The AI Implementation Paradox in Danish SMEs: Why Positive Intentions Fail to Translate into Sustained Use

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A substantial gap persists between organizational intention to adopt artificial intelligence (AI) marketing tools and their sustained use. This study investigates why Danish small and medium-sized enterprises (SMEs) with clear implementation intentions nonetheless fail to implement or scale AI adoption. Drawing on a qualitative multiple case study of six Danish SMEs and integrating the Technology Acceptance Model (TAM), Resource-Based View (RBV), and organizational AI capability research, we identify five mechanisms that systematically undermine intention-to-use translation: expectation-reality mismatches, time paradoxes, organizational structure constraints, tool proliferation, and support vacuums. We introduce the "intention-expansion gap," in which successful initial adoption stabilizes at partial use despite persistent expansion intentions. We extend TAM by positioning implementation capability as a moderator of the intention-behavior relationship and reconceptualize perceived ease of use as dynamically evolving; we extend RBV by showing resource constraints operate as implementation rather than adoption barriers.

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1 Introduction

The proliferation of accessible artificial intelligence (AI) tools has substantially reduced the technical and financial barriers to AI adoption for organizations of all sizes. Marketing applications, encompassing content generation, customer targeting, and data-driven decision support, are now technically within reach of small and medium-sized enterprises (SMEs) that previously lacked the specialist staff and budgets associated with such capabilities (Brynjolfsson & McElheran, 2016). Yet widespread availability has not produced commensurate adoption. A substantial body of evidence documents a persistent gap between organizational intentions to adopt AI and the sustained use of AI in practice (Ghobakhloo et al., 2021; Dwivedi et al., 2021; Alsheibani et al., 2020).

This gap is particularly salient in Denmark, where digital infrastructure is advanced and technological literacy high relative to international comparisons (Statistics Denmark, 2024). Danish SMEs operate in a high-readiness institutional environment characterized by strong broadband penetration, broad adoption of digital administrative tools, and government-supported digitalization initiatives (Danish Business Authority, 2023). If the intention-behavior gap in AI adoption persists in such an environment, the barriers are likely organizational and processual rather than infrastructural, making Denmark a theoretically informative context for investigating these dynamics.

With approximately 415,000 SMEs comprising 99.7% of Danish businesses (Danish Business Authority, 2023), understanding the AI implementation gap carries significant economic implications. Substantial prior research has examined technology adoption in SMEs, including barriers and drivers of digitalization (Ghobakhloo et al., 2021; Ramdani et al., 2022). However, most work focuses on whether SMEs adopt new technologies rather than on how adoption intentions succeed or fail during implementation. This distinction is particularly consequential for AI marketing tools, where the literature remains sparse and concentrated on large enterprise contexts (Alsheibani et al., 2020; Dwivedi et al., 2021).

This paper addresses three interrelated research questions:

RQ1: What is the nature and extent of the intention-behavior gap regarding AI marketing tool adoption among Danish SMEs?

RQ2: Which mechanisms explain this gap: why do SMEs with positive intentions nonetheless fail to implement AI marketing tools?

RQ3: How can Danish SMEs successfully bridge the intention-behavior gap in AI adoption?

We make three principal theoretical contributions. First, extending TAM, we demonstrate that implementation capability moderates the intention-behavior relationship in resource-constrained contexts, and that perceived ease of use evolves dynamically during implementation. Second, extending RBV, we reveal that resource constraints manifest as implementation barriers rather than adoption barriers. Third, we introduce the "intention-expansion gap", a stable partial-adoption equilibrium driven by satisficing dynamics that prevents broader diffusion despite strong expansion intentions.

