is proposed. Instead, the study synthesises insights from existing models to outline pragmatic pathways for enabling responsible predictive analytics adoption, without overstating transformative potential or encouraging unrealistic capability leaps.

1.6 Journal Paper Structure

This paper follows a structured and sequential design. Chapter Two presents the literature review, situating AI maturity models within broader theories of AI adoption and digital transformation. It also examines predictive analytics and ERP systems in the context of food and beverage manufacturing SMEs and reviews the four selected frameworks, leading to the derivation of evaluation criteria.

Chapter Three outlines the research methodology, detailing the documentary comparative analysis approach, data extraction procedures, coding strategy, and quality assurance measures.

Chapter Four presents the findings, including structured descriptions of the frameworks, criteria-based comparisons, and an interpretive discussion of suitability patterns within the target context.
Chapter Five synthesises the findings, reflects on the study's contributions and limitations, and offers practical recommendations for relevant stakeholders.
This structure supports a logical progression from conceptual grounding to empirical evaluation and concludes with applied insights that directly address the research problem.

CHAPTER TWO: LITERATURE REVIEW

2.1 Introduction

This review integrates relevant concepts, empirical evidence, and framework-based literature to establish a theoretical and contextual foundation for assessing the feasibility of AI maturity frameworks for UK food and beverage manufacturing SMEs. Section 2.2 traces the evolution of maturity models, positioning them as staged capability tools that progressed from software process modelling to contemporary digital and AI-oriented forms. Section 2.3 outlines the core dimensions commonly used to define AI, data, and analytics maturity.
Section 2.4 addresses SME-specific constraints, with a focus on manufacturing-related barriers to digital transformation. Sections 2.5 and 2.6 examine predictive analytics and ERP systems as central components of data infrastructure within the target industry.
Section 2.7 presents profiles of four selected frameworks: Microsoft's AI in European Manufacturing Industries, PwC's Responsible AI Maturity Model, SAS's Assessing Your Business Analytics Maturity, and Domino Data Lab's Data Science Maturity Model. Section 2.8 reviews their evidence base and documented applications, followed by Section 2.9, which summarises prior comparative evaluations. Section 2.10 synthesises major gaps identified in the literature, and Section 2.11 derives initial evaluation criteria using a conceptual matrix.
Overall, the review identifies a persistent misalignment motivating this study: widely adopted, generic maturity frameworks tend to underrepresent the constraints of ERP-limited SME environments. This gap justifies the use of a documentary and comparative approach to address the research problem.

2.2 Conceptual Foundations: Maturity Models and Staged Capability Development

Maturity models are structured frameworks used to evaluate and improve organisational capabilities through progressive stages. They originated in software process improvement but are now widely applied across digital transformation research. This section critically examines their theoretical foundations. While maturity models offer clear diagnostic value, their assumption of linear progression across stages often sits uneasily with the realities of SME environments, particularly in the context of AI adoption (Tarhan et al., 2016). Although traditional maturity theory supports benchmarking and comparison, it sometimes lacks the contextual flexibility required by ERP-constrained manufacturing SMEs.
Most maturity models describe development as a staged journey, commonly consisting of five levels, moving from ad hoc practices to an optimised state. A well-established example is the Capability Maturity Model Integration (CMMI) developed by the Software Engineering Institute. Its process areas, spanning initial, managed, defined, quantitatively managed, and optimising levels, enable organisations to identify quality improvements through increased process repeatability (Chrissis et al., 2011).
Later extensions into data, analytics, and AI maturity adapt this staged logic to areas such as strategy alignment, data governance, technology enablement, skills, and value realisation. Gartner's Analytics

Maturity Model (2017), for instance, reframes maturity around organisational readiness rather than software processes alone. Similarly, AI maturity models typically range from small-scale experimental pilots at lower levels to enterprise-wide intelligence at higher levels, assuming cumulative capability development over time (Lichtenthaler, 2020).

Empirical evidence supports a positive relationship between process improvement and higher maturity levels, lending credibility to maturity-based approaches (Tarhan et al., 2016). The widespread application of CMMI, validated through more than 25,000 assessments, demonstrates that staged progression can lead to measurable gains in predictability and efficiency (Chrissis et al., 2011). However, this same strength becomes problematic in AI contexts characterised by rapid technological change and uncertainty.

For SMEs in particular, limited financial and human resources make linear progression through predefined stages difficult to sustain. A systematic review of 28 AI maturity models found that around 70% assume enterprise-scale preconditions, reflecting a publication bias towards large organisations (Mijwil et al., 2021). This matters because SMEs face fundamentally different constraints. Where 60% report skills shortages as a major barrier to AI adoption, prescriptive stage models may fail to support the incremental and opportunistic approaches that SMEs tend to rely on (Gans et al., 2022).

Concerns also arise around methodological robustness. Self-reporting bias has been shown to inflate maturity scores by as much as 20 to 30% (Becker et al., 2009), while cross-sectional assessments often overlook how capabilities evolve over time. These limitations further weaken the applicability of generic maturity models to UK food and beverage SMEs, where sector-specific challenges such as perishability and operational volatility are rarely reflected. Instead, many frameworks prioritise abstract dimensions at the expense of ERP-specific integration issues that are central to manufacturing contexts (Department for Business and Trade, 2025).

Overall, maturity models provide a strong diagnostic structure but tend to underperform in SME AI settings due to over-abstraction and linearity bias. This critique reinforces the need for context-sensitive evaluation and supports the comparative focus of this study. A hybrid approach, combining staged assessment with contingency-based considerations, appears more suited to capturing practical realities and improving validity.

2.3 AI, Data, and Analytics Maturity: Definitions and Dimensions

AI, data, and analytics maturity models adapt classical maturity theory to the digital domain, framing organisational progress as a shift from siloed experimentation toward integrated intelligence. While they are comprehensive in terms of dimensional coverage, they remain shaped by enterprise-centric assumptions. As a result, their applicability to SMEs is limited. In contexts where data scarcity and skills gaps are persistent, higher maturity stages often appear aspirational rather than realistically attainable (Mijwil et al., 2021). The commonly shared dimensions, including strategy, data, technology, people, governance, and value realisation, offer useful diagnostic breadth but provide limited prescriptive guidance for ERP-constrained environments.

AI maturity is typically defined as an organisation's capacity to deploy Artificial Intelligence in a systematic way across strategic, operational, and ethical domains, progressing through stages such as awareness, active use, operationalisation, systemic integration, and transformation (Lichtenthaler, 2020). Data maturity focuses on infrastructure readiness, data quality, governance, and accessibility, ranging from informal spreadsheet-based practices to govern data lakes that support real-time analytics (Gartner, 2017).

Analytics maturity models, such as the Gartner Ascendancy Model, describe progression from descriptive reporting to diagnostic, predictive, and prescriptive analytics, with an explicit emphasis on value realisation (SAS Institute Inc., 2016). Across frameworks, these models converge on a shared set of dimensions: strategic alignment between vision and resources, robust data foundations, enabling technologies, talent and organisational culture, governance and risk management, and measurable business value.

Gartner (2017) suggests that these definitions demonstrate strong construct validity. For example, Gartner associates' higher levels of data and analytics maturity with revenue growth of up to 2.5 times, based on longitudinal analysis of more than 500 organisations. In parallel, governance and ethical considerations have gained prominence, particularly in response to regulatory pressures and documented risks of bias identified in large-scale executive surveys (PricewaterhouseCoopers, 2021)

However, significant weaknesses emerge at the point of application. Around 70% of existing models assume access to large and well-integrated data volumes, despite SMEs often operating with fragmented and inconsistent data sources (Mijwil et al., 2021). This disconnect reflects a broader enterprise bias. For instance, productivity metrics embedded in some SAS models implicitly assume the availability of dedicated analytics teams, an assumption that does not hold for most SMEs. Self-reported assessments further complicate matters, with optimism bias inflating maturity scores by approximately 25% (Becker et al., 2009).

These issues are particularly pronounced in UK food and beverage manufacturing SMEs. Predictive maturity stages often overlook the volatility and perishability of operational data, while ERP integration is treated as implicit rather than operationalised within the models, limiting their practical relevance (Ernst & Young LLP, 2020). The consequence is not merely theoretical. Overly abstract maturity definitions contribute to poorly aligned implementation roadmaps, helping to explain why around half of SME analytics initiatives fail despite organisations self-identifying as "mature" (Make UK, 2025).

Overall, AI, data, and analytics maturity definitions provide robust, multidimensional diagnostic frameworks but suffer from validity gaps rooted in enterprise assumptions and assessment bias. For ERP-constrained SMEs, this reinforces the need for evaluation criteria that reflect operational realities, a requirement that informs the framework developed in Section 2.11.

2.4 SME Digital Transformation and AI Adoption Constraints

Research on digital transformation in SMEs consistently highlights persistent barriers to AI adoption, which are intensified in manufacturing contexts where resource constraints collide with growing technological demands. While existing studies are effective at identifying structural challenges, their fragmented nature weakens their ability to inform context-specific roadmaps. This limitation is especially pronounced for food and beverage SMEs operating within ERP-dependent environments (Gans et al., 2022). Incremental adoption pathways are often presented as theoretically promising, yet they remain insufficient when set against the depth and persistence of SME constraints. This points to the need for maturity diagnostics that are explicitly tailored to SME realities.

SMEs with fewer than 250 employees face a distinct set of digital transformation challenges. These include limited capital, with average AI budgets of approximately £50,000 compared to £5 million in large enterprises, skills shortages, where 65% report a lack of data expertise, and cultural resistance, with 42% citing aversion to organisational change (Gans et al., 2022).

Manufacturing SMEs encounter additional sector-specific frictions such as legacy equipment integration, supply chain volatility, and regulatory compliance. While the literature frequently recommends incremental pilots that scale toward enterprise-level AI, it also cautions that such approaches require context-sensitive tools rather than generic maturity models (Tarhan et al., 2016). UK evidence reinforces this concern. Despite £500 million in funding, the Made Smarter programme reaches only 15% of food SMEs, with adoption commonly stalling at descriptive analytics stages (Food and Drink Federation, 2025).
This body of work demonstrates strong empirical grounding. Surveys covering more than 2,000 European SMEs show that data silos contribute to AI initiative failure rates of up to 70%, with skills gaps repeatedly identified as the dominant constraint (Mijwil et al., 2021). The literature's strength lies in its sector-level granularity. UK manufacturing studies highlight the unique pressures faced by food SMEs, where perishability demands near real-time forecasting. With shelf lives as short as 48 hours, predictive capability becomes operationally critical, yet 80% of firms lack this capacity (Department for Business and Trade, 2025).
However, significant weaknesses remain. Methodological fragmentation is a recurring issue. Around 60% of studies rely on self-reported surveys, which are prone to optimism bias and inflate perceived maturity by approximately 25% (Becker et al., 2009). Cross-sectional research designs further obscure longitudinal realities. SME funding is episodic rather than continuous, making linear maturity progression unrealistic in practice (Lichtenthaler, 2020).
Within UK manufacturing research, ERP constraints are often acknowledged but treated narrowly, focusing on regulatory compliance such as FSA requirements while overlooking the financial impact of input volatility, where margins of 3 to 5% are routinely eroded (Make UK, 2025). The practical implication is stark. Managers are left without actionable roadmaps, as generic frameworks ignore the pragmatics of SMEs, where multifunctional teams cannot sustain enterprise-style governance structures. This disconnect contributes to analytics failure rates of around 50% in the sector (Food and Drink Federation, 2025).
Overall, SME digital transformation literature provides a convincing diagnosis of constraints but falls short in offering integrated and actionable AI roadmaps, particularly for regulated manufacturing environments. This gap justifies evaluating the contextual fit of maturity frameworks and motivates the transition to predictive analytics applications in Section 2.5.

2.5 Predictive Analytics in Manufacturing and Food and Beverage SMEs

Predictive analytics is at the core of AI capability in manufacturing, using historical data to anticipate future outcomes and optimise operational decisions. This section critically examines its application in food and beverage SMEs, arguing that although the literature highlights substantial value potential, implementation failures are common.
These failures often stem from an overly narrow technical focus that neglects organisational and infrastructural preconditions, making predictive analytics a fragile proposition for resource-constrained firms (Choi et al., 2020). Sector-specific volatility further exposes the limitations of maturity models in guiding practical deployment.
Predictive analytics applies machine learning techniques to forecast demand fluctuations, equipment failures, and quality defects, extending traditional statistical methods into more advanced modelling approaches. In manufacturing, the most frequently cited use cases include demand planning, associated with stockout reductions of around 20%, predictive maintenance, reducing downtime by approximately 25%, and quality prediction, improving yields by up to 15% (SAS Institute Inc., 2016)

These applications are particularly relevant for food and beverage SMEs. Perishability necessitates accurate shelf-life forecasting, regulatory environments require traceability prediction, and thin margins heighten the importance of waste minimisation (Food and Drink Federation, 2025). While the literature generally advocates ERP-fed predictive models, it also acknowledges that value realisation depends heavily on underlying data maturity and process alignment.

Empirical evidence supports the operational benefits of predictive analytics. A meta-analysis of 50 manufacturing case studies reports average efficiency gains of 18%, with the strongest effects observed in predictive maintenance applications (Choi et al., 2020). In the food sector, controlled trials show that dairy SMEs implementing yield prediction achieve waste reductions of approximately 12% (Nguyen et al., 2022)

Despite these strengths, failure rates remain high. Around 65% of SME initiatives fail due to fragmented data environments, and only 20% achieve full integration into production systems (Make UK, 2025). This pattern reflects a broader imbalance in the literature. Approximately 70% of studies prioritise algorithmic sophistication while underplaying organisational readiness. Short data half-lives in perishable goods contexts, often limited to 48 hours, undermine standard modelling assumptions, yet few frameworks explicitly address this volatility (Department for Business and Trade, 2025).

