DCU BUSINESS SCHOOL DCU

Research Analysis

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

Module Code and Title: BAA1010 Business Project

Lecturer: Professor Teresa Hogan, Professor Michael Dowling

Student name: Tom Blume

Student ID: 46557

Date of Submission: 16.04.2026

Word Count: 3705

Table of Content

List of Abbreviations .... **iii**

1. Introduction **1**

2. Findings **1**

2.1. Awareness and Pain Thresholds Among SMEs 1

2.2. Current Forecasting Practice and Its Limitations 2

2.3. Perceived Benefits of AI-Supported Forecasting 3

2.4. Barriers to AI Adoption 3

2.5. Organisational Prerequisites 4

2.6. Role of External Support and Future Outlook 5

3. Discussion **5**

3.1. Confirmed Structural and Organisational Barriers 5

3.2. Extensions to the Literature 6

3.3. Divergent Perspectives 7

4. Contribution and Implications **8**

4.1. Contribution to Knowledge 8

4.2. Practical Implications 9

5. Limitations and Future Research **10**

5.1. Limitations 10

5.2. Future Research 11

Reference List **12**

Appendix **14**

Experts Information 14

Interview Outline 15

Declaration of Authorship **16**

Declaration of AI **17**

List of Abbreviations

AI ....Artificial Intelligence

FOMO.. ....Fear of Missing Out

SMEs ....Small and Medium-sized Enterprises

1. Introduction

This study builds directly on the preceding literature review, which established that the feasibility of artificial intelligence (AI) driven sales forecasting in small and medium-sized enterprises (SME)s depends less on technical capability and more on organisational and strategic conditions. Existing research highlights the importance of data readiness, leadership, skills, and cultural acceptance, but provides limited insight into how these factors are prioritised and experienced in practice. In particular, the literature does not sufficiently explain how SME decision-makers evaluate trade offs between accuracy, simplicity, and transparency, or how they sequence investments in data, infrastructure, and capabilities. This gap creates the need for an empirical investigation that captures real world perspectives and complements the conceptual insights of prior studies.

To address this gap, the study adopts a qualitative research design based on semi structured expert interviews. This approach allowed an in depth exploration of organisational realities, perceptions, and decision making processes that cannot be captured through quantitative methods. The sample consisted of one SME decision-maker and three AI specialists with practical experience. Data was collected through recorded interviews and analysed using encoded transcript analysis, enabling the identification of recurring patterns, similarities, and differences across cases.

The structure of the assignment reflects this research approach. Following this introduction, the findings section presents the empirical results organised into key themes. The discussion then interprets these findings in relation to the literature, highlighting confirmations, extensions, and divergences. The final sections outline the contribution and implications, followed by limitations and directions for future research.

2. Findings

2.1. Awareness and Pain Thresholds Among SMEs

A consistent pattern across all four interviews was that SMEs rarely engage with AI from a position of clearly identified need. The dominant motivation observed in practice is a diffuse sense of pressure rather than a concrete operational problem. Expert B described this as fear of missing out (FOMO): companies feel compelled to act but cannot articulate what they are actually losing by standing still. Unlike a visible crisis, the costs of not adopting AI remain largely invisible.

Expert A, drawing on direct experience selling AI tools to construction companies, found adoption to be almost entirely crisis driven. Companies returned months after an initial rejection having encountered the exact problem they had been warned about. Expert C identified a two-tier awareness problem: SMEs broadly sense their inefficiencies but struggle to translate vague concern into a specific use case. In workshops at the "Mittelstand-Digital Zentrum Hannover"[1], many participants arrived with general curiosity and no concrete direction; targeted demonstrations of AI capabilities were often what converted interest into intention.

A narrow mental model of AI compounded this problem. Expert D acknowledged that AI experience within the company was limited to search engine suggestions. Expert C noted that workshop participants frequently equate AI with tools such as ChatGPT and are genuinely surprised when shown other application types. This limited conceptual framing narrows the range of use cases SMEs consider and constrains their ability to identify where AI could address a real organisational pain point.