2 Theoretical background

2.1 AI Capability, Digital Maturity, and Resource Constraints in SMEs

From a Resource-Based View (RBV), competitive advantage depends on resources that are valuable, rare, inimitable, and organizationally embedded (Barney, 1991). Recent research distinguishes the possession of AI tools from the organizational capacity to extract value from them (Mikalef & Gupta, 2021). AI capability encompasses data resources, technical infrastructure, analytical skills, and the process integration competencies required to embed AI meaningfully into business operations. Bharadwaj (2000) demonstrated that digital capabilities constitute a firm-level resource that translates technology investments into competitive outcomes; without such capabilities, technology adoption produces limited value regardless of tool quality. Alsheibani et al. (2020) extended this perspective to AI readiness, identifying organizational readiness as a prerequisite for realizing AI value at the firm level.

Owner and manager characteristics strongly shape adoption decisions in SMEs, where strategic, financial, and operational authority are frequently concentrated in one person (Thong, 1999). External support networks become critical compensatory resources given limited in-house expertise (Levy et al., 2001). SMEs often operate with informal processes for evaluating and implementing new information systems (Thong et al., 1996), which enables agility but also increases the risk of ad hoc implementations that fail to deliver sustainable value.

2.2 Technology Acceptance Model and the Intention-Behavior Link

The Technology Acceptance Model (TAM), developed by Davis (1989) and extended by Venkatesh et al. (2003), posits that perceived usefulness and ease of use shape attitudes toward technology, influencing behavioral intention and actual usage. However, a critical limitation is the assumption that intention reliably predicts behavior (Sheeran, 2002). Meta-analyses reveal that intentions account for only 28% of variance in behavior (Sheeran, 2002), indicating that even strong intentions frequently fail to materialize into action. This gap is particularly pronounced when behaviors require sustained effort, face implementation obstacles, or compete with other priorities (Gollwitzer & Sheeran, 2006), all characteristics describing AI implementation in resource-constrained SMEs.

In the context of AI adoption in SMEs, TAM remains useful for understanding how owners and managers form positive intentions based on perceived usefulness and ease of use. However, the intention-behavior gap literature suggests that strong intentions alone are unlikely to guarantee sustained use when implementation is time-consuming, technically demanding, and embedded in competing day-to-day operational priorities.

2.3 Intention-Behavior Gaps in Organizational Technology Implementation

Research on implementation intentions (Gollwitzer, 1999) suggests gaps can be bridged through specific planning mechanisms: defining when, where, and how to act; identifying potential obstacles in advance; and creating concrete action plans. However, this research has primarily focused on individual behaviors rather than organizational technology implementation. The translation of individual intentions to organizational action involves additional complexities including coordination costs, consensus requirements, and the need to align implementation with existing routines and workflows.

For AI technologies specifically, studies show that many firms underestimate the organizational work required to benefit from AI (Alsheibani et al., 2020; Dwivedi et al., 2021). Value creation depends on aligning AI initiatives with business goals and processes rather than simply installing tools (Mikalef & Gupta, 2021). Empirical studies focusing on SMEs identify financial constraints, lack of technical expertise, and limited organizational readiness as persistent barriers (Ghobakhloo et al., 2021).

2.4 Integrated Framework

To understand the AI implementation paradox in Danish SMEs, this study integrates insights from RBV, TAM, AI capability research, and research on intention-behavior gaps. RBV and AI capability research highlight how limited organizational resources and digital maturity make SMEs particularly vulnerable during implementation. TAM explains how SME owners form positive intentions based on perceived usefulness and ease of use. Research on intention-behavior gaps demonstrates that strong intentions frequently fail to produce sustained behavior when implementation is effortful, contextually constrained, or dependent on complex organizational processes.

Within this integrated framework, we focus on the implementation stage of AI adoption. Positive intentions form when AI tools are perceived as useful and accessible. These intentions then encounter the organizational realities of SME resource constraints, digital maturity limitations, and the concrete characteristics of AI implementation. The intention-behavior gap emerges when three conditions coincide: AI tools are presented as attractive and accessible; SME decision-makers express clear adoption intentions; and resource constraints, organizational readiness gaps, and AI-specific implementation complexity undermine sustained use.