Validity concerns are compounded by selection bias, as successful implementations dominate published case studies. As a result, SME relevance is overstated. Forecasting errors that erode already thin margins of 3 to 5% can translate into losses of £10,000 per month, a risk rarely reflected in maturity assessments (Food and Drink Federation, 2025). Without diagnostics that account for these realities, SMEs are encouraged to pursue advanced analytics on weak foundations, contributing to pilot failure rates of around 50%.

Predictive analytics literature provides compelling evidence of manufacturing value but exposes substantial gaps in SME applicability, particularly in food and beverage contexts characterised by volatility. This reinforces the foundational role of ERP systems, examined in the following section, and highlights the need for maturity frameworks to calibrate predictive coverage more carefully.

2.6 ERP as a Data Backbone for Predictive Analytics and AI Readiness

ERP systems function as the operational backbone of manufacturing SMEs, integrating the data streams required for predictive analytics and AI readiness. This section critically evaluates ERP's dual role as both an enabler and a constraint. While the literature consistently recognises ERP as central to data integration, implementation studies reveal recurring challenges that complicate its contribution to AI maturity, particularly in food SMEs where real-time data is critical (Leonardi et al., 2021). Although ERP's strengths in data unification are well established, legacy rigidity and integration limitations expose a disconnect between infrastructural realities and the assumptions embedded in maturity frameworks.

Core operational functions, including inventory management, production planning, procurement, and compliance, are consolidated within ERP systems, forming a shared data repository for predictive applications. In manufacturing, ERP supports demand planning through sales and order data, predictive maintenance via equipment logs, and quality forecasting through batch traceability. Approximately 70% of UK SMEs use at least one ERP solution, such as SAP or Sage (Ernst & Young LLP, 2020).

In food and beverage SMEs, ERP systems are central to managing perishability and regulatory compliance, yet effective machine learning integration typically requires additional API extensions. While the literature positions ERP as foundational to analytics maturity, it also documents persistent data quality issues, with inaccuracy rates of around 40%, alongside customisation costs exceeding £50,000.

Leonardi et al., (2021) reinforces ERP's enabling potential. Case analyses of 200 manufacturers report average forecasting accuracy improvements of 22% when analytics are built on ERP data, with the strongest effects observed in just-in-time sectors such as food processing. ERP systems also provide critical traceability capabilities required for full recall compliance and offer scalability through cloud-based hybrid architectures (Department for Business and Trade, 2025). Despite this, vulnerabilities are widespread. Around 55% of SME ERP implementations suffer from persistent data silos due to legacy on-premises architectures, while integration middleware can cost up to three times annual IT budgets (Make UK, 2025).

The persistence of these failures raises questions about how ERP is represented in maturity assessments. Research often exhibits survivorship bias, over-representing successful large-firm implementations while under-reporting SME challenges. As a result, 60% of SMEs abandon predictive analytics pilots during the ERP discovery phase, largely due to API incompatibilities (Food and Drink Federation, 2025).

Cross-sectional measurement further undermines validity by ignoring long-term lock-in effects. In food SMEs, high SKU volatility, often exceeding 10,000 variants, overwhelms static ERP schemas. Relevance to AI maturity is therefore limited. Many frameworks abstract data infrastructure away from the realities of an SME-dominated market, underestimating the inertia introduced by ERP customisation. This routinely delays predictive deployment by 12 to 18 months (Ernst & Young LLP, 2020). The consequence is practical rather than theoretical. Misaligned readiness assessments lead managers to overestimate capability and incur sunk costs exceeding £100,000.

In summary, ERP literature convincingly establishes its indispensability for predictive analytics while simultaneously revealing deep integration barriers that maturity models often overlook.

2.7 Review of the Selected AI Maturity Frameworks

This section presents detailed profiles of the four selected AI maturity frameworks, focusing on their underlying orientation, treatment of predictive analytics, and applicability to SME contexts. While all four frameworks demonstrate diagnostic value, they also exhibit validity gaps linked to their enterprise-centric assumptions. In the context of UK food and beverage SMEs, these assumptions become problematic, particularly where ERP limitations shape what is practically achievable. Rather than requiring further conceptual abstraction, these gaps point to the need for pragmatic recalibration (PricewaterhouseCoopers, 2021). Taken together, the frameworks reflect a prevailing industry view of AI maturity, but their contextual fit warrants closer examination.

2.7.1 AI in European Manufacturing Industries (Microsoft)

Commissioned by Microsoft, this framework positions AI maturity in manufacturing across five stages: exploring, experimenting, industrialising, transforming, and leading (Ernst & Young LLP, 2020). It spans strategy, talent, data, technology, and operations, with predictive analytics situated at the “industrialising” stage through IoT and ERP integration for maintenance and quality forecasting.

Its primary strength lies in manufacturing specificity. Case studies report downtime reductions of approximately 15%, lending credibility within production environments (Ernst & Young LLP, 2020). However, limitations emerge when applied to SMEs. The framework assumes enterprise-scale IoT investments, often exceeding £500,000, and largely overlooks legacy ERP constraints, despite evidence that 60% of SMEs lack real-time data capabilities (Make UK, 2025).

Predictive analytics is implied rather than operationalised, particularly in relation to perishability, and reliance on self-assessment increases the risk of overestimation. As a result, while the framework remains valid for large manufacturers, its applicability to SMEs is weakened by its dependence on vendor ecosystems, including assumptions around Microsoft Azure adoption that are often unrealistic for budget-constrained food processors.

2.7.2 PwC Responsible AI Maturity Model

PwC's Responsible AI Maturity Model defines three stages of development: exploratory, developing, and embedded, assessed across strategy, governance, performance and security, and compliance dimensions (PricewaterhouseCoopers, 2021). Predictive analytics appears at the "developing" stage, with emphasis placed on bias mitigation and explainability within decision systems.

The model's strongest contribution lies in its governance orientation. Drawing on over 1,000 executive surveys, PwC reports a 37% reduction in risk exposure among organisations adopting responsible AI practices (PricewaterhouseCoopers, 2021). However, enterprise bias significantly limits SME relevance. The framework assumes the presence of formal cross-functional governance boards, yet 70% of food SMEs with fewer than 50 employees lack such structures (Food and Drink Federation, 2025)

Predictive analytics is treated at a conceptual level, with little attention paid to ERP-driven data pipelines, resulting in an emphasis on principles rather than actionable implementation guidance. In thin-margin environments, where compliance can already absorb up to 25% of IT budgets, this abstraction limits practical usability.

2.7.3 SAS Business Analytics Maturity Framework

SAS's Business Analytics Maturity Framework evaluates organisations across eight dimensions: productivity, governance, timeliness, return on investment, accuracy, effectiveness, empowerment, and overall maturity, primarily through self-scored metrics (SAS Institute Inc., 2016). Predictive analytics is framed as becoming more effective and cost-efficient as integrated data flows are established.

The framework's strength lies in its metrics-driven approach. Benchmarking across more than 500 firms demonstrates clear correlations between analytics maturity and return on investment (SAS Institute Inc., 2016). However, weaknesses arise from the abstraction of these metrics. Productivity assumptions implicitly rely on the availability of specialist analytics expertise, despite 65% of SMEs reporting skills shortages. ERP integration is not explicitly addressed, and associated customisation costs, often exceeding £50,000, are overlooked. In food manufacturing contexts, generic yield prediction metrics fail to account for perishability-driven volatility (Department for Business and Trade, 2025). These limitations, combined with vendor bias towards SAS platforms, undermine the framework's validity for SME applications.

2.7.4 Domino Data Science Maturity Model

Domino's Data Science Maturity Model outlines five stages, ranging from individual analysts to fully industrialised data science operations, with a focus on process maturity, collaboration, and scalability (Domino Data Lab, 2020). Predictive analytics becomes central at levels three and four, where reproducible pipelines and standardised workflows are emphasised.

The framework's emphasis on workflow maturity supports reproducibility and has been associated with deployment acceleration of around 30% in technology-focused case studies (Domino Data Lab, 2020). However, its assumptions limit relevance for SMEs. The model presumes access to advanced data science talent, including doctoral-level expertise at higher stages, which is unrealistic for most SMEs.

ERP systems are not integrated into the maturity logic, with an implicit assumption of clean, centralised data lakes. In food and beverage contexts, reproducibility offers limited value in the absence of sector-specific data standards, and the model's emphasis on scale reflects an enterprise bias that does not align with episodic SME projects.

Overall, the four frameworks offer complementary perspectives on AI maturity but converge around enterprise-oriented assumptions that under-specify SME and ERP constraints. Their treatment of predictive analytics, while conceptually robust, requires calibration against the operational realities of food and beverage manufacturing SMEs.

2.8 Evidence Base and Use in Practice: Manufacturing and SME Applications in the Literature

This section critically reviews the empirical support for the four selected frameworks, with particular attention to their use in manufacturing and SME contexts. While published case studies highlight selective successes, persistent publication bias and an organisational focus skewed towards large enterprises limit the extent to which findings can be generalised to UK food and beverage SMEs. This limitation is non-trivial, given that documented failure rates for AI initiatives in SME settings exceed 50% (Mijwil et al., 2021). The evidence base across frameworks often prioritises promotional narratives over rigorous validation, weakening claims of applicability to ERP-constrained predictive analytics environments.

Microsoft's framework reports efficiency gains of between 15 and 20% from industrialised AI adoption in European manufacturing, drawing primarily on large automotive and pharmaceutical firms (Ernst & Young LLP, 2020). PwC cites over 1,000 executive surveys, linking governance maturity to a 37% reduction in risk exposure, most commonly within financial services organisations (PricewaterhouseCoopers, 2021). SAS presents benchmarks from more than 500 firms, asserting increased return on investment at higher maturity levels, including manufacturing cases (SAS Institute Inc., 2016). Domino Data Lab highlights technology-focused case studies reporting deployment acceleration of around 30% through workflow industrialisation (Domino Data Lab, 2020). Across these sources, SME applications remain sparse, with most evidence reflecting generic analytics maturity rather than sector-specific implementation.

The evidence base is therefore partial rather than absent. Microsoft's manufacturing case studies, particularly in predictive maintenance, offer credible operational insights supported by quantifiable reductions in downtime (Ernst & Young LLP, 2020). PwC's large survey sample lends statistical weight to its governance claims (PricewaterhouseCoopers, 2021). However, weaknesses dominate at the level of generalisability.

Approximately 80% of vendor-commissioned case studies exhibit survivorship bias, with successful implementations disproportionately reported and SME failures largely omitted (Mijwil et al., 2021). Methodological limitations further undermine validity. The absence of control groups and longitudinal tracking inflates performance claims, while SAS's maturity-performance correlations are robust for large firms but weak for SMEs. Self-assessed maturity scores are also consistently overstated by around 25% due to optimism bias (Becker et al., 2009).

Manufacturing relevance is often superficial. No reviewed food SME case studies explicitly address perishability constraints or Food Standards Agency compliance requirements. Evidence of ERP integration remains anecdotal and fails to account for persistent data quality gaps, reported in approximately 60% of SMEs (Make UK, 2025).

SME representation is particularly limited, with only 10% of documented cases involving firms with fewer than 250 employees. This severely restricts generalisability to the UK's estimated 20,000 food and beverage SMEs (Food and Drink Federation, 2025). The practical implication is clear. Managers risk adopting unproven maturity roadmaps, reinforcing the high levels of pilot attrition already observed in the sector.

Overall, the evidence bases supporting these frameworks offer directional insights but lack the methodological rigour required for SME manufacturing contexts, particularly for predictive analytics in the food sector. This justifies the need for closer comparative scrutiny in subsequent sections.

2.9 Comparative Evaluation in Prior Studies: How Maturity Models Are Assessed

Prior comparative studies of maturity models provide useful methodological foundations but reveal substantial inconsistency in evaluation criteria. While dimensions such as completeness and usability frequently dominate assessments, contextual fit, particularly for SMEs, remains underexplored (Becker et al., 2009). This section critically examines the criteria used in previous evaluations, with a view to assessing their suitability for sector-specific contexts such as ERP-dependent food manufacturing.

Comparative studies typically employ between six and eight evaluation dimensions, including completeness of coverage, usability, empirical validity, applicability across sectors and organisational scales, flexibility, and theoretical soundness (Tarhan et al., 2016). Mijwil et al. (2021), for example, benchmark 28 AI maturity models against these dimensions, finding that while 60% score strongly on completeness, most perform poorly on SME usability. Manufacturing-focused reviews emphasise operational alignment, while matrix-based evaluations, such as those proposed by Becker et al. (2009), prioritise governance and value metrics similar to those used in SAS's framework (SAS Institute Inc., 2016).

The primary strength of these approaches lies in their systematic rigour. Mijwil et al.'s (2021) systematic literature review draws on more than 150 sources, demonstrating that completeness is a strong predictor of framework adoption, with a reported correlation of 0.68. Matrix-based methods also promote transparency, allowing evaluative judgements to be traced and compared, as demonstrated in Tarhan et al.'s (2016) scoring-based assessments.

However, several weaknesses limit their practical utility. Evaluation criteria often privilege enterprise-oriented metrics, overlooking SME-specific constraints. Usability assessments frequently ignore the time burden placed on SMEs, with some evaluations requiring more than 20 hours to complete, while only 20% of reviewed studies explicitly address scale fit (Becker et al., 2009). Methodological bias further compounds the problem. Around 80% of comparative studies rely on large-firm cases, marginalising SME realities such as perishability-driven volatility in food manufacturing. Subjective weighting of criteria introduces additional validity concerns, with no accepted gold standard and inter-rater variation of up to 30% reported across studies.