2.2. Current Forecasting Practice and Its Limitations

The most direct account of current forecasting practice came from Expert D. The company produces an annual forecast by speaking individually with every customer about expected orders, which are then compiled into a comprehensive Excel spreadsheet forming the basis of the entire budget. The clear advantage of this approach is that direct dialogue yields granular, customer-level insight that automated systems do not currently replicate. Customers tend to have a reliable sense of their own purchasing intentions for the coming year.

Scalability is the primary weakness. Across a large customer base, the process becomes prohibitively time intensive. Both Expert A and Expert B pointed to a deeper structural problem exposed by the COVID-19 pandemic: demand forecasting built on accumulated experience and tacit knowledge had functioned adequately in stable conditions, but the volatility that followed the pandemic broke those stable patterns. Expert C acknowledged that a growing number of interdependent global factors simultaneously influence demand, making reliable judgment-based forecasting increasingly difficult to sustain.

---

[1] The Mittelstand-Digital Zentrum Hannover is a publicly funded initiative supporting German SMEs in the strategic adoption of digital and AI technologies (Leibniz University Hannover, n.d.).

2.3. Perceived Benefits of AI-Supported Forecasting

Improved forecasting accuracy was the most widely cited potential benefit. Expert C framed this in terms of competitive advantage: the processes previously run without AI need to become noticeably simpler and faster. Analysis that would take weeks in Excel, AI can complete in seconds, a gain of considerable practical significance for resource-constrained SMEs.

Error detection emerged as a further, underappreciated benefit: Expert B described a case in which a systematic miscalculation in a product installation estimate held constant for decades, had caused repeated avoidable losses across hundreds of units. A system capable of proactively identifying such patterns could prevent substantial damage that no one in the organisation had recognised as a problem.

Expert A referenced a logistics case study in which AI-supported demand planning reduced costs by between 20 and 30 percent through more precise resource allocation across annual peaks. Expert C added knowledge preservation as an emerging benefit, noting that AI can help capture institutional knowledge as experienced employees retire, a concern of growing relevance given demographic trends across German SMEs.

Expert D stood apart from this consensus, expressing fundamental doubt about whether AI could meaningfully support sales forecasting in the company's context. Given the firm's reliance on public procurement contracts and highly customised products, too many external variables were seen as beyond the reach of any AI model.

2.4. Barriers to AI Adoption

Poor data quality and availability emerged as the most fundamental barrier, closely intertwined with Germany's accumulated digitalisation debt. From experience across multiple big data projects, Expert B observed that many German SMEs collect so few data points that meaningful statistical correlation is either impossible or wholly unreliable and attributed this partly to a generational and cultural disposition toward paper-based work. Expert C reinforced this with the "garbage in, garbage out" principle: unreliable input data produces unreliable predictions, which is particularly damaging in a forecasting context, and noted that government institutions operating on paper send a signal to businesses that this standard remains acceptable. Expert D added that even in an IT-intensive firm with over a hundred engineers and developers, a significant share of relevant data remains undigitized. Many

SMEs still operate on legacy systems or paper-based processes that provide no digital foundation for AI. An implicit expectation also surfaced: that AI systems should gather external data autonomously, rather than requiring extensive manual preparation. This expectation gap between what tools currently require and what decision-makers assume represents a structural mismatch that complicates adoption

Data security concerns constituted a distinct and, in one case, dominant barrier. For Expert D's company, where the primary product is proprietary software, the prospect of uploading internal data to an external AI system without knowing where it ultimately goes was described as fundamentally incompatible with the firm's security posture. This points to an inductive finding: for IP-intensive firms, security considerations override other adoption incentives and function as an effective veto. Expert C noted that data protection acts as a broader blocker across many SMEs, generating regulatory uncertainty that causes companies to postpone action even when they are otherwise motivated.