3 Methodology

3.1 Research Design

This study adopts an interpretive epistemological stance and employs a qualitative multiple case study design (Yin, 2018; Eisenhardt, 1989). The case study methodology is appropriate for examining contemporary phenomena in which the boundaries between phenomenon and context are blurred. We build theory from multiple cases by iterating between within-case analysis and cross-case comparison (Eisenhardt, 1989).

3.2 Case Selection and Overview

Table 1: Case Overview

Case	Sector	Size	Digital Maturity	AI Tools Attempted	Primary Goal	Outcome
Case 1	Restaurant (B2C)	6 employees	Low-Medium	ChatGPT, Canva	Automate social content; reduce owner time	Failed (abandoned, 3-4 months)
Case 2	Social services (B2G)	14 employees	Medium	ChatGPT, Canva, HubSpot AI	Accelerate client-facing content production	Failed (paused Q1 2025)
Case 3	Restaurant (B2C)	8 employees	Medium -High	ChatGPT, Jasper, Canva AI, Hootsuite, Copy.ai	Identify optimal AI tool for all marketing	Failed (abandoned, 2 months)
Case 4	Consultant (B2G)	1 employee	High	ChatGPT Plus	Augment document writing; 30%+ time savings	Success (sustained, 12+ months)
Case 5	Digital agency (B2B)	10 employees	Very High	Multiple AI tools	Integrate AI across all service delivery	Success (integrated workflows)
Case 6	E-commerce (B2C)	3 employees	High	ChatGPT	Automate product descriptions and customer responses	Partial (limited, failed to expand)

Source: Authors' analysis

We employed purposeful, maximum variation sampling to select six Danish SMEs spanning the main outcome types of AI marketing tool implementation (Patton, 2015). Selection required that each organization: (1) qualified as an SME (fewer than 250 employees); (2) employed marketing activities as a central component of its business model; and (3) had considered, piloted, or implemented AI-based marketing tools within the preceding two years. It is analytically important to distinguish adoption failure (declining to proceed after evaluation), implementation failure (beginning use but discontinuing before achieving sustained integration), and scaling failure (achieving initial success but failing to expand). All six cases experienced some form of post-intention failure, they represent not non-adoption but adoption attempts that did not achieve intended scope. This distinction shapes how we interpret the mechanisms identified in findings.

Recruitment through professional networks introduces a selection bias toward more digitally aware organizations than the average SME. The sample should be interpreted as representing relatively favorable contexts for AI implementation; similar or stronger challenges likely characterize less digitally oriented SMEs.

Note. All cases are Danish SMEs that expressed interest in or attempted AI marketing tool adoption within 2023-2025. Digital maturity assessed based on prior digital tool adoption, process documentation, and staff technical proficiency reported in interviews.

3.3 Data Collection

We employed multiple methods to enable triangulation. Semi-structured interviews were conducted with SME owners and key employees during March through October 2024, ranging from 45 to 90 minutes (mean: 62 minutes), yielding approximately 7.5 hours of recorded data. All interviews were audio-recorded with informed consent and subsequently transcribed.

Interview protocols followed a semi-structured format covering six thematic areas: (1) company background and marketing context; (2) prior technology adoption history and digital maturity; (3) initial intentions and expectations regarding AI tools; (4) the implementation journey, including specific steps taken and barriers encountered; (5) outcomes and current AI use status; and (6) retrospective assessment and recommendations. Protocols were developed iteratively from the theoretical framework and refined through pilot discussions with two SME owners outside the final sample.

Documentary materials collected during the same period included examples of marketing content produced before and after AI introduction, screenshots from AI tools, configuration notes, and time-tracking records.