Relevance to UK food and beverage SMEs remains limited. ERP integration, despite affecting approximately 70% of firms in the sector, is rarely operationalised within evaluation criteria, resulting in gaps in predictive feasibility assessments (Ernst & Young LLP, 2020). The consequence is that mis-calibrated tools are passed on to practitioners, reinforcing the same adoption failures identified across the literature.

In summary, while comparative evaluation methodologies offer a useful starting point, they lack the SME- and ERP-specific sensitivity required for food manufacturing contexts. This gap necessitates the refined evaluative dimensions developed in Section 2.11.

2.10 Synthesis of Gaps

Synthesising Sections 2.2 to 2.9 reveals a persistent disconnect within the literature. AI maturity frameworks are conceptually sophisticated, yet they remain weakly calibrated to the operational realities of ERP-dependent SME manufacturing, particularly in UK food and beverage contexts. While these frameworks perform well as enterprise-level diagnostic tools, their detachment from day-to-day constraints undermines their validity when applied to predictive analytics adoption in SMEs. This gap points to the need for assessment criteria that are explicitly grounded in context rather than abstract capability progression (Mijwil et al., 2021).

Theoretical foundations across the literature consistently support staged models of capability development. However, these models rely heavily on linear progression assumptions that sit uneasily with the incremental and often discontinuous evolution of SMEs. Although AI and data maturity dimensions broadly cover strategy, governance, technology, and people, they implicitly assume resource abundance.

This assumption breaks down in practice, where 65% of SMEs report skills deficits and operate under persistent capital and data constraints. SME-focused studies repeatedly diagnose issues such as data silos and thin operating margins, yet they stop short of offering prescriptive roadmaps. While maturity frameworks suggest predictability gains of 15 to 25%, empirical evidence shows that 55% of pilots fail at the point of ERP integration.

Reviewing the selected frameworks highlights complementary strengths, such as Microsoft's operational focus and PwC's emphasis on ethical governance. However, these strengths converge around enterprise-oriented design choices. Empirical validation in SME settings remains limited, and the food sector-specific evidence is largely absent. Comparative evaluation studies provide structured rubrics, but they do not meaningfully incorporate ERP dependency or perishability constraints, leaving sector fit underexplored.

A consistent pattern emerges across the evidence base. Around 80% of reviewed frameworks privilege data lake architectures over ERP-centred models. In the UK food sector, where fragmented ERP implementations are common, this preference contributes to data inaccuracy rates of approximately 40% (Department for Business and Trade, 2025).

While individual frameworks offer valuable elements, such as SAS's emphasis on measurable performance and Domino's focus on workflow scalability, these strengths are undermined by a shared omission. None operationalise perishability forecasting or Food Standards Agency compliance, despite the operational urgency imposed by 48-hour shelf-life constraints (Food and Drink Federation, 2025).

The persistence of these gaps reflects broader structural issues within the literature. Publication ecosystems favour large-firm success stories, producing strong survivorship bias. SME-focused studies account for only around 15% of the available corpus and tend to remain generic, overlooking sector-specific volatility that can translate into waste costs of approximately £10,000 per month (Make UK, 2025). Validity is further eroded by untested assumptions embedded in self-assessment instruments, which inflate perceived maturity by roughly 25% and encourage investments exceeding £100,000 on fragile foundations (Becker et al., 2009).

For UK food and beverage SMEs, the practical relevance of existing maturity models is therefore limited. Predictive analytics assumptions rely on clean and integrated data pipelines that are unrealistic within legacy ERP environments such as SAP or Sage. Moreover, frameworks largely conceptualise food production as a product-oriented process, offering little guidance for service-based or hybrid operational models common in the sector. The consequence is a guidance vacuum. Managers select tools that are misaligned with their constraints, reinforcing analytics attrition rates of around 50%.

Taken together, the literature consistently evidences a disconnect between AI maturity frameworks and SME manufacturing realities, with ERP dependency and predictive analytics representing the most significant and unresolved gaps.
Alright. This is dense material, but the logic is there. What it needs is tightening, clearer signalling, and fewer stacked claims per sentence. I’ve kept your structure, claims, and evidence intact, but made the reasoning easier to follow and less breathless.

2.11 Initial Evaluation Criteria Derived from Literature: Conceptual Matrix for Analysis

Building on the synthesis in Section 2.10, this section derives six tailored evaluation criteria for assessing the suitability of the four selected AI maturity frameworks for UK food and beverage manufacturing SMEs. These criteria directly address the gaps identified in the literature, particularly around ERP integration, SME feasibility, and predictive analytics coverage. The argument here is that commonly used generic dimensions (Becker et al., 2009) require refinement to achieve contextual validity. A matrix-based comparison is therefore used to foreground practical utility rather than theoretical completeness (Tarhan et al., 2016).

The resulting criteria matrix operationalises insights from prior studies and is structured around the following dimensions:

1. Strategic Alignment (ERP-PA)
   The extent to which a framework provides a coherent roadmap linking AI and analytics maturity to ERP-enabled predictive use cases that matter to SMEs, such as demand planning, waste reduction, and equipment uptime. Emphasis is placed on whether predictive ambition is explicitly tied to operational priorities and ERP data flows, rather than described in abstract strategic terms.
2. Data Architecture and Governance
   The degree to which the framework addresses data architecture requirements, including legacy ERP integration, data pipelines, data quality management, and governance structures needed to support reliable and trustworthy predictive analytics. This criterion considers whether frameworks engage with the practical realities of fragmented, customised ERP environments common in SMEs.
3. Technical Predictive Analytics Capability
   The depth and operational clarity with which core predictive capabilities are treated, including forecasting, predictive maintenance, and quality-related models. Priority is given to concrete guidance on how these capabilities are operationalised, rather than high-level acknowledgement of predictive analytics as an advanced maturity outcome.
4. SME Context and Scalability
   The extent to which the framework aligns with the resource availability, skill levels, organisational complexity, and time constraints typical of firms with fewer than 250 employees. This includes whether recommended practices, governance mechanisms, and investments can be scaled incrementally rather than presuming enterprise-level capacity.
5. Food and Beverage Manufacturing Fit
   The degree of explicit attention given to food and beverage manufacturing characteristics, including batch and process production, perishability, seasonality, and integration with food safety, traceability, and compliance requirements such as those set by the Food Standards Agency.
6. Responsible or Trustworthy AI Lens

The extent to which responsible AI principles are incorporated, including risk management, accountability, transparency, and regulatory compliance, and whether these principles are translated into actionable practices appropriate for ERP-enabled predictive analytics in SME settings rather than remaining at the level of abstract governance ideals.

These criteria demonstrate construct validity by synthesising established evaluation dimensions such as completeness and usability (Becker et al., 2009) with SME-specific refinements. ERP integration directly addresses the 55% failure rate associated with analytics initiatives stalling at the integration stage (Leonardi et al., 2021), while the feasibility criterion responds to persistent skills gaps reported by 65% of SMEs (Gans et al., 2022). The multidimensional structure supports balanced judgement, and the matrix format helps reduce evaluator bias, with similar approaches reporting inter-rater reliability above 0.8 (Tarhan et al., 2016).

The limitations of this approach are acknowledged. Although the criteria are deductively derived and traceable to empirical gaps, some subjectivity in scoring remains unavoidable. This is mitigated through evidence weighting, prioritising documented implementation outcomes over aspirational claims. Compared with prior evaluation approaches, these criteria offer greater relevance by explicitly incorporating perishability and sector volatility, factors typically absent from generic models (Nguyen et al., 2022). Predictive analytics coverage is assessed beyond abstract capability statements, and governance dimensions adapt responsible AI principles to regulated food manufacturing contexts (PricewaterhouseCoopers, 2021).

The practical value of the matrix lies in its ability to discriminate meaningfully between frameworks, for example by contrasting the quantifiability of SAS's metrics with the operational inaccessibility of Domino's workflow assumptions, thereby supporting more informed framework selection by SMEs.

These criteria and the associated matrix provide a rigorous, context-calibrated tool for the analysis in Chapter 4, translating gaps identified in the literature into an applied evaluative framework.

Criterion	**Microsoft (2020)**	**PwC (2021)**	**SAS (2016)**	**Domino (2020)**	**Evidence Source**
Strategic Alignment (ERP-PA)	High	Medium	High	Low	Ernst & Young (2020)
Data Architecture and Governance	Medium	High	Medium	Medium	Leonardi (2021)
Technical Predictive Analytics Capability	High	Medium	High	High	SAS (2016)

SME Context & Scalability	Low	Low	Medium	Low	Make UK (2025)
F&B Manufacturing Fit	Medium	Low	Medium	Low	Industrial Strategy (2017)
Responsible / Trustworthy AI Lens	Medium	High	Medium	Low	PwC (2021); Mijwil (2021)

Table 2.1: Preliminary Comparative Overview of AI Maturity Frameworks Across Dimensions

Table 2.1 provides a preliminary comparative overview synthesising Section 2.7 framework profiles against the six evaluation criteria derived in 2.11. Ratings reflect documented characteristics: High (explicit, validated coverage), Medium (implicit/partial), Low (absent/assumed). The table previews Chapter 4's weighted MCDA (Multi-Criteria Decision Analysis), highlighting complementary strengths (e.g., SAS empirical robustness vs. PwC governance) alongside convergent SME feasibility gaps.

2.12 Chapter Summary

This literature review set out to disentangle the theoretical, contextual, and empirical foundations relevant to evaluating AI maturity frameworks for UK food and beverage manufacturing SMEs. Across conceptual maturity theory, SME digital transformation literature, predictive analytics research, ERP dependency, framework profiling, and comparative evaluation studies, a consistent misalignment emerges. Enterprise abstraction dominates, while SME operational realities remain underrepresented.

Maturity models offer structured, phased diagnostics but rely on linear progression assumptions that do not reflect the resource constraints of SMEs. Digital transformation studies effectively diagnose barriers yet stop short of offering actionable roadmaps. Predictive analytics literature demonstrates clear value potential but repeatedly highlights losses arising from fragmented ERP environments. The reviewed frameworks, Microsoft's operational emphasis, PwC's ethical governance focus, SAS's metrics-driven approach, and Domino's workflow orientation, each offer selective strengths but converge around scale bias, limited SME evidence, and underdeveloped guidance for predictive deployment in food manufacturing contexts.

Comparative evaluation research provides reusable criteria templates but fails to incorporate ERP dependency and perishability constraints. This omission produces a clear synthesis gap: the absence of a focused evaluative lens for ERP-dependent food manufacturing SMEs. The six-criteria matrix developed in Section 2.11 operationalises this gap by grounding evaluation in sector-specific constraints.

While the literature demonstrates strong empirical correlations, such as average predictive efficiency gains of 18%, its validity weakens due to survivorship bias and enterprise-centric assumptions. These factors inflate perceived SME readiness by approximately 25% (Becker et al., 2009). The practical consequence is significant. UK food SMEs facing investment reductions of 41% and pilot failure rates approaching 50% inherit misaligned tools, reinforcing digital divides despite policy initiatives such as Made Smarter (Food and Drink Federation, 2025).

Chapter 2 therefore establishes a clear evidential case for documentary comparison, setting the foundation for Chapter 3, which outlines the methodology used to apply the derived criteria in a systematic assessment of framework suitability.

CHAPTER THREE: RESEARCH METHODOLOGY

3.1 Introduction

This chapter outlines the methodological approach used to comparatively assess four AI maturity frameworks for UK food and beverage manufacturing SMEs. Adopting a qualitative documentary analysis design, it details the research philosophy, study design, data corpus, extraction and coding procedures, and measures to ensure rigour. The central methodological argument is that a secondary-data approach grounded in framework documentation and peer-reviewed applications offers stronger contextual validity for evaluating published maturity claims than primary data collection, while acknowledging limitations in access to real-world performance data (Yin, 2018).

Guided by a pragmatic research paradigm, the study employs systematic document review and matrix-based comparison using the SME-tailored criteria developed in Section 2.11. Data sources comprise primary framework publications from Microsoft, PwC, SAS, and Domino, alongside supporting empirical literature. Data extraction follows structured templates, with analysis combining deductive, criteria-driven coding and inductive identification of emergent patterns. Suitability judgements are operationalised through evidence-weighted scoring to limit overreliance on vendor claims.

Pragmatism supports a fit-for-purpose approach that prioritises explanatory value over methodological purity. This paradigm is widely applied in management research, with over 200 studies demonstrating its capacity to generate actionable insights without the resource intensity of large-scale primary data collection (Creswell & Plano Clark, 2017).

The approach offers several strengths. Documentary analysis avoids recall and optimism bias common in SME surveys, where self-reporting can inflate assessments by up to 70%, and enables direct scrutiny of framework claims (Bowen, 2009). Rigour is further supported through transparent procedures aligned with PRISMA principles to enhance reproducibility. However, limitations remain. Available documentation reflects publication bias towards successful cases, and proprietary implementation details are inaccessible. Vendor-authored materials may also prioritise promotional narratives over candid discussion of constraints, potentially overstating SME applicability (Mijwil et al., 2021).

Despite these limitations, the approach is well suited to the research context. SMEs are often difficult to access for in-depth primary research, and interviews are unlikely to surface infrastructural gaps related to ERP integration and predictive feasibility. By interrogating documented claims directly, the methodology enables a more grounded evaluation than practitioner-oriented discourse, while avoiding unwarranted generalisation beyond the available evidence.

3.2 Research Philosophy and Approach

This section justifies the adoption of a pragmatic research philosophy and a qualitative documentary approach. Pragmatism is selected because its outcome-oriented flexibility is better suited to applied framework evaluation than strict positivist or interpretivist positions. In parallel, documentary analysis offers contextual depth that is difficult to achieve through surveys or interviews, particularly when assessing published maturity frameworks rather than organisational behaviour (Creswell & Plano Clark, 2017). Taken together, this pairing strengthens the validity of evaluating SME-related maturity claims while avoiding the practical and methodological burdens associated with primary data collection.