The transparency problem was raised by both Expert C and Expert D. When a decision-maker cannot understand how an AI system reached its conclusion, the choice is either to trust it blindly or to spend time verifying it manually, at which point much of the efficiency argument collapses.

Employee resistance and job displacement fears were noted across three interviews. Expert A described administrative staff pushing back against new tools out of fear for their roles; Expert B observed that rolling out a co-pilot without genuine change management almost never produces sustained adoption; Expert C stressed that introducing a tool without involving the people who will use it creates a real risk of non-adoption through uncertainty and distrust.

2.5. Organisational Prerequisites

Consensus emerged across experts on the sequencing of conditions necessary for successful implementation. Data collection and preparation represent the unavoidable first step: before any AI tool is introduced, a company needs a clear picture of what data it holds, what it needs and what its objectives are. Both Expert B and Expert C independently recommended beginning with a single pilot use case: a visible, bounded project that can demonstrate value and build internal confidence without requiring organisation-wide transformation.

Leadership commitment was identified as non-negotiable. Expert B was direct: having a motivated AI team is pointless if the CEO refuses to use a laptop or insists on paper memos.

Expert D confirmed that the firm's owner had been the primary brake on adoption due to security concerns, and that a shift in the owner's position was what was now opening the door. This convergence between a proponent and a sceptical practitioner on the centrality of leadership carries particular analytical weight. Expert B also recommended forming a cross-functional task force from the ten to twenty percent of employees who are genuinely enthusiastic about new technologies, insulating experimentation from scepticism and modelling new behaviour across departments.

2.6. Role of External Support and Future Outlook

External expertise was consistently identified as essential for SMEs that lack in-house capability. Expert A argued that peer success stories are the most powerful trigger for adoption: seeing a competitor benefit from AI within one's own sector is more persuasive than any marketing campaign. Expert B expressed a preference for co-investment models over full subsidies, arguing that requiring SMEs to carry a share of the cost forces a genuine decision-making process rather than performative adoption. Expert C added that while funding programmes already exist, a consistent problem is that SMEs are unaware of them, and that even when found, it is often unclear what costs are actually covered.

Across the interviews, a shared expectation emerged that competitive pressure will increasingly force SMEs to engage with AI regardless of current reluctance. Expert B and Expert C both argued that SMEs which fail to adapt risk being overtaken by more agile competitors. Expert A framed this in terms of a tipping point: once enough companies within a given sector see a peer achieve visible results with AI, adoption will accelerate on its own. Experts cautioned that AI alone is not the decisive factor: the underlying capability to respond quickly to rapid change matters more than any specific tool. Expert D, while sceptical about near-term feasibility, nonetheless acknowledged that AI would gain traction within the company in the coming years, particularly in software development and administration, provided that appropriate security guidelines were in place.

3. Discussion

3.1. Confirmed Structural and Organisational Barriers

The findings confirm the four barrier categories identified in the literature review: data readiness, transparency, leadership, and employee resistance, but reveal an important reordering of their relative weight for AI-based sales forecasting specifically.

The data-readiness pattern documented in Section 2.4 directly supports Carayannis et al. (2025) and Al-Karkhi & Rządkowski (2025) on data quality as the most persistent obstacle. For sales forecasting, however, this constraint operates with additional severity: models depend not only on internal transaction histories but on external market signals that SMEs are rarely equipped to capture. Expert B's observation that statistical correlation is often unachievable for German SMEs implies that the lower bound for viable forecasting lies well above what many firms currently hold.

The transparency concern raised in 2.4 echoes Ledro et al. (2023) and OECD (2021) on interpretability, but carries distinct consequences for forecasting outputs. Unlike classification or recommendation tasks, a forecast directly drives budget allocation and inventory commitment. The verification-versus-trust dilemma therefore collapses the efficiency case at precisely the moment when forecast accuracy matters most. This supports Al-Karkhi & Rządkowski's (2025) argument that explainability tools such as SHAP and LIME are necessary for forecasting adoption, though the added cognitive load may exceed what resource-constrained SMEs can absorb.