Table 2: Data Collection by Case

Case	Interviews (duration)	Observation Sessions	Documents
Case 1	1 interview (58 min)	None	Marketing content examples, tool screenshots
Case 2	2 interviews (45 min, 62 min)	None	Internal AI guidelines, content samples
Case 3	1 interview (71 min)	None	Tool comparison notes, content examples
Case 4	2 interviews (52 min, 48 min)	2 sessions	Work samples, time-tracking records
Case 5	3 interviews (90 min, 65 min, 58 min)	3 sessions	Workflow documentation, tool audit records
Case 6	2 interviews (55 min, 70 min)	1 session	Product descriptions pre/post AI, expansion planning notes

Source: Authors' analysis

3.4 Data Analysis

We followed a systematic five-stage analytical process. Stage 1 produced detailed case narratives capturing context, adoption journey, barriers, and critical turning points, shared with participants for member checking. Stage 2 involved open coding of all transcripts using NVivo, generating approximately 180 initial codes organized into five areas: decision-making processes, barriers encountered, implementation failures, success factors, and external support role.

To illustrate the coding approach: the code "time investment exceeds expectations" emerged from Case 1's owner's account that AI initially added one hour to each social media post, and from Case 2's director's observation that AI output required three to four times the anticipated editing effort. These codes, combined with "learning curve underestimated" and "operational urgency competing with implementation," formed the axial category "time constraints," which contributed to the cross-case mechanism "time paradox."

Stage 3 involved axial coding, organizing 180 initial codes into 12 larger categories. Stage 4 involved systematic cross-case analysis using comparison matrices examining expectation framing, implementation approach, time allocation, organizational structure, tool strategy, and support access. Stage 5 involved theoretical integration, interpreting empirical patterns through the integrated framework and developing propositions. Thematic saturation was reached after the fifth case, with Case 6 providing confirmatory evidence of the intention-expansion gap pattern.

3.5 Research Quality

We attended to multiple criteria for qualitative research quality (Lincoln & Guba, 1985). Credibility was supported through multiple data sources per case, member checking of case narratives, and active search for disconfirming evidence. Transferability was encouraged through thick description of organizational contexts and implementation processes. Dependability was supported by documenting sampling decisions, data collection procedures, and analytical steps in an audit trail. Confirmability was addressed by grounding interpretations in data excerpts and reflecting on researcher positionality.

4 Findings

4.1 Nature and Extent of the Intention-Behavior Gap (RQ1)

All six cases exhibited strong initial intentions toward AI adoption, with rated importance ranging from 7 to 10 out of 10, and all had taken concrete initial steps, including subscribing to tools, allocating time for experimentation, or aligning staff around adoption. Despite this, three cases (Cases 1-3) abandoned AI within two to six months, one case (Case 6) achieved partial implementation that did not expand as intended, and even the two successful cases (Cases 4 and 5) reported implementation complexity substantially exceeding initial expectations.

The gap operates along two dimensions. A binary gap between intention and any sustained use characterizes Cases 1-3, where abandonment occurred despite strong initial intentions. A graduated gap between intention and intended scope characterizes Cases 4-6, where implementation was achieved but fell short of broader goals initially envisioned. This two-dimensional character refines the binary framing common in adoption literature, suggesting a spectrum of partial implementation outcomes that the conventional adopted/not-adopted distinction cannot capture.

4.2 Failed Implementations: The Expectation-Reality Collapse

All three failed cases (Cases 1-3) abandoned AI within two to six months despite initial enthusiasm and high importance ratings (6-7 out of 10), exhibiting progressive disillusionment as implementation reality contradicted expectations.

Case 1 conceptualized AI as a "digital employee" that would autonomously generate social media content. Initial trials produced outputs requiring substantial editing to match the restaurant's authentic voice and local cultural context. The owner reported: "I thought it would save time, but initially it took more. I had to both learn the tools and correct their output." Creating a single Instagram post using AI required approximately one hour more than manual creation. After three months, the owner abandoned AI entirely. Key barriers included time investment exceeding expectations, expectation mismatch between plug-and-play assumptions and learning curve reality, and absence of contextually appropriate guidance.