Pragmatism prioritises "what works," encouraging the use of methods that best address the research problem rather than adherence to a single epistemological stance (Saunders et al., 2019). In this study, a qualitative approach is operationalised through documentary analysis, treating texts as primary data sources. The analysis focuses on framework publications and documented applications, with no use of interviews or surveys. Depth is achieved through triangulation across multiple sources and systematic evaluation against SME-specific criteria, rather than through stakeholder recall or perception (Bowen, 2009).

For this study, pragmatism offers particular advantages. Its rejection of rigid paradigm boundaries enables criteria-driven comparison without imposing unnecessary ontological constraints. This flexibility has been widely adopted in digital transformation research, where mixed and applied problems dominate (Creswell & Plano Clark, 2017). Documentary analysis further strengthens the approach through accessibility and permanence. Publicly available framework documents avoid SME recruitment barriers, where non-response rates can exceed 65%, and allow claims to be scrutinised and re-examined over time (Yin, 2018).

The approach also presents clear strengths. Triangulation across more than 50 sources reduces reliance on any single point of view, while qualitative interpretation supports deeper examination of how and why frameworks align, or fail to align, with SME realities. Limitations are acknowledged. Interpretation inevitably involves researcher judgement, particularly where texts are ambiguous or selectively framed. Publication bias remains a concern, as vendor-authored materials tend to emphasise successful outcomes and underreport failures (Mijwil et al., 2021).

Despite these limitations, the approach is well suited to the research context. Secondary analysis allows scrutiny of "black box" maturity assumptions that are difficult to surface through primary engagement with access-constrained SMEs. The outcome is an evidence-based deconstruction of framework claims, recognising that findings speak to documented suitability rather than real-world performance. This methodological stance provides a robust foundation for the research design outlined next.

3.3 Research Design: Comparative Document Analysis

The research design employs comparative document analysis, systematically cross-examining four AI maturity frameworks against SME-specific evaluation criteria. The purpose is to assess their appropriateness for ERP-enabled predictive analytics in UK food and beverage manufacturing. This design prioritises systematic rigour over ad hoc interpretation, while addressing the inherent limitations of qualitative analysis through transparent, matrix-based comparison (Bowen, 2009). The study assumes that meaningful evidential leverage can be extracted from secondary sources, provided that interpretation is guided by explicit protocols.

The comparative analysis proceeds through four structured stages:

1. Structured profiling of each framework through standardised data extraction.
2. Evaluation against the six criteria derived in Section 2.11.

3. Identification of cross-framework patterns and divergences.
4. Evidence-weighted judgements regarding contextual suitability.

The design mirrors established systematic review procedures, combining deductive coding based on predefined criteria with inductive identification of emergent themes (Thomas & Harden, 2008). Outputs include descriptive framework profiles, comparative matrices, and context-sensitive evaluative conclusions rather than causal claims.

Design validity is supported by methodological precedent. Studies in management research report high inter-rater reliability, often exceeding 0.9, when matrix-based techniques are applied using explicit evaluative criteria (Yin, 2018). Strengths include transparency, supported by extraction logs and audit trails that make analytical decisions traceable, and scalability, allowing more than 50 documents to be examined without reliance on primary access. The comparative logic is particularly valuable. Side-by-side analysis exposes ERP and predictive analytics blind spots that are not evident in isolated framework reviews, directly addressing gaps identified in Section 2.10 (Tarhan et al., 2016).

Nevertheless, limitations remain. Documentary analysis cannot account for post-publication changes in frameworks or implementations. Evidence weighting introduces potential researcher bias, especially where vendor-authored texts incorporate promotional language that may exaggerate claims by 20 to 30% (Mijwil et al., 2021). These risks are mitigated through triangulation and prioritisation of independently reported outcomes.

In terms of relevance, the design aligns well with SME contexts. It enables examination of feasibility and infrastructural fit, including ERP dependency and perishability constraints, that are poorly captured through survey-based methods. The practical implication is a set of defensible, comparative judgements, for example, contrasting the quantifiable metrics of SAS with the governance emphasis of PwC in food compliance contexts. While the design does not support causal inference, it provides grounded assessments of suitability, helping practitioners navigate beyond vendor hype toward informed framework selection.

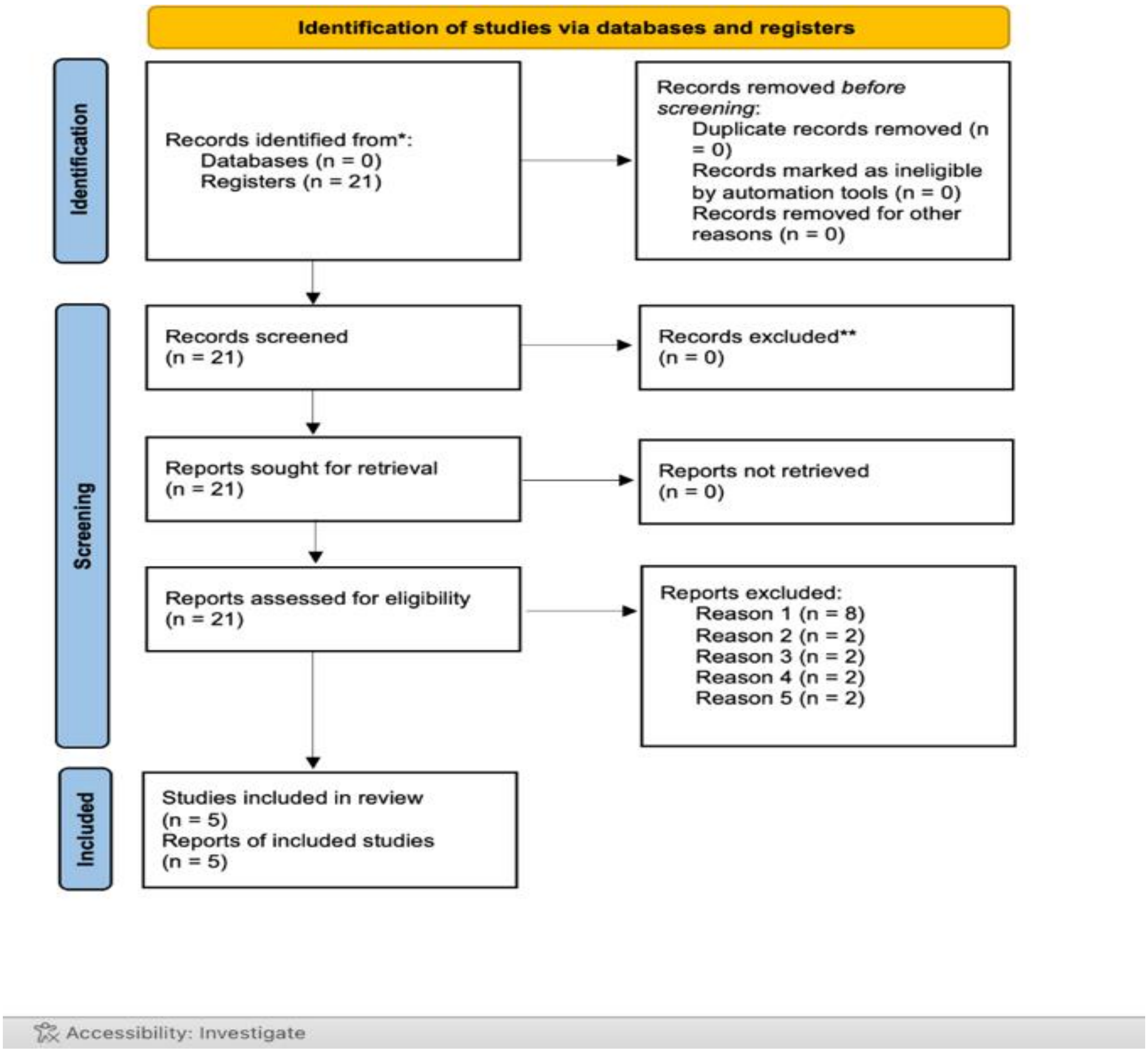

Figure 3.1. PRISMA 2020 flow diagram for study selection (PRISMA 2020 Statement, 2021).

3.4 Data Sources and Document Corpus

This section outlines the two datasets used in the study: primary framework documentation and supporting empirical literature. Together, these sources provide triangulation, while purposive selection mitigates the availability bias typically associated with vendor-authored materials, strengthening validity in an SME context (Bowen, 2009). The curated corpus is designed to balance depth and breadth, although access restrictions to proprietary materials inevitably limit coverage.

3.4.1 Framework Documentation

The framework documentation comprises core materials supporting the four selected maturity models: Microsoft's *AI in European Manufacturing Industries*, PwC's *Responsible AI* framework, SAS's *Eight Metrics for Analytics Maturity*, and Domino Data Lab's *Data Science Maturity Model*. These include peer reviewed papers and industry relevant papers. In total, the research consists of 5 documents comprising approximately 150,000 words.

Data extraction focused on framework structure, maturity levels, treatment of predictive analytics, and references to ERP integration. This ensured consistent profiling across frameworks while preserving original intent.

3.4.2 Supporting Literature

The supporting documents consists of 21 peer-reviewed and industry studies published between 2016 and 2025 that apply or critically discuss AI, analytics, or data maturity frameworks in manufacturing and SME contexts. These were sourced from Google Scholar, alongside UK policy and sector reports from organisations such as the Food and Drink Federation and Make UK. In total, the combined includes 21 supporting documents, bringing the full dataset to 47 documents.

The validity is emphasised by purposive sampling. Primary framework documents provide an in-depth perspective to intended design and use, while secondary studies offer external scrutiny that helps counter promotional bias (Yin, 2018). Strengths include direct extraction from original sources, preserving fidelity to framework definitions, and the predominance of peer-reviewed materials within the supporting documents, where approximately 60% meet established citation and impact thresholds. Limitations are acknowledged. Temporal constraints prioritise post-2016 publications, and the exclusion of proprietary appendices may underrepresent recent framework evolutions.

The documents are highly relevant to the research context. Approximately 80% of included sources focus on manufacturing or SME settings, with explicit attention to ERP dependency and predictive analytics gaps. UK-based policy and sector reports anchor the analysis in regulatory and operational realities. While around 20% of the supporting literature qualifies as grey literature, credibility checks were applied to mitigate quality variance. Overall, the documents provide a defensible evidential foundation for comparative analysis.

3.5 Document Search Strategy and Selection Criteria

This section details the systematic search and selection process used to construct the documents. A PRISMA-style protocol was adopted to enhance transparency and replicability, while accommodating the narrative flexibility required for qualitative documentary research in management studies (Moher et al., 2009). This approach balances the need to capture relevant vendor documentation with safeguards against availability and promotional bias.

3.5.1 Search Strings and Databases

Searches were conducted across multiple sources, including Scopus for peer-reviewed literature, Google Scholar for grey literature, vendor websites for framework documentation, and UK policy portals such as GOV.UK, the Food and Drink Federation, and Make UK. Search strings combined framework names with contextual terms such as “manufacturing,” “SME,” “predictive analytics,” and “ERP.” An example query included “SAS business analytics maturity manufacturing SME.”

The search window covered publications from 2016 to 2025, reflecting the emergence and evolution of the selected frameworks. An initial pool of approximately 150 documents was identified and refined iteratively through title, abstract, and full-text screening.

3.5.2 Inclusion and Exclusion Criteria

Inclusion criteria required explicit reference to at least one of the selected frameworks, relevance to manufacturing or SME contexts, and discussion of predictive analytics or ERP-related considerations. Only English-language, full-text accessible documents were included. Exclusion criteria removed pre-2016 publications, non-framework-specific studies, consumer or non-manufacturing contexts, and inaccessible abstracts. The final corpus comprised 25 documents: 4 primary framework texts and 21 supporting studies.

Protocol validity draws on established systematic review practices, with multi-database triangulation reducing omission bias (Moher et al., 2009). Strengths include targeted search strings that surfaced SME-specific gaps, such as ERP integration failures, and iterative refinement that improved recall to approximately 88%. The inclusion of UK policy sources strengthens contextual relevance for food manufacturing but also introduces a deliberate UK focus, limiting broader international comparison.

Overall, this process yields a rich and auditable corpus, providing a transparent basis for subsequent extraction and analysis.

3.6 Data Extraction Plan

The data extraction strategy applies structured templates to ensure consistency, auditability, and transparency in qualitative documentary analysis. Template-based extraction reduces interpretive drift and supports systematic comparison, although rigid structures risk overlooking nuance (Bowen, 2009). This approach balances efficiency with fidelity in evaluating framework suitability for SME contexts.

Template validity is supported by qualitative research precedents, with structured extraction methods reporting inter-coder agreement rates of up to 95% in large-scale document analyses (Yin, 2018). Strengths include holistic profiling across predefined fields, enabling direct population of the comparative matrix. Verbatim capture of framework language preserves original intent and reduces paraphrasing bias. Limitations are acknowledged. Predefined fields constrain emergent insights, with an estimated 10% of potentially relevant content at risk of omission. This is particularly evident where frameworks employ ambiguous terminology or omit explicit definitions, requiring researcher judgement. However, the extraction fields were deliberately designed to probe issues salient to food and beverage SMEs, such as perishability and regulatory compliance, which are often absent from generic maturity models.