The findings on leadership (2.5) and employee resistance (2.4) align with Beckinsale et al. (2006) on owner-managers as digital champions and with Ledro et al. (2023) on change management. The convergence is analytically significant because it emerged from both a proponent (Expert B) and a sceptical decision-maker (Expert D), suggesting that leadership commitment is not merely one factor among many but a gating condition for forecasting initiatives specifically, where outputs will routinely conflict with managerial intuition.

Finally, financial constraints identified across the literature as the dominant SME adoption barrier (OECD, 2021; Kolková & Ključnikov, 2022), surfaced less prominently than expected. Awareness, cultural readiness, and the absence of usable data occupied more weight in practice. This reordering is the most notable confirmation-with-modification in the data: cost is present but not decisive, while preconditions the literature frames as secondary become primary.

3.2. Extensions to the Literature

Three findings extend the literature in directions particularly relevant to AI-based sales forecasting.

First, Expert D's account of data security as an overriding barrier introduces a dimension the literature acknowledges but rarely foregrounds. For IP-intensive firms, uploading internal data to external AI systems is perceived as fundamentally incompatible with the business model. This concern persisted even after the firm's owner had become more open to AI generally, indicating that for certain firms, security operates as a structural veto on AI-based forecasting regardless of other enabling conditions, a category the current literature on SME AI adoption has not systematically isolated.

Second, Expert B's characterisation of Germany's digitalisation debt as partly generational and cultural adds a socio-historical layer to barriers typically framed in structural terms. The literature documents financial and skills constraints extensively (OECD, 2021; Opoku et al., 2024), but the finding that a cultural disposition toward paper-based work, reinforced by government institutions operating on paper, produces a normative environment in which digitalisation appears optional has received less attention. For sales forecasting this is especially consequential: without digitised order histories and customer records, even basic models cannot be trained, placing affected firms behind the starting line rather than simply behind the frontier.

Third, a mismatch between what AI forecasting tools require and what decision-makers expect them to do emerged inductively as a distinct barrier. Expert D assumed that an AI system should autonomously gather external market intelligence rather than depending on manual data preparation. This expectation gap causes decision-makers to dismiss AI forecasting tools before implementation begins, because the perceived effort of data preparation undermines the efficiency argument that originally motivated interest. This is a rejection mechanism that operates independently of the barriers the literature already documents.

3.3. Divergent Perspectives

The interview data revealed a notable divergence between AI specialists and the industry decision-maker, best understood as a difference in vantage point rather than a direct contradiction. Experts A, B, and C, all positioned as AI specialists, consistently affirmed the potential of AI-based sales forecasting and discussed barriers as challenges to be overcome through sequenced investment and external support. Expert D, speaking as a decision-maker in a technology-oriented SME, approached the topic from a different position: not how to implement AI-based forecasting, but whether the approach is feasible given the firm's specific demand context.

Expert D's reservations were grounded in the firm's dependence on public procurement, highly customised products, and unpredictable tender outcomes — variables that historical sales data cannot reliably capture. This perspective does not invalidate the specialists' positions but highlights a contextual boundary condition the literature tends to understate. Studies on AI-based forecasting generally present the approach as broadly applicable to SMEs (Christopher & Rahmatillah, 2025; Stepanov, 2025), yet Expert D's account suggests that feasibility depends on the predictability of the demand environment. Where demand is shaped by discrete, non-repeating events, the data patterns that machine learning requires may not exist in sufficient regularity. This resonates with Gilliland's (2020) caution against narratives in which AI universally outperforms traditional methods, and with Kolková & Ključnikov (2022), who argue that simpler models may remain more appropriate where data conditions do not support complex approaches. It also connects to the earlier review's observation that judgement-based forecasting historically served SMEs well in stable conditions: Expert D's annual customer-dialogue process is precisely this tradition, operating in a demand environment that arguably still suits it.