Case 2 encountered a values alignment problem apparent only through implementation. For a social services provider where authenticity and professional empathy constitute core organizational identity, AI-generated content carried a register that staff experienced as incompatible with their professional standards. The director reported: "We had to put it somewhat on pause after Q1 2025. The time it took to get outputs that matched our values was simply too much." Time requirements exceeded initial estimates by a factor of three to four. Organizational structure concentrated all AI experimentation burden on the director, while field staff remained focused on service delivery.

Case 3, despite the owner's high digital fluency, illustrates how tool proliferation undermines implementation even where individual tools are technically manageable. Simultaneously testing ChatGPT, Jasper, Canva AI, Hootsuite, and Copy.ai, the owner reported: "I felt I was constantly switching between tools and never became really good at any of them. In the end, I couldn't justify continuing when I wasn't seeing clear results." Abandonment occurred after approximately two months.

Cross-case pattern: Failed implementations shared three characteristics: automation framing expecting AI to work autonomously rather than as augmentation requiring human expertise; ad hoc approach lacking structured implementation plans; and resource-time mismatches preventing sustained learning investment.

4.3 Successful Implementations: Realistic Expectations and Strategic Focus (RQ3, partial)

Case 4 achieved sustained success through four complementary factors: realistic augmentation framing, focused tool selection, deliberate time protection, and the structural advantage of solo operation. The consultant framed AI as a collaborative tool from the outset: "I knew from the start that it couldn't replace my expertise. I know the procurement processes, I know what evaluators look for. But I hoped AI could help with formulation and structuring." This framing transformed moments when AI required substantial expert input into confirmation of expectations rather than violations of them.

Strategic time allocation proved decisive: "I blocked 2 hours every Friday morning for experimenting and learning. I treated it like client work: non-negotiable time." This protected period enabled the sustained learning investment that failed cases could not maintain. As solo operator, she faced zero organizational barriers, all adoption decisions were concentrated in one technically capable individual with clear motivation and no coordination overhead. After approximately six weeks of dedicated learning, she achieved 30 to 40 percent time savings on document creation while maintaining output quality. Implementation has been sustained for over one year.

Case 5, the digital agency, succeeded through organizational capability compensating for the coordination complexity of a distributed ten-person team. The agency's technical sophistication meant team members framed AI adoption as an extension of existing digital practice. The founder reported: "In January 2023, I told the team: AI is not . We're going all-in. Everyone needs to start experimenting and learning." An internal Slack channel for knowledge sharing and the presence of team members with prior AI experimentation experience provided the contextual support that failed cases lacked.

The founder acknowledged, however, that success carried its own complexity: "I was looking at our tool subscriptions and realized we were spending over 1,500 euros per month on various AI tools. I tried to calculate ROI and couldn't clearly show which tools were worth it." One team member observed that they were "spending more time managing tools than saving with AI", a second-order challenge requiring ongoing organizational attention.

Cross-case pattern: Successful implementations shared augmentation framing, focused mastery strategy (one tool for one specific use case before expanding), and either structural simplicity (solo operation eliminating coordination costs) or organizational capability (established processes, technical sophistication, distributed implementation responsibility).

4.4 Partial Success: The Intention-Expansion Gap

Case 6 reveals a distinct failure mode: successful initial adoption that stabilizes without expanding despite persistent intentions. The e-commerce owner successfully adopted ChatGPT for product descriptions and customer service responses, achieving 40 to 50 percent time savings on these specific tasks over eight months of sustained use. The owner recognized clear expansion opportunities: "I know I should be using it for video scripts, newsletters, social media posts. I see others doing it successfully. I want to expand, but somehow it just doesn't happen."