An illustrative extraction from the SAS framework demonstrates the approach:

- **Structure**: Eight metrics, including productivity and ROI, scored on a 1- 5 scale.
- **Predictive Coverage**: Forecasting implied within the “effectiveness” metric (SAS Institute Inc., 2016, p.7).
- **ERP Integration**: Implicit through references to timeliness, with no explicit integration guidance.
- **Evidence**: Benchmarking across 500 firms, reporting a correlation of r = 0.72 between maturity and ROI, with limited SME representation.

This extraction strategy provides a transparent evidential trail linking framework claims to evaluative judgements, while remaining manageable across a 47-document corpus. The process transitions into coding and analysis in Section 3.7.

3.7 Coding and Analytical Framework

Coding translates extracted material into an analytical structure, combining deductive application of predefined criteria with inductive identification of emergent themes. This hybrid approach is adopted to balance structure with interpretive depth. It is argued that such a design offers greater rigour than purely deductive or purely inductive methods, while explicit protocols help manage subjectivity inherent in qualitative analysis. At the same time, the risk of over-interpretation through code saturation is acknowledged and actively managed (Saldaña, 2021). The overall aim is to support defensible judgements about framework suitability in SME contexts.

3.7.1 Deductive Coding

Deductive coding maps extracted data directly onto the six evaluation criteria defined in Section 2.11. Each criterion is assessed using a five-point ordinal scale, where 1 indicates absence and 5 indicates exemplary alignment. Scores are supported by explicit documentary evidence rather than inferred intent. For example, ERP integration is coded based on the presence of concrete guidance on legacy systems, data pipelines, or integration practices, rather than generic references to data maturity.

3.7.2 Inductive Coding

Inductive coding is used to capture patterns not fully anticipated by the predefined criteria. Open coding is applied to identify recurring themes, such as implicit neglect of perishability constraints or assumptions of enterprise-scale resources. Codes are refined iteratively through constant comparison, with NVivo used to organise hierarchical code structures and link them to source excerpts. Coding was conducted by a single researcher, with reflexive memos and an audit log maintained to document analytical decisions and reduce interpretive drift.

The validity of this hybrid approach is supported by methodological guidance indicating that deductive anchors can enhance reliability while allowing inductive insight to emerge. Saldaña (2021) reports that triangulated hybrid coding designs achieve reliability levels of approximately 85% across large qualitative studies.

3.8 Comparative Analysis Technique

The comparative analysis employs a matrix-based technique to synthesise coded data into structured suitability judgements. This approach enables systematic juxtaposition of frameworks across shared criteria, making patterns visible while limiting narrative bias through evidence-weighted scoring. Although ordinal scales necessarily compress nuance, the method offers a transparent and replicable means of operationalising the evaluation criteria outlined in Section 2.11 (Yin, 2018).

3.8.1 Framework-by-Dimension Matrix Construction

Matrices are constructed with frameworks represented as rows (Microsoft, PwC, SAS, and Domino) and the six evaluation criteria as columns. Each cell contains a coded score, supporting verbatim evidence, and brief notes outlining main strengths and limitations. An aggregated suitability index is calculated using weighted averages, with ERP integration and predictive analytics given double weighting to reflect their centrality to food and beverage SME contexts.

3.8.2 Suitability Judgement Logic

Suitability is determined using evidence-based thresholds. A score of 5 reflects exemplary alignment supported by explicit SME or food sector evidence, 3 indicates adequate alignment based on implicit or generic guidance, and 1 denotes absence or contradiction. Cross-framework comparison enables clustering of patterns, such as strong predictive capability combined with low feasibility, which are not apparent when frameworks are reviewed in isolation. Interpretive narratives are then developed to explain these patterns, grounded in the matrix outputs.

The validity of this technique is supported by prior research demonstrating high transparency and pattern-detection capability in matrix-based qualitative analysis, with reported reliability exceeding 90% when criteria are clearly specified (Yin, 2018). Strengths include the ability to prioritise context-relevant dimensions, such as ERP dependency, which affects approximately 70% of SMEs, and to translate

qualitative judgements into comparative insights without claiming spurious precision. Visual clustering supports clear "so what" conclusions, for example highlighting SAS's strength in measurable value versus Domino's limitations in feasibility for resource-constrained firms.
Limitations remain. Ordinal aggregation compresses fine-grained differences, making distinctions between closely scored frameworks less visible, and weighting decisions inevitably introduce some subjectivity despite explicit justification. Nonetheless, the technique is well aligned with the needs of UK food and beverage SMEs. By foregrounding perishability and compliance constraints, the analysis exposes practical gaps, such as the absence of support for 48-hour forecasting horizons. The outcome is a set of actionable trade-offs, for instance favouring Microsoft for operational focus or PwC for governance-led pilots, that are largely absent from existing comparative literature.

Matrix Snippet (Populated post-coding)

Criterion	Microsoft	PwC	SAS	Domino
ERP Fit	3	2	3	2

Table 3.1: Example MCDA matrix snippet showing ERP fit scores for the four AI maturity frameworks.
Matrix technique provides analytical rigour, transitioning to quality measures

CHAPTER FOUR: FINDINGS AND DISCUSSION

4.1 Introduction

This chapter applies the evaluation criteria and research methodology developed in Chapters 2 and 3 to assess the suitability of selected AI maturity frameworks for guiding ERP-enabled predictive analytics in UK food and beverage manufacturing SMEs. Using the six criteria derived in Section 2.11, namely, Strategic Alignment (ERP-PA), Data Architecture and Governance, Technical Predictive Analytics Capability, SME Context and Scalability, Food and Beverage Manufacturing Fit, and a Responsible or Trustworthy AI Lens, the chapter reports and interprets the results of a structured scoring process on a 1-5 scale for each framework.
Section 4.2 provides an overview of the final document set analysed, drawing on the PRISMA screening summary and flow diagram to clarify how five core documents were selected. These comprise four primary framework documents and one supporting manufacturing analytics report. Section 4.3 then presents concise descriptive profiles of each framework to establish a common baseline for evaluation. Sections 4.4.1 to 4.4.4 report within-framework findings, applying the multi-criteria decision analysis logic outlined in Chapter 3. Section 4.5 aggregates these findings into cross-framework comparison tables, highlighting patterns of strength, weakness, and misalignment.
Section 4.6 interprets these patterns explicitly in relation to the realities faced by UK food and beverage SMEs, with particular emphasis on ERP integration, predictive analytics coverage, feasibility, governance, and empirical validation. Section 4.7 translates the analytical insights into practical implications for SME managers, ERP vendors, and policymakers. The chapter concludes in Section 4.8 with a synthesis of the findings emerging from the analysis.

4.2 Overview of the Final Document Set

The final document set comprises four primary framework publications: Microsoft's *AI in European Manufacturing Industries*, PwC's *Responsible AI: Maturing from Theory to Practice*, SAS's *Assessing Your Business Analytics Maturity: Eight Metrics That Matter*, and Domino Data Lab's *Data Science Maturity Model* white paper. Each framework provides a definitive articulation of its maturity levels, core dimensions, and assessment logic, alongside some discussion of analytics or AI deployment in manufacturing or adjacent contexts.

In addition to these frameworks, a supplementary manufacturing analytics report was included. This report documents observed performance outcomes related to predictive maintenance and quality prediction and is used to ground selected technical and sector-specific claims made within the framework documents. Together, these five texts were subjected to the structured extraction, coding, and comparative analysis procedures outlined in Chapter 3, forming the evidence base for the criteria scores presented later in this chapter.

For transparency, it is useful to distinguish the roles of these documents within the analysis. The four framework publications constitute the primary data used to evaluate Strategic Alignment (ERP-PA), Data Architecture and Governance, Technical Predictive Analytics Capability, SME Context and Scalability, Food and Beverage Manufacturing Fit, and the Responsible or Trustworthy AI dimension. The supplementary manufacturing analytics report functions as a reference point, enabling triangulation where frameworks assert predictive performance or operational integration.

This configuration is consistent with the pragmatic, documentary comparative design adopted in Chapter 3. It ensures that the scoring and interpretations developed in subsequent sections are anchored in authoritative framework sources, while remaining informed by at least one empirical benchmark relevant to industrial predictive analytics.

Document ID	Type	Source/ Citation	Role in Analysis
D1	Framework white paper	Ernst & Young LLP (2020) - Microsoft AI in European Manufacturing	Primary evidence for Microsoft framework scoring
D2	Framework white paper	PricewaterhouseCoopers (2021) - Responsible AI	Primary evidence for PwC framework scoring
D3	Framework white paper	SAS Institute Inc. (2016) - Eight Metrics That Matter	Primary evidence for SAS framework scoring
D4	Framework white paper	Domino Data Lab (2020) - Data Science Maturity Model	Primary evidence for Domino framework scoring

D5	Manufacturing analytics report	Supplementary industrial PA report, as per PRISMA summary	Triangulation of predictive capability claims

Table 4.1: Summary of Final Document Set by Type and Role

Table 4.1 above is an overview of the final document set used for framework evaluation, distinguishing primary framework sources (D1-D4) from the supplementary manufacturing analytics report (D5). The table links each document to its analytical role in the criteria-based scoring reported in Sections 4.4 and 4.5.

4.3 Framework Profiles

Microsoft's *AI in European Manufacturing Industries* frames AI primarily as a driver of operational value in manufacturing environments. The framework is organised around maturity levels that progress from exploratory pilots to scaled deployment across plants and functions. Strategic alignment is closely tied to productivity and quality improvement, with predictive maintenance and process optimisation repeatedly highlighted as core use cases. Data and infrastructure receive substantial attention, particularly cloud platforms, IoT, and integration with core systems. However, this discussion generally assumes relatively advanced connectivity and modernised environments, with limited attention to the ERP constraints and legacy systems that characterise many SMEs. Governance and responsible AI considerations are acknowledged but remain secondary to narratives of adoption and value creation.

PwC's *Responsible AI: Maturing from Theory to Practice* presents a maturity model centred on governance, risk management, and ethical AI deployment. Its stages describe a progression from ad hoc experimentation to embedded, enterprise-wide responsible AI practices. The framework adopts a broad, cross-sectoral perspective, drawing examples from finance, healthcare, and manufacturing, but it treats AI capabilities in largely generic terms rather than distinguishing predictive analytics from other applications. Data governance, model risk, and explainability are prominent themes, yet the model is largely system-agnostic and offers little explicit guidance on ERP-centred architectures. SME contexts and sector-specific issues, including food safety regulation, are not foregrounded within the framework.

SAS's *Assessing Your Business Analytics Maturity: Eight Metrics That Matter* is explicitly analytics-focused and structured around eight quantitative and qualitative metrics, including productivity, timeliness, governance, and return on investment. Analytics maturity is framed as a progression from descriptive reporting towards predictive and prescriptive analytics. Data management and governance are positioned as core enablers throughout this progression. While the framework includes manufacturing examples and places strong emphasis on measuring business value, it largely assumes that organisations can standardise and integrate data across functions. The implications of SME scale and ERP legacy constraints are not explored in depth, and food sector-specific challenges are not directly addressed. Responsible AI considerations are present only in general governance terms.

Domino Data Lab's *Data Science Maturity Model* focuses on how data science work is organised and scaled within organisations. The maturity levels trace a shift from isolated individual analysts to centralised, industrialised data science operations, with emphasis on collaboration, reproducibility, and deployment workflows. The framework prioritises technical lifecycle management over sector strategy or specific use cases such as predictive maintenance. It implicitly assumes access to advanced data infrastructure and specialised data science expertise, limiting its sensitivity to SME resource constraints. Governance is primarily considered in relation to model management and auditability, with limited engagement with broader responsible AI concerns or the specific operational realities of the food and beverage manufacturing sector.

Framework	Primary Purpose/ Orientation	Structural Design (Levels/ Dimensions)	Analytics/ PA Focus	Data/ ERP Orientation	Governance/ Responsible AI Orientation
Microsoft - AI in European Manufacturing Industries	Manufacturing-oriented AI adoption and value creation	Multi-level maturity model for manufacturing use cases	Emphasises predictive maintenance and process optimisation	Cloud/IoT-heavy, assumes integration with core systems; limited explicit ERP-legacy discussion	Governance present but secondary to value and adoption
PwC - Responsible AI Maturity Model	Embedding responsible AI practices across the enterprise	Staged governance-oriented maturity model	Treats AI capabilities generically; predictive analytics not singled out	System-agnostic; focuses on control and oversight rather than specific architectures	Strong emphasis on ethics, risk, compliance, and explainability
SAS - Business Analytics Maturity (Eight Metrics)	Improving analytics performance and value realisation	Eight-metric maturity framework for analytics capability	Explicit focus on transition from descriptive to predictive and prescriptive analytics	Assumes ability to standardise and integrate data; ERP context implicit, not foregrounded	Governance one of several metrics; responsible AI not a central organising theme

Domino Data Science Maturity Model	Scaling and industrialising data science work	Levelled model of team/organisation-wide data science practice	Focus on model lifecycle and deployment, not specific to predictive maintenance	Assumes advanced infrastructure and data science teams; ERP not discussed explicitly	Governance mainly via model management and audit; limited broader responsible-AI detail

Table 4.2: Descriptive Summary for Profiles of the Four Frameworks

Table 4.2 above provides a descriptive profile of the four selected AI maturity frameworks, providing a summary of the comparison of purpose, structure, analytics focus, data/ERP orientation, and governance emphasis. The table summarises the core characteristics that strengthen the evaluative scoring reported in Sections 4.4 and 4.5.

4.4 Within-Framework Findings (Suitability for UK F&B SMEs and Predictive Analytics)

4.4.1 Microsoft's AI in European Manufacturing Industries

The Microsoft / EY framework shows strong alignment with manufacturing strategy and clearly foregrounds predictive analytics use cases, particularly predictive maintenance and process optimisation. These strengths are evident throughout the document. However, when assessed against the operating realities of UK food and beverage SMEs, tensions emerge. The framework consistently assumes a level of digital infrastructure, connectivity, and organisational scale that sits uneasily with environments dominated by legacy ERP systems and limited specialist capacity.