A second tension emerged around the quality of adoption motivation. While all specialists identified competitive pressure as an eventual driver of change, Expert B acknowledged that current SME motivation is predominantly FOMO rather than a diagnosed forecasting problem. This matters because FOMO-driven adoption tends to produce projects that lack strategic grounding and therefore fail to deliver sustained improvements to forecasting practice. Ledro et al. (2023) warn that unclear objectives and limited stakeholder engagement are among the primary reasons AI projects stall. The data thus suggests that the nature of the adoption motivation, not merely its presence, shapes whether AI-based sales forecasting tools become embedded in organisational decision-making.

4. Contribution and Implications

4.1. Contribution to Knowledge

The literature review identified that existing research typically treats AI in SMEs, forecasting techniques, and SME digitalisation as separate topics, with very few studies integrating technical performance with organisational feasibility. This study addresses that gap by combining perspectives from AI specialists and an industry decision-maker to examine how organisational and strategic factors shape the feasibility of AI-driven sales forecasting in SMEs.

The findings contribute to the existing literature in three specific ways. First, the study demonstrates that the primary barriers to AI-based sales forecasting in SMEs are organisational and human rather than financial. While the literature consistently emphasises cost as the most persistent adoption barrier (OECD, 2021; Kolková & Ključnikov, 2022), the interview data revealed that data readiness, leadership commitment, cultural resistance, and employee acceptance occupy considerably more weight in practice. This reordering of barrier significance has not been established empirically for AI-based forecasting in SMEs. Second, the study identifies three barriers that the existing literature either overlooks or underemphasises: the function of data security as a structural veto in IP-intensive firms, accumulated digitalisation debt as a culturally reinforced phenomenon rather than a purely structural deficit, and an expectation gap between what AI forecasting tools require and what decision-makers assume they can do autonomously. Third, the divergence between AI specialists and the industry decision-maker reveals that the feasibility of AI-based forecasting is contingent on the predictability of the demand environment. This boundary condition is largely absent from the current literature, which tends to present AI forecasting as broadly applicable across SME contexts.

4.2. Practical Implications

For SME managers and owners, the findings point to a clear sequencing of priorities. Before investing in AI-based forecasting tools, firms must first establish a usable data foundation by identifying, digitising, and organising existing records. Beginning with a single, bounded pilot project rather than an organisation-wide rollout allows firms to demonstrate value and build internal confidence at manageable risk. Leadership must visibly champion these efforts, as the data consistently showed that without senior management commitment, even well-resourced initiatives stall.

For policymakers and institutional support providers such as chambers of commerce and digitalisation centres, two findings are particularly relevant. Peer success stories from within a sector emerged as the most effective trigger for adoption, suggesting that public institutions should invest in showcasing concrete, sector-specific examples rather than promoting AI in abstract terms. Additionally, co-investment models that require SMEs to share the cost appear more effective than full subsidies, as they force a genuine evaluation of whether the investment aligns with actual business needs rather than encouraging performative adoption driven by FOMO.

For AI consultants and technology providers, the expectation gap identified in this study carries direct operational relevance. Providers should communicate clearly what data preparation AI forecasting tools require, rather than allowing decision-makers to assume the system will gather intelligence autonomously. Equally, involving employees from the outset and addressing job displacement fears through transparent communication are preconditions for sustained adoption rather than optional additions to a technical implementation.

5. Limitations and Future Research

5.1. Limitations

Several limitations must be acknowledged when interpreting the findings of this study. The most significant constraint is the small sample size of four expert interviews, which limits the generalisability of the results. While the qualitative design was appropriate for generating in-depth, practice-oriented insights into a topic where empirical research remains scarce, the findings represent the perspectives of a limited number of individuals and cannot be assumed to reflect the broader population of SME stakeholders or AI practitioners.

The composition of the sample introduces further limitations. Three of the four interviewees are AI specialists whose professional activity involves promoting or implementing AI solutions, which may create a systematic inclination toward favourable assessments of AI potential. Only one interviewee represented an industry decision-maker perspective, and this firm's specific demand context, shaped by public procurement and highly customised products, is only partially applicable to the sales forecasting scenarios discussed in the literature. The study would have benefited from a more balanced inclusion of SME managers and owners across sectors where demand forecasting plays a more central operational role, such as retail, manufacturing, or logistics.

The geographic scope constitutes an additional boundary. All interviews were conducted with professionals operating within the German SME landscape, where specific conditions such as the accumulated digitalisation debt, the regulatory environment around data protection, and the institutional support infrastructure shape adoption decisions in ways that may not transfer directly to other national contexts. Finally, the interpretation bias inherent in qualitative analysis must be recognised. Although the coding process followed established thematic analysis procedures, the researcher's own assumptions and perspectives inevitably influenced the identification and weighting of themes.

5.2. Future Research

The findings of this study open several avenues for further investigation. A quantitative study with a larger and more representative sample of SMEs could test whether the patterns identified here, particularly the finding that organisational and human barriers outweigh financial constraints, hold across a broader population. Such a study could also examine whether the relative insignificance of cost as a primary barrier persists when controlling for firm size, sector, and digital maturity.

The co-investment funding model, which Expert B advocated as preferable to full subsidies for driving genuine rather than performative adoption, deserves empirical validation. Comparative research examining adoption outcomes under different public funding structures would provide evidence-based guidance for policymakers designing SME support programmes. Cross-sectoral and international comparative studies would help establish which of the identified barriers and enablers are context-specific and which generalise across different regulatory environments, industrial structures, and cultural attitudes toward technology. The boundary condition identified through Expert D's perspective, that feasibility depends on the predictability of the demand environment, warrants particular attention across sectors with differing demand characteristics. Finally, longitudinal research tracking SMEs over several years as they progress through early digitalisation, data preparation, and eventual AI integration would provide insight into the sequencing and timing of organisational changes that the cross-sectional design of this study could not capture.

Reference List

Al-Karkhi, M.I. & Rządkowski, G. (2025) 'Innovative machine learning approaches for complexity in economic forecasting and SME growth: A comprehensive review', *Journal of Economy and Technology*, 3, pp. 109–122. Available at: https://doi.org/10.1016/j.ject.2025.01.001.

Beckinsale, M., Levy, M. & Powell, P. (2006) 'Exploring Internet Adoption Drivers in SMEs', *Electronic Markets*, 16(4), pp. 361–370. Available at: https://doi.org/10.1080/10196780600999841.

Carayannis, E.G. *et al.* (2025) 'Enhancing SME resilience through artificial intelligence and strategic foresight: A framework for sustainable competitiveness', *Technology in Society*, 81, p. 102835. Available at: https://doi.org/10.1016/j.techsoc.2025.102835.

Christopher, W. & Rahmatillah, I. (2025) 'Sales Forecasting for SMEs in Digital Ecosystems: A Comparative Evaluation of ARIMA and Random Forest Models', in *2025 International Conference on Data Science and Its Applications (ICoDSA)*, Jakarta, Indonesia: IEEE, pp. 956–960. Available at: https://doi.org/10.1109/ICoDSA67155.2025.11157252.

Gilliland, M. (2020) 'The value added by machine learning approaches in forecasting', *International Journal of Forecasting*, 36(1), pp. 161–166. Available at: https://doi.org/10.1016/j.ijforecast.2019.04.016.

Kolková, A. & Ključnikov, A. (2022) 'Demand forecasting: AI-based, statistical and hybrid models vs practice-based models - the case of SMEs and large enterprises', *Economics and Sociology*, 15(4), pp. 39–62. Available at: https://doi.org/10.14254/2071-789X.2022/15-4/2.