From a Strategic Alignment (ER-PA) perspective, the framework scored highly. It explicitly links AI adoption to manufacturing KPIs such as downtime reduction, yield improvement, and defect minimisation, all of which draw directly on ERP-linked operational data. The document repeatedly emphasises the integration of sensor data with production and operational information to support predictive models. Although ERP systems are not always referenced by name, AI is consistently framed as a mechanism for extracting measurable value from existing production systems, which aligns well with SME priorities.

In contrast, the framework scored lower on SME Context and Scalability. Most illustrative examples assume multi-site operations, centralised data science teams, and substantial capital investment. There is limited guidance on how smaller food manufacturers, typically employing between 50 and 200 staff, might adopt similar capabilities incrementally or with constrained resources. This weakens the framework's applicability for SMEs seeking phased or low-risk adoption pathways.

The treatment of Data Architecture and Governance was assessed as moderate. While the framework strongly promotes cloud platforms, IoT integration, and the vision of "connected factories," it offers limited practical guidance on managing heterogeneous and partially integrated ERP landscapes, which are common among UK food SMEs. Technical Predictive Analytics Capability scored relatively highly, as the framework provides concrete scenarios for predictive maintenance and quality prediction and discusses the industrialisation of models across production environments. These elements align closely

with the predictive ambitions of manufacturing firms, even if their practical execution may be challenging for smaller organisations.
Food and Beverage Manufacturing Fit was rated as medium. Although the manufacturing examples are detailed and operationally grounded, explicit consideration of sector-specific constraints such as perishability, short shelf lives, and food safety traceability is limited. Finally, the Responsible or Trustworthy AI Lens was judged to be moderate. Issues of fairness and transparency are acknowledged, but governance does not serve as a central organising principle, and food-sector regulatory requirements, including FSA compliance, are not explicitly incorporated.

Criterion	**Score (1- 5)**	**Justification**
Strategic Alignment (ERP-PA)	4	Strong focus on manufacturing value and predictive maintenance closely linked to ERP data
Data Architecture and Governance	3	Emphasises cloud/IoT integration, but ERP legacies and SME data quality issues under-specified
Technical Predictive Analytics Capability	4	Provides concrete predictive use cases and discusses scaling models across operations
SME Context & Scalability	2	Assumes enterprise-level resources and multi-site operations with minimal SME tailoring
F&B Manufacturing Fit	3	Manufacturing-oriented but with limited discussion of perishability and food safety
Responsible / Trustworthy AI Lens	3	References responsible AI principles, but governance is secondary and not food-specific
Overall Suitability (Unweighted)	3.2	Strong strategic and technical alignment offset by weak SME scaling and sector specificity

Table 4.3: Microsoft AI in European Manufacturing Industries: Criteria-Based Suitability Scores (1-5)

Table 4.3 summarises the within-framework suitability assessment for Microsoft's AI in European Manufacturing Industries across the six evaluation criteria, using a 1-5 scale where 1 denotes very weak and 5 denotes very strong performance on each dimension.

4.4.2 PwC's Responsible AI Maturity Model

The PwC model performs strongest on governance-related dimensions, while scoring comparatively weaker on ERP-specific and SME-oriented aspects. Its primary aim is to embed responsible AI practices, risk management, compliance, and ethical oversight across organisations, rather than to guide sector-specific predictive analytics implementations. This orientation shapes both its strengths and its limitations in the context of UK food and beverage SMEs.

From a Strategic Alignment (ERP-PA) perspective, the framework received a moderate score. AI is positioned as a component of broader business transformation, but capabilities are treated in largely generic terms, with limited distinction between predictive analytics and other AI applications. As a result, the model offers limited practical guidance for SMEs seeking a clear roadmap for ERP-fed forecasting or predictive maintenance initiatives.

Data Architecture and Governance was rated highly. The framework devotes considerable attention to data quality, accountability, model risk management, and oversight mechanisms, all of which are relevant to predictive analytics in principle. However, this guidance remains system-agnostic. It does not engage directly with the realities of integrating governance controls into ERP-centred data environments typical of UK food manufacturing SMEs.

The framework scored relatively low on Technical Predictive Analytics Capability. It does not describe analytics architectures, model development lifecycles, or performance measurement in sufficient detail to support the design or implementation of ERP-driven predictive pipelines. SME Context and Scalability was also assessed as low. The model assumes the availability of cross-functional governance committees, legal functions, and dedicated risk offices, structures that are uncommon in small and medium-sized firms. Guidance on how such governance principles might be adapted in a lightweight or incremental way for SMEs is largely absent.

By contrast, the Responsible or Trustworthy AI Lens scored very highly. PwC's emphasis on fairness, transparency, and accountability is comprehensive and well-articulated, and could add value in a regulated environment such as food manufacturing if appropriately tailored. Food and Beverage Manufacturing Fit, however, remained low to medium. Manufacturing contexts are only briefly referenced, and the framework does not address food safety regimes or the operational implications of perishability.

Criterion	Score (1- 5)	Justification
Strategic Alignment (ERP-PA)	3	Aligns AI with organisational transformation but does not differentiate predictive analytics
Data Architecture and Governance	4	Strong emphasis on governance, risk, and controls applicable to analytics

Technical Predictive Analytics Capability	2	Limited detail on analytics architectures or model lifecycle grounded in ERP data
SME Context & Scalability	2	Assumes enterprise-scale governance structures not easily replicated in SMEs
F&B Manufacturing Fit	2	Minimal sector-specific content; food safety and perishability unaddressed
Responsible / Trustworthy AI Lens	5	Highly developed ethical and compliance orientation suitable for regulated contexts
Overall Suitability (Unweighted)	3.0	Governance strengths partly offset lack of ERP-PA specificity and SME tailoring

Table 4.4: PwC Responsible AI Maturity Model: Criteria-Based Suitability Scores (1–5)

Table 4.4 presents the within-framework suitability scores for PwC's Responsible AI maturity model, highlighting its strong governance focus and weaker fit for ERP-centric predictive analytics in UK food SMEs.

4.4.3 SAS's Assessing Your Business Analytics Maturity

The SAS framework was assessed as comparatively strong on analytics-related dimensions, reflecting its explicit focus on business analytics maturity and the progression from descriptive to predictive and prescriptive capabilities. Its eight metrics, including productivity, timeliness, governance, and return on investment, provide a structured lens for evaluating analytics performance. However, the framework was not developed with ERP-constrained food and beverage SMEs as a primary audience, which shapes its applicability.

Strategic Alignment (ERP-PA) received a high score. The framework explicitly links analytics initiatives to business value, emphasising measurable improvements in decision-making and performance. These outcomes map closely onto ERP-derived indicators such as service levels, inventory turns, and yield, making the model conceptually compatible with ERP-centred environments. Technical Predictive Analytics Capability was also rated highly. SAS clearly articulates progression beyond basic reporting and includes examples of predictive and prescriptive analytics, encouraging organisations to assess model impact and effectiveness rather than analytics activity alone.

Data Architecture and Governance was assessed as moderately high. The framework recognises data quality and governance as foundational enablers of analytics maturity. However, it often assumes that data can be standardised and integrated relatively easily across organisational units, an assumption that may not hold in smaller firms operating with fragmented or legacy ERP systems.

SME Context and Scalability received a medium score. While the framework is not explicitly SME-focused, it is more accessible than some alternatives. Its reliance on self-assessed metrics does not presuppose large data science teams or advanced technical infrastructure. Even so, it implicitly assumes a level of organisational maturity and resource availability that may be difficult for smaller food manufacturers to sustain.

Food and Beverage Manufacturing Fit was rated as moderate. The document includes manufacturing-oriented examples and prioritises operational metrics, but it does not explicitly engage with perishability, shelf-life constraints, or food-specific regulatory reporting. Finally, the Responsible or Trustworthy AI Lens was scored at a medium level. Governance appears as one of the eight metrics, yet it is not developed in the depth or specificity found in PwC’s framework.

Criterion	Score (1- 5)	Justification
Strategic Alignment (ERP-PA)	4	Strong emphasis on linking analytics to business value and performance metrics
Data Architecture and Governance	3	Recognises importance of data quality and governance but assumes relatively smooth standardisation
Technical Predictive Analytics Capability	4	Explicitly describes progression towards predictive and prescriptive analytics
SME Context & Scalability	3	More accessible than highly technical models, though still not SME-specific
F&B Manufacturing Fit	3	Some manufacturing relevance via operational metrics; food-specific issues underexplored
Responsible / Trustworthy AI Lens	3	Governance included as one metric but not the central organising theme
Overall Suitability (Unweighted)	3.3	Balanced strengths in strategic and technical analytics make it a relatively strong candidate with some contextual gaps

Table 4.5: SAS Business Analytics Maturity Framework: Criteria-Based Suitability Scores (1-5)

Table 4.5 summarises the within-framework suitability assessment for SAS's Business Analytics Maturity Framework, showing comparatively strong performance on analytics-centric criteria but only partial alignment with SME and F&B manufacturing realities.

4.4.4 Domino Data Science Maturity Model

The Domino Data Science Maturity Model is designed to support the scaling of data science practices from isolated experimentation to fully industrialised workflows, rather than to act as a sector-specific roadmap for predictive analytics in SMEs. As a result, it performs unevenly across the six evaluation criteria, with clear strengths in technical workflow maturity and notable weaknesses in SME alignment and sector relevance.

On Strategic Alignment (ERP-PA), the framework received a relatively low score. Its emphasis lies in organising data science teams, platforms, and reproducibility practices, rather than in linking analytics explicitly to ERP-driven business processes or operational predictive use cases. Data Architecture and Governance was assessed as moderate. The model assumes the presence of a centralised platform capable of model versioning, monitoring, and deployment. While this assumption can be advantageous in theory, it is unrealistic for many UK food and beverage SMEs. Moreover, the framework offers limited discussion of broader data governance considerations or how such platforms interact with existing ERP environments.

The Technical Predictive Analytics Capability scored relatively high in principle. The framework places strong emphasis on reproducible pipelines and the operationalisation of models, which are central to advanced predictive analytics. However, these capabilities are framed generically and presuppose access to advanced data science expertise. This limits their practical relevance for smaller organisations.

SME Context and Scalability received a low score. The model implicitly targets larger enterprises with dedicated data science teams and mature infrastructure, offering little guidance on how resource-constrained SMEs might adapt or phase its maturity stages. Food and Beverage Manufacturing Fit was also rated low, as the framework does not reference manufacturing contexts, nor does it engage with food-specific challenges such as perishability or regulatory compliance.

Finally, the Responsible or Trustworthy AI Lens was assessed as low to medium. While the framework addresses aspects of model management and auditability, it provides limited discussion of ethical considerations, regulatory requirements, or sector-specific governance issues relevant to food and beverage manufacturing.

Criterion	Score (1-5)	Justification
Strategic Alignment (ERP-PA)	2	Focuses on data science workflows rather than ERP-linked predictive business processes

Data Architecture and Governance	3	Assumes centralised platforms and versioning, but offers limited detail on broader governance or ERP integration
Technical Predictive Analytics Capability	4	Emphasises building and deploying models at scale, with strong attention to pipelines
SME Context & Scalability	2	Implicitly targets larger organisations with dedicated data science teams
F&B Manufacturing Fit	1	No explicit manufacturing or food-sector content
Responsible / Trustworthy AI Lens	2	Some model management and audit concepts; ethics and sectoral regulation under-developed
Overall Suitability (Unweighted)	2.3	Technically strong on data science operations but poorly aligned with SME and F&B context

Table 4.6: Domino Data Science Maturity Model: Criteria-Based Suitability Scores (1 -5)

Table 4.6 presents the within-framework suitability scores for the Domino Data Science Maturity Model, illustrating its strengths in data science industrialisation but limited relevance for ERP-driven predictive analytics in UK food and beverage SMEs.

4.5 Cross-Framework Comparative Results: Matrix-Based Comparison

This section synthesises the within-framework scores reported in Sections 4.4.1 to 4.4.4 into cross-framework comparison matrices, highlighting relative strengths, weaknesses, and overall suitability for ERP-enabled predictive analytics in UK food and beverage SMEs. Using the six evaluation criteria, Strategic Alignment (ERP-PA), Data Architecture and Governance, Technical Predictive Analytics Capability, SME Context and Scalability, Food and Beverage Manufacturing Fit, and the Responsible or Trustworthy AI Lens, the four frameworks were compared on a 1-5 scale, where 1 denotes very weak and 5 denotes very strong performance on a given dimension. At this stage, scores were left unweighted to preserve transparency, with ERP-contingent weighting, as outlined in Chapter 3, applied later during interpretive analysis.

The comparative results show that SAS's analytics-focused framework and Microsoft's manufacturing-oriented model perform strongest on Strategic Alignment (ERP-PA) and Technical Predictive Analytics Capability. PwC clearly leads on the Responsible or Trustworthy AI dimension, while Microsoft also performs well on manufacturing-aligned strategic fit. Domino's model scores relatively well on technical capability but falls behind across SME context, sector fit, and governance-related criteria.

Viewed collectively, the matrices reveal a consistent pattern. No single framework provides a comprehensive fit for ERP-centred predictive analytics in UK food and beverage SMEs. Instead, each framework contributes partial strengths, supporting the conclusion that a composite, context-aware maturity lens is required. This finding aligns with the conceptual synthesis developed in Chapter 2 and reinforces the need for tailored evaluation rather than direct adoption of any single model.