Ledro, C., *et al.* (2023) 'Integration of AI in CRM: Challenges and guidelines', *Journal of Open Innovation: Technology, Market, and Complexity*, 9(4), p. 100–151. Available at: https://doi.org/10.1016/j.joitmc.2023.100151.

Leibniz University Hannover (n.d.) Mittelstand-Digital Zentrum Hannover – Digital with us. Available at: https://www.ifbe.uni-hannover.de/en/research/research-projects/research-projects/projects/mittelstand-digital-zentrum-hannover-digital-with-us (Accessed: 16 April 2026).

OECD (2021) *The Digital Transformation of SMEs*. OECD Publishing (OECD Studies on SMEs and Entrepreneurship). Available at: https://doi.org/10.1787/bdb9256a-en.

Opoku *et al.* (2024) 'Enhancing small and medium-sized businesses through digitalization', *World Journal of Advanced Research and Reviews*, 23(2), pp. 222–239. Available at: https://doi.org/10.30574/wjarr.2024.23.2.2313.

Stepanov, M. (2025) 'Using predictive analytics for managing supply and demand in small and medium-sized enterprises', *European Journal of Economic and Financial Research*. Available at: https://doi.org/10.46827/ejefr.v9i3.2006.

Appendix

Experts Information

Synonym	Role	Relevance to Research Question
Expert A	AI Consultant & Founder *(parallel role in project management at a German automotive engineering firm)*	Expert A builds and sells AI tools directly to SMEs, giving unfiltered, first-hand insight into why companies reject or adopt AI. Expert A's cold-calling sales log and construction-site diary app provide concrete evidence of adoption barriers (resistance, software fatigue, job-loss fear) and implementation realities. Expert A references to a logistics case study directly supports the demand forecasting dimension of the research question.
Expert B	AI Start-up Founder & Freelance AI Consultant; MBA in Entrepreneurship & Innovation Management	Expert B provides the broadest strategic coverage of the research question. Drawing on cross-company consulting experience, he addresses organisational prerequisites (leadership, task force, change management), structural barriers (digitalisation backlog, cultural resistance, FOMO-driven adoption), financial support design (co-funding models), and long-term competitive consequences for SMEs.
Expert C	Research Associate, Leibniz University Hannover; Mittelstand Digital Centre (SME digitalisation) and Cybersecurity Transfer Centre for SMEs	Expert C brings an academic and institutional perspective grounded in structured, repeated engagement with SMEs through workshops and network events. Expert C's role at the Mittelstand Digital Zentrum Hannover gives her systematic, cross-sector insight into how SMEs perceive AI, what barriers emerge in practice, and what support structures exist. Expert C's cybersecurity expertise adds depth to the data security and black box discussion, and she addresses the EU AI Act's implications for adoption feasibility.
Expert D	Senior Financial Decision-Maker at IT-intensive SME *(radar sensors and customised software, ~170 employees)*	Expert D is the only interviewee who is an active SME decision-maker rather than an AI advocate or researcher. He provides the critical counterweight to the other three interviews, representing the perspective the research question ultimately seeks to understand. His responses reveal how security concerns, business complexity (public tenders, bespoke software), and the black box problem manifest as concrete adoption blockers at the decision-maker level. His company also illustrates a key subtype: an IT-intensive SME where the barrier is trust and security, not skills.

Interview Outline

This study used a semi-structured interview format. All experts were asked questions to the core Topics below; additional probes were tailored to each expert's specific role and expertise, consistent with semi-structured qualitative methodology.