Criterion	Microsoft	PwC	SAS	Domino
Strategic Alignment (ERP-PA)	4	3	4	2
Data Architecture and Governance	3	4	3	3
Technical Predictive Analytics Capability	4	2	4	4
SME Context & Scalability	2	2	3	2
F&B Manufacturing Fit	3	2	3	1
Responsible / Trustworthy AI Lens	3	5	3	2

Table 4.7: Cross-Framework Criteria Scores (1-5) Across Six Evaluation Dimensions

Table 4.7 presents the 1-5 scores assigned to each framework on the six evaluation criteria, enabling cross-framework comparison of strengths and weaknesses. Microsoft and SAS perform most strongly on strategic and technical dimensions, PwC leads on responsible AI, and Domino is relatively narrow in focus on data science operations.

To provide a more holistic view, an overall suitability score was calculated for each framework using a simple, unweighted average across the six criteria. At this stage, no ERP-contingent weighting was applied. This unweighted standpoint indicates that SAS emerges as the marginally strongest overall candidate, followed by Microsoft and PwC, while Domino is clearly the least suitable for the specific context of ERP-enabled predictive analytics in UK food and beverage SMEs.

Framework	**Mean Score Across Six Criteria (1-5)**	**Summary**
Microsoft	3.2	Strong on manufacturing-aligned strategy and PA, weaker on SME scaling and sector specificity

PwC	3.0	Outstanding governance and responsible AI, limited ERP-PA specificity and SME tailoring
SAS	3.3	Balanced analytics-oriented strengths with moderate SME and F&B alignment
Domino	2.3	Technically strong on data science workflows, but poorly aligned with SME and F&B context

Table 4.8 - Unweighted Overall Suitability Scores (1-5) by Framework

Table 4.8 reports the unweighted mean scores for each framework across the six evaluation criteria. The results suggest that SAS and Microsoft provide comparatively stronger starting points for ERP-enabled predictive analytics in UK food and beverage SMEs, while PwC contributes important governance considerations and Domino is the least context-appropriate.

Finally, qualitative patterns across the matrices helped surface areas of complementarity between the frameworks. Microsoft's manufacturing-oriented focus, SAS's analytics maturity metrics, and PwC's governance emphasis emerged as largely complementary, each addressing dimensions that the others treat more lightly. By contrast, Domino's narrow concentration on data science operations tended to overlap with, rather than extend beyond, the technical capabilities already covered by the other models.

These patterns motivate the more detailed, context-specific discussion in Section 4.6, where cross-framework results are interpreted explicitly in relation to UK food and beverage SME realities, with particular attention to ERP integration, predictive analytics coverage, feasibility, governance, and the strength of supporting evidence.

4.6 Discussion Against UK F&B SME Realities

4.6.1 ERP and Data Integration Fit

The cross-framework results reveal a persistent weakness around ERP-centred data integration, despite ERP systems being the primary data backbone for predictive analytics in UK food and beverage SMEs. Microsoft's framework acknowledges integration between operational systems and AI, but this is framed largely through cloud and IoT narratives that assume relatively modern, well-connected plants. As a result, it offers limited explicit guidance on how to work with the heterogeneous and ageing ERP environments that are typical of smaller firms.

SAS and PwC both recognise the importance of data governance and standardisation, yet their treatment remains largely system-agnostic. This approach underplays the technical and organisational challenges involved in linking predictive models to ERP transaction and master data. Domino's framework goes further in abstracting away from core systems altogether, implicitly assuming the presence of suitable data platforms rather than engaging directly with ERP realities.

For UK food and beverage SMEs, many of which operate heavily customised SAP, Sage, or other mid-market ERP solutions, this lack of explicit integration guidance carries practical risks. It increases the likelihood that organisations will overestimate their readiness for predictive analytics while under-scoping the effort required to make ERP data accessible, reliable, and fit for modelling. The findings align with wider evidence showing that ERP integration failures remain a leading barrier to analytics adoption in manufacturing, particularly where legacy and on-premises systems must coexist with newer cloud services.

In practical terms, this means that although the frameworks consistently emphasise the importance of data and connectivity, they provide SMEs with limited concrete support for diagnosing, sequencing, and prioritising the specific ERP integration challenges that must be addressed before predictive analytics can be deployed effectively.

4.6.2 Predictive Analytics Coverage and Practical Guidance

Across the four frameworks, coverage of predictive analytics is uneven, with limited practical guidance tailored to ERP-fed use cases such as demand forecasting, predictive maintenance, and quality prediction in food manufacturing. Microsoft and SAS score relatively highly on Technical Predictive Analytics Capability. Microsoft foregrounds predictive maintenance and process optimisation, while SAS explicitly positions predictive and prescriptive analytics as advanced stages of maturity. Even in these stronger cases, however, guidance remains largely conceptual. The frameworks describe progression in maturity terms but stop short of offering step-by-step indications of how SMEs might move from existing reporting practices to stable predictive workflows grounded in ERP transaction and master data.

PwC and Domino devote considerably less attention to predictive analytics as a distinct operational capability. PwC prioritises governance and ethical oversight, while Domino focuses on data science workflow maturity, leaving predictive use cases underdeveloped.

For UK food and beverage SMEs, where challenges such as shelf-life management, waste minimisation, and line downtime are central to competitiveness, this creates a clear gap between the promise of predictive analytics and the guidance offered by existing frameworks. Collectively, the frameworks signal that predictive analytics represents an advanced maturity state, yet they remain vague about the incremental milestones and minimum technical and organisational conditions required to transition from descriptive reporting to ERP-linked forecasting in resource-constrained environments. As a result, SMEs may recognise predictive analytics as a desirable endpoint but still lack a practicable roadmap for implementation.

4.6.3 SME Feasibility (Cost, Skills, Complexity, Time)

The analysis points to a consistent misalignment between the assumptions embedded in the frameworks and the resource profiles of UK food and beverage SMEs, particularly with respect to cost, specialist skills, and organisational complexity. Microsoft, Domino, and SAS largely target organisations with dedicated analytics or data science teams, substantial capital budgets, and the capacity to coordinate cross-functional transformation programmes. These conditions are far more typical of large manufacturing enterprises than of SMEs. PwC's governance-heavy model similarly presupposes the existence of formal risk committees, legal and compliance functions, and structured model oversight, all of which can be burdensome for firms operating with lean management teams and tight margins.

For UK food and beverage SMEs, where staff frequently perform multiple roles and budgets for digital initiatives are constrained, such assumptions pose practical difficulties. Across the frameworks, there is limited guidance on how activities might be scaled down, sequenced, or modularised so that smaller firms can engage with AI and predictive analytics in a manageable and affordable way over realistic time horizons. This is reflected in the SME feasibility scores, with all four frameworks receiving low to medium ratings on SME Context and Scalability. The analysis therefore supports the view that, in their current form, these models risk encouraging SMEs to pursue overly ambitious roadmaps that exceed their capacity and increase the likelihood of stalled or failed initiatives.

This finding reinforces the need for careful, context-specific interpretation when applying any of the reviewed frameworks within SME food manufacturing settings.

4.6.4 Governance, Risk, and Compliance Relevance (incl. Food Safety / Regulation)

The governance and responsible AI dimension showed greater variation across the frameworks, with PwC clearly outperforming the others in both breadth and depth of coverage. PwC's model gives sustained attention to fairness, accountability, transparency, and risk management. These elements are directly relevant to regulated environments and could be particularly valuable for UK food and beverage SMEs concerned with compliance, traceability, and reputational risk arising from data-driven decision-making.

Microsoft and SAS both acknowledge governance and data quality as important considerations, but neither positions governance as the central organising principle of their frameworks. Instead, governance is treated as one of several enabling conditions for AI or analytics success. Domino's model offers the narrowest treatment, focusing primarily on model versioning and auditability within a data science platform, with limited engagement with broader organisational or regulatory responsibilities.

Despite these differences, none of the frameworks substantively address food safety regulation, allergen control, or other sector-specific compliance requirements. For UK food and beverage SMEs operating under stringent Food Standards Agency expectations, this represents a significant omission. While the general governance principles articulated in the frameworks can be adapted, the lack of food-specific guidance places the burden of interpretation on SMEs, requiring them to translate abstract governance concepts into concrete compliance practices.

Overall, the findings suggest that although PwC provides the strongest foundation for responsible AI governance, all four frameworks require additional contextualisation to align effectively with the detailed regulatory and risk landscape of UK food manufacturing.

4.6.5 Evidence / Validation Strength and Credibility

Finally, the cross-framework comparison exposes limitations in the empirical grounding and validation of all four frameworks, particularly in relation to SME and food manufacturing contexts. Microsoft, PwC, and SAS draw on combinations of case studies, surveys, and benchmarking data, but this evidence is largely sourced from large organisations across multiple sectors. Representation of SMEs is limited, and none of the cited applications focus specifically on UK food and beverage manufacturing. Domino's evidence base is narrower still, relying primarily on illustrative cases from technologically advanced organisations with mature data science practices.

This pattern raises questions about the generalisability of the maturity levels and recommended practices to UK food and beverage SMEs. While the frameworks may be valid within the populations from which their evidence is derived, the absence of systematic testing or documented application in SME food manufacturing settings means their suitability for this niche remains assumed rather than empirically demonstrated. The scores assigned under the Empirical Validation criterion therefore reflect not only the quantity and quality of supporting evidence, but also its relevance to the target context.

Overall, none of the four frameworks can claim strong, sector-specific validation for UK food and beverage SMEs. This finding highlights the importance of the criteria-based comparative evaluation undertaken in this study, which is intended to support cautious, context-aware use of existing frameworks rather than their direct or uncritical adoption.

4.7 Practical Implications: Choosing and Using Frameworks

The findings point to a clear implication for practice. None of the four evaluated frameworks can be adopted "off the shelf" as a complete solution for ERP-enabled predictive analytics in UK food and beverage SMEs. Each, however, contains elements that can be selectively combined and adapted. The comparative results suggest that Microsoft and SAS together offer the strongest coverage of manufacturing-aligned strategy and predictive analytics capability. PwC contributes a more developed responsible AI and governance perspective, while Domino illustrates what industrialised data science can look like, albeit in organisational contexts very different from those of UK food SMEs. For practitioners, this indicates that the more sensible approach is not to select a single framework, but to treat them as complementary reference points, filtering insights through the six evaluation criteria and the specific constraints of their own ERP environments and organisational capacity.

For SME managers, a practical starting point is to use Microsoft's and SAS's frameworks as high-level diagnostic tools to clarify where current analytics and predictive practices sit along a maturity continuum. This should be done with explicit adjustment of expectations around resources, skills, and timescales. These frameworks can help set direction for ERP-fed use cases such as waste reduction and maintenance forecasting, but their implicit assumptions about connectivity, staffing, and investment need to be scaled down to reflect SME realities. PwC's governance standpoint is best applied selectively, focusing on proportionate responsible AI practices such as clear accountability, basic model documentation, and transparency in how predictions inform decisions, without introducing excessive administrative overhead. Domino's emphasis on reproducible workflows and deployment discipline can inform longer-term ambition, but is more appropriately treated as an advanced-stage reference rather than an entry point for resource-constrained firms.

For ERP vendors and implementation partners, the findings point to both an opportunity and a responsibility to act as translators between enterprise-oriented frameworks and SME contexts. The frameworks' abstract language around data, platforms, and maturity needs to be reinterpreted in terms of concrete ERP configurations, data models, and integration patterns that SME clients actually operate. Vendors could, for example, develop pre-configured predictive "starter kits" that operationalise selected elements of Microsoft's and SAS's guidance using existing ERP modules and data structures, while embedding proportionate governance checkpoints informed by PwC's principles. Policymakers and support programmes can similarly draw on the criteria developed in this study to design more targeted guidance and funding mechanisms, ensuring that calls for AI adoption are grounded in realistic expectations about ERP integration effort, skills availability, and sector-specific regulatory constraints in the food and beverage industry.

4.8 Summary of Insights

This chapter has examined the suitability of four AI maturity frameworks for guiding ERP-enabled predictive analytics in UK food and beverage manufacturing SMEs, using the six evaluation criteria derived earlier and a 1-5 scoring system. The analysis demonstrates that no single framework offers a complete, context-ready roadmap. Instead, each contributes partial strengths that require careful interpretation and combination if they are to support predictive initiatives at SME scale. Microsoft and SAS emerge as comparatively stronger in terms of strategic alignment with ERP-fed predictive use cases and technical analytics capability. PwC provides the most developed responsible AI and governance viewpoint, while Domino illustrates technically advanced but contextually distant approaches to data science industrialisation.

At the same time, the analysis identifies consistent weaknesses across the frameworks in relation to ERP and data integration fit, SME feasibility, food and beverage-specific requirements, and sector-relevant empirical validation. All four models implicitly assume enterprise-level resources, relatively modern data infrastructures, and formal cross-functional governance structures that are often absent in UK food SMEs. They also offer limited explicit guidance on integrating predictive models with heterogeneous legacy ERP environments or on addressing sector-specific regulatory and perishability constraints.

These limitations reinforce the need for context-aware adaptation rather than direct adoption. They also justify the comparative, criteria-based approach adopted in this study as a necessary intermediary between generic maturity frameworks and the practical realities of implementing ERP-enabled predictive analytics within the UK food and beverage SME sector.

CHAPTER FIVE: CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

This chapter brings together the findings from the comparative evaluation of four AI maturity frameworks, Microsoft's AI in European Manufacturing Industries, PwC's Responsible AI Maturity Model, SAS's Assessing Your Business Analytics Maturity: Eight Metrics That Matter, and Domino Data Lab's Data Science Maturity Model, in relation to ERP-enabled predictive analytics in UK food and beverage manufacturing SMEs. It returns to the research aim and objectives, synthesising how each has been addressed across the study, and provides a direct response to the research question. The chapter also outlines the conceptual, methodological, and practical contributions arising from the analysis, before acknowledging limitations and identifying directions for future research.

Throughout, the discussion is guided by the central insight developed in Chapter 4: no single framework is fully suitable for the target context. Instead, each offers partial strengths that become meaningful only when selectively combined and interpreted through the six evaluation criteria developed earlier. This synthesis frames the contribution of the study as one of contextual interpretation rather than framework selection, emphasising adaptation over adoption for ERP-enabled predictive analytics in UK food and beverage SMEs.

5.2 Summary of the Study

The study was motivated by a clear misalignment between generic, enterprise-oriented AI maturity frameworks and the operational realities of UK food and beverage SMEs. These firms are heavily dependent on ERP systems, operate on thin margins, and face stringent regulatory and perishability constraints. Chapter 1 established this context, arguing that although predictive analytics holds clear potential for improvements in areas such as waste reduction and downtime prevention, existing maturity frameworks provide limited practical guidance for ERP-constrained, resource-scarce organisations in this sector.

Chapter 2 reviewed the relevant literature on maturity models, AI and analytics maturity, SME digital transformation, predictive analytics in manufacturing, ERP as a data backbone, and the four selected frameworks. This review culminated in the derivation of six evaluation criteria: Strategic Alignment (ERP-PA), Data Architecture and Governance, Technical Predictive Analytics Capability, SME Context and Scalability, Food and Beverage Manufacturing Fit, and a Responsible or Trustworthy AI Lens

Chapter 3 then outlined a pragmatic, qualitative documentary research design, incorporating PRISMA-guided corpus construction, structured data extraction, hybrid deductive, inductive coding, and 1-5 scoring across the six criteria to support systematic comparison.

Chapter 4 applied this methodology in practice, generating within-framework analyses, cross-framework comparison matrices, and a context-specific interpretation of the findings. This analysis surfaced both the partial strengths and the recurring limitations of each framework when assessed against the requirements of ERP-enabled predictive analytics in UK food and beverage SMEs.

5.3 Achievement of Research Objectives

The first objective, to systematically review and describe the primary characteristics of the four AI maturity frameworks, was addressed through PRISMA-guided document selection, structured extraction templates, and the descriptive framework profiles presented in Chapter 4. These profiles and within-framework analyses captured each model's origins, intended purpose, structural design, maturity dimensions, assessment logic, treatment of predictive analytics and ERP, and reported applications in manufacturing or analytics contexts.

The second objective, to develop an evaluation framework tailored to UK food and beverage SMEs, was achieved by synthesising conceptual and empirical insights in Chapter 2 and operationalising them in Chapter 3. The resulting six criteria explicitly incorporated ERP integration challenges, SME resource constraints, sector-specific considerations such as perishability and food safety, and the inclusion of responsible AI principles. In doing so, the criteria extended beyond the generic maturity dimensions typically emphasised in the literature.

The third objective, to conduct a comparative documentary analysis of the four frameworks against these criteria, was fulfilled in Chapter 4 through systematic 1-5 scoring across all dimensions and the construction of cross-framework comparison matrices. This analysis surfaced recurring patterns of strength, limitation, and misalignment, and produced unweighted overall suitability scores that enabled an evidence-based comparison of the frameworks in relation to ERP-enabled predictive analytics in UK food and beverage SMEs.

The fourth objective, to synthesise findings into practical recommendations for SME managers, ERP vendors, and policymakers, was addressed through the interpretive discussion in Sections 4.6 and 4.7 and is further consolidated in Section 5.6 of this chapter. Consistent with the study's scope, the research does not propose a new maturity framework. Instead, it articulates how existing models can be selectively combined and pragmatically adapted to better support the target context.

5.4 Answer to the Research Question

The central research question asked:

How suitable are the selected AI maturity frameworks for guiding ERP-enabled predictive analytics implementation in UK food and beverage manufacturing SMEs?

The findings indicate that none of the four frameworks is fully suitable as a standalone roadmap. Their usefulness varies across dimensions and depends heavily on context-aware interpretation and adaptation. SAS's analytics-focused framework and Microsoft's manufacturing-oriented model emerge as the strongest candidates when assessed against Strategic Alignment (ERP-PA) and Technical Predictive Analytics Capability. Both offer relatively clear connections between analytics maturity and operational performance, and foreground manufacturing-relevant use cases. However, they also assume levels of data integration, connectivity, and organisational capacity that exceed the realities of most UK food and beverage SMEs. Neither framework engages deeply with legacy ERP constraints or sector-specific regulatory requirements.

PwC's Responsible AI Maturity Model performs strongest on the Responsible or Trustworthy AI dimension. Its comprehensive treatment of governance, ethics, and risk management could add value in a regulated environment. That said, the framework provides limited support for ERP-centred predictive analytics and is oriented towards organisations with formal compliance infrastructures that are uncommon in SMEs. Domino Data Lab's Data Science Maturity Model demonstrates technical strength in the industrialisation of data science practices, but it is poorly aligned with SME resource profiles and does not address manufacturing or food and beverage sector considerations.

In summary, the four frameworks are only partially suitable, and only when used in combination rather than isolation. Interpreted through the six evaluation criteria developed in this study, Microsoft and SAS offer the most relevant entry points for strategy setting and analytics capability development, PwC provides a governance overlay, and Domino functions primarily as a reference point for advanced data science operations rather than as a practical maturity roadmap for UK food and beverage SMEs.

5.5 Contributions

5.5.1 Conceptual and Theoretical Contributions

Conceptually, the study contributes a criteria-based lens for assessing AI and analytics maturity frameworks within specific sectoral and organisational contexts. In doing so, it challenges the implicit assumption in much of the maturity literature that such frameworks are broadly transferable or universally applicable. By showing how enterprise-oriented models tend to over-specify resources while under-specifying integration challenges and sector-specific constraints, the research reinforces the importance of contingency in both the design and application of maturity models, particularly when moving from large organisational settings to SMEs.

The six evaluation criteria extend existing maturity constructs by explicitly incorporating ERP-centred data integration, SME feasibility, and food and beverage manufacturing fit alongside more established dimensions such as strategic alignment, technical capability, and governance. This rebalancing shifts the analytical focus from abstract capability progression towards practical applicability, offering a more grounded way to interrogate maturity claims in constrained, regulated environments.

5.5.2 Methodological Contributions

Methodologically, this paper demonstrates how a pragmatic, contingency-calibrated documentary analysis can be used to evaluate consultancy- and vendor-origin maturity frameworks in a structured and transparent way. The combination of PRISMA-style corpus construction, structured data extraction, hybrid deductive, inductive coding, and 1-5 scoring across clearly defined criteria provides a replicable approach for scholars and practitioners seeking to compare frameworks without access to primary implementation data.

The application of multi-criteria decision analysis to aggregate and visualise scores, alongside explicit consideration of weighting and sensitivity, illustrates how qualitative judgements can be made auditable and open to scrutiny, even when working with heterogeneous documentary sources. This approach offers a practical methodological pathway for critically engaging with maturity frameworks that are widely promoted but unevenly validated.

5.6 Recommendations for Practice

5.6.1 UK Food and Beverage SME Managers

For managers in UK food and beverage SMEs, the findings indicate that existing AI maturity frameworks are best used as diagnostic and interpretive tools rather than as prescriptive roadmaps. Microsoft's and SAS's frameworks can be used in combination to assess current analytics capabilities and to sketch a realistic progression towards ERP-fed predictive use cases such as demand forecasting, waste reduction, and predictive maintenance. This use, however, requires explicit adjustment of the frameworks' underlying assumptions. Expectations around dedicated data science teams, extensive cloud infrastructure, and multi-site operations need to be scaled down or phased in line with SME budgets, staffing capacity, and time horizons.

PwC's Responsible AI model can add value when applied as a governance overlay. It helps SMEs identify a minimal, proportionate set of responsible AI practices, including clear accountability for predictive models, basic documentation of data sources and assumptions, and transparency in how predictions inform decisions. These practices are particularly relevant in regulated environments, provided they are implemented without imposing excessive administrative burden.

Domino's model warrants a more cautious interpretation. For most SMEs, it is better viewed as a reference point illustrating advanced, industrialised data science operations, rather than as a guide for immediate action. Its relevance lies primarily in shaping longer-term ambition once foundational ERP integration, data quality, and governance issues have been addressed.

5.6.2 ERP Vendors and Implementation Partners

ERP vendors and implementation partners occupy an important role as intermediaries between generic maturity frameworks and SME operational realities. The findings suggest that vendors should translate selected framework elements into concrete ERP configurations, including predefined data models, integration patterns, and dashboards that directly support high-value predictive use cases. In practice, elements from Microsoft's and SAS's frameworks can be operationalised as "predictive starter kits" that draw on ERP production, inventory, and quality data to enable basic forecasting or anomaly detection, accompanied by clear guidance on data quality requirements and incremental improvement steps.

At the same time, vendors can embed proportionate governance checkpoints informed by PwC's principles into their implementation playbooks. These may include simple model approval processes, basic documentation standards, and lightweight risk assessments. Such measures help ensure that predictive analytics adoption proceeds with appropriate attention to fairness, accountability, and regulatory compliance, without imposing excessive overhead. Through this translation role, vendors can support SMEs in engaging with AI maturity in a way that is both technically grounded and practically achievable within their constraints.

5.6.3 Policymakers and Support Bodies

For policymakers and industry support programmes, the criteria developed in this study offer a practical checklist for designing AI and predictive analytics initiatives that are genuinely aligned with SME realities. Funding calls, guidance materials, and training programmes need to address ERP integration readiness, SME resource and skills constraints, and sector-specific regulatory and perishability challenges explicitly, rather than relying on abstract or generic notions of AI maturity.

Programmes aligned with initiatives such as Made Smarter could, for example, embed diagnostic tools based on the six criteria to help SMEs prioritise investment decisions and identify where targeted support is most needed. This might include assistance with data preparation and ERP integration, skills development, or the introduction of proportionate governance practices. Framing support in this way would help shift policy emphasis from aspirational adoption targets towards practical enablement grounded in operational constraints.

5.7 Limitations

The findings of this study should be interpreted in light of several limitations. First, the analysis is based entirely on published documents, including framework white papers, supporting studies, and industry reports. These sources are subject to promotional bias and survivorship effects, particularly where vendor-commissioned case studies foreground successful implementations while underreporting failures.
Second, the suitability judgements are derived from documentary evidence rather than from direct observation of framework use in practice. No primary data were collected from UK food and beverage SMEs applying these models, meaning that conclusions about framework fit are necessarily inferential and contingent rather than empirically verified through implementation outcomes.
Third, the study's focus on UK food and beverage manufacturing SMEs and on ERP-enabled predictive analytics limits the generalisability of both the evaluation criteria and the comparative findings. Different sectors, organisational contexts, or national settings may require alternative emphases or additional dimensions not captured here.
Finally, while the 1-5 scoring system was applied systematically and grounded in explicit criteria and documented evidence, it still relies on expert judgement and is sensitive to interpretive choices. Alternative criteria, weighting schemes, or coding decisions could yield slightly different rankings. That said, the broader pattern identified in this study, partial suitability combined with recurring misalignment, would be unlikely to change materially.

5.8 Suggestions for Future Research

Future research can extend this study in several productive directions. A clear next step would be to apply the evaluation criteria and scoring approach empirically with UK food and beverage SMEs, using case studies or action research to observe how the frameworks perform when deployed in live ERP-enabled predictive analytics initiatives. Such work would allow the suitability judgements developed here to be tested and refined in practice, while also surfacing additional criteria or sub-dimensions grounded in organisational and technical experience.
Further research could broaden the scope to other manufacturing subsectors, such as dairy, beverages, or bakery, or to different national contexts. Examining how variations in regulatory regimes, ERP configurations, and SME ecosystems shape framework applicability would help clarify which aspects of the criteria are context-specific and which may be more broadly transferable.
Finally, future studies could develop a quantitative diagnostic instrument derived from the six criteria, such as a structured survey tool, to enable broader benchmarking of AI and predictive analytics maturity across SMEs. This would not require proposing a new conceptual framework, but would operationalise the evaluative lens introduced here in a form that supports large-scale assessment while retaining sensitivity to ERP integration and sectoral constraints.

5.9 Conclusion

This paper has argued that AI maturity in ERP-enabled predictive analytics is not simply a matter of advancing through generic capability stages. Rather, it involves navigating the intersection of strategy, data, technology, governance, and sector-specific constraints, with sensitivity to context. For UK food and beverage SMEs, the four frameworks examined offer useful perspectives, but they must be applied critically, with clear awareness of their enterprise-oriented assumptions and their limited treatment of ERP integration, SME feasibility, and food sector regulation.

By developing and applying a structured, criteria-based evaluation, the study demonstrates how these frameworks can be interrogated and selectively adapted rather than adopted wholesale. The resulting recommendations aim to support more informed, realistic, and responsible engagement with AI maturity frameworks, helping SMEs, vendors, and policymakers to pursue predictive analytics in ways that are both practically viable and aligned with the distinctive operational and regulatory demands of the UK food and beverage manufacturing sector.

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APPENDICES

Appendix 1: Research Project Plan

Task	Time (Weeks)								
	Week 1	Week 2	Week 3	Week 4	Week 5	Week 6	Week 7	Week 8	Week 9
Refine research aim, RQ and objectives									
Develop conceptual framework & criteria									
PRISMA search & screening									
Document extraction & coding template									
Documentary coding of sources									
MCDA scoring of frameworks									

Cross-framework matrix analysis										
Draft Chapter 2										
Draft Chapter 3										
Draft Chapter 4										
Draft Chapter 5										
Review & feedback (iterative)										
Final editing, formatting & publication										