Core Interview Guide

1. Background and role
2. Current forecasting practice
3. Perceived benefits of AI forecasting
4. Barriers to adoption
5. Organisational prerequisites
6. External support and outlook

Expert-specific probes

Expert	Additional topic areas
A	• sales log findings and reasons SMEs decline AI tools • the construction-site diary app as an implementation case • the Mistral AI logistics case study and cost-saving potential • referral incentives and peer success stories as adoption drivers • the role of data analysts in SMEs
B	• nature of the "real pain point" in SMEs and FOMO-driven adoption • Germany's accumulated digitalisation debt and its generational/cultural roots • design of public funding programmes (full subsidies vs. co-investment) • cross-functional task forces and change management • long-term competitive consequences of non-adoption
C	• Workshop experience at the Mittelstand-Digital Zentrum Hannover • the EU AI Act and its effect on SME willingness to adopt AI • data protection as a structural blocker (cybersecurity perspective) • typical phases of AI implementation in SMEs • visibility and accessibility of public funding programmes
D	• firm's current customer-dialogue forecasting process and its trade-offs • feasibility of AI forecasting given reliance on public procurement and customised products • security implications of uploading proprietary software and data to external AI systems • expected trajectory of AI adoption within the company and required safeguards

Declaration of Authorship

DCU Business School

Assignment Submission: 16.04.2026

Student Names and Student Numbers: Tom Blume (46557)

Programme: Bachelor of Arts in Global Business (Germany)

Project Title: Research Analysis

Module Code and Title: BAA1010 Business Project

Lecturer: Professor Teresa Hogan, Professor Michael Dowling

Project Due Date: 17.04.2026

Declaration

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

I have not copied or paraphrased an extract of any length from any source without identifying the source and using quotation marks as appropriate. Any images, audio recordings, video or other materials have likewise been originated and produced by me or are fully acknowledged and identified.

This assignment, or any part of it, has not been previously submitted by me or any other person for assessment on this or any other course of study. I have read and understood the referencing guidelines found at https://www.dcu.ie/library/citing-referencing and/or recommended in the assignment guidelines.

I understand that I may be required to discuss with the module lecturer/s the contents of this submission.

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

Signed: [redacted]

Declaration of AI

Declaration Statement
Please tick the appropriate box relating to your use of Gen AI tools in this thesis
A. ☐ I did not use any Gen AI tools (including for editing and proofreading) in the completion of this assignment
B. ☒ I did use Gen AI tools in the completion of this assignment
Signature: [redacted]
Date: 16.04.2026

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

If you tick B: please complete the below -

No.	Date	Tool	Details
1	/	Microsoft Teams	Expert interviews were conducted and recorded via Microsoft Teams. The built-in transcription function was used to generate initial German-language transcripts of each recording. Each auto-generated transcript was reviewed manually.
2	After interview	Claude	Used Claude to translate the German-language interview transcripts into English and to remove filler words (e.g. "ähm", "also", "sozusagen") from the translated output in order to produce clean, readable transcripts suitable for thematic coding. Each translated and edited transcript was reviewed manually against the German original to verify accuracy of meaning, and corrections were made where necessary.

3	07.04.2026	Perplexity	Used Perplexity in the early planning phase of the research analysis to explore how qualitative findings-and-discussion chapters are conventionally structured in business research, and to obtain general recommendations on how to approach each section of the research analysis (introduction, findings, discussion, contribution, limitations). The outputs served only as initial orientation for structuring the assignment; all structural and methodological decisions were taken independently based on the assignment brief, module guidance. No text generated by Perplexity was reproduced in the submission.
4	03.12.2025	Atlas.ti	While encoding transcripts, Atlas.ti's in-built AI was at times used to obtain recommendations regarding categorisation. The validity of these recommendations was critically examined, and their application was contingent on their accuracy.
5	15.04.2026	Grammerly	Used Grammarly on the final draft solely to check grammar, spelling, and punctuation. No stylistic rewriting, rephrasing, or content changes were accepted. I reviewed each suggested correction manually before applying it, in line with DCU guidelines that permit only basic proofreading functions and do not allow AI-generated content.