4.5 Five Mechanisms Underlying the Intention-Behavior Gap (RQ2)

Figure 1: The AI Implementation Paradox: A Conceptual Model				
INTENTION FORMATION (TAM: Perceived Usefulness + Ease of Use)	→	**IMPLEMENTATION** (RBV: Resource Constraints + Digital Maturity)	→	**EXPANSION** (IDT: Diffusion + Scaling)
		5 Moderating Mechanisms: 1. Expectation-Reality Gap 2. Time Paradox 3. Organizational Structure 4. Tool Proliferation Trap 5. Support Vacuum		**Intention-Expansion Gap:** Satisficing equilibrium prevents scaling

Figure 1: The AI Implementation Paradox: A Conceptual Model
Source: Authors' analysis

Synthesizing patterns across all six cases reveals five mechanisms that systematically undermine the translation of positive intentions into sustained AI implementation.

Mechanism 1: The Expectation-Reality Gap: All failed cases exhibited expectation-reality gaps across four dimensions. Capability expectations: failed cases framed AI as autonomous agent, successful cases as augmentation requiring human judgment. Ease-of-use expectations: failed cases anticipated plug-and-play simplicity; successful cases anticipated learning curves requiring dedicated effort. Time investment expectations: failed cases expected immediate savings; successful cases anticipated upfront investment before returns. Actual time requirements in failed cases ran three to four times higher than expected. Timeline expectations: failed cases expected value within days or weeks; successful cases planned for four to eight-week learning periods.

Mechanism 2: The Time Paradox: SMEs face a circular constraint where AI promises time savings but requires upfront time investment to realize those savings. For owners operating at full capacity with no organizational slack, no time is available to learn the tool that would eventually save time. Failed cases could not sustain learning investment long enough to realize eventual returns. Operational urgencies consistently won priority battles against implementation activities. Successful cases either possessed capacity slack enabling protected learning time or deliberately created such slack through strategic time blocking.

Mechanism 3: Organizational Structure as Implementation Moderator: Organizational structure proved more decisive than size in determining implementation success. The solo operator (Case 4) achieved the cleanest success by eliminating coordination overhead entirely. Small co-located teams (Cases 1-3) concentrated implementation burden on already-overextended owners. The distributed team (Case 5) encountered the highest coordination costs yet succeeded through strong leadership, clear role definitions, and distributed implementation responsibility across technically capable team members. Digital maturity moderated this relationship: Case 5's very high digital maturity provided the organizational infrastructure, documented processes, established communication channels, a culture of tool experimentation, that enabled coordination. Cases 1-3's lower maturity levels meant that AI implementation competed with, rather than built upon, existing digital workflows.

Mechanism 4: The Tool Proliferation Trap: Case 3's multi-tool exploration strategy created cognitive overload and decision paralysis. Attempting to simultaneously evaluate and learn five tools fragmented attention, preventing mastery of any single tool. This contrasts sharply with successful cases' focused mastery approach, selecting one tool, achieving competence in one specific use case, then potentially expanding. Even Case 5, which ultimately used multiple tools, built this breadth sequentially through organized team-based experimentation rather than simultaneous individual evaluation.

Mechanism 5: The Support Vacuum: All failed cases attempted implementation without access to contextually appropriate guidance. Professional consulting proved uniformly unaffordable. Peer learning networks provided validation but no concrete context-matched solutions. Vendor support addressed interface functionality but not business context integration. Successful cases accessed contextually relevant guidance: Case 4 found a LinkedIn group for consultants sharing practical AI prompts for procurement documents; Case 5 had internal team members with prior experimentation experience who could guide others.

5 Discussion

5.1 Theoretical Contributions

Extending the Technology Acceptance Model (RQ1, RQ2): Our findings extend TAM by demonstrating that in resource-constrained contexts, implementation capability moderates the relationship between behavioral intention and actual usage. Traditional TAM posits that perceived usefulness and perceived ease of use shape attitudes, which influence behavioral intention, leading to actual usage (Davis, 1989; Venkatesh et al., 2003). Cases 1 and 2 formed strong intentions (rating importance 7 out of 10) based on perceived usefulness and initial perceived ease of use, yet failed to achieve sustained implementation.

Our data reveal that implementation capability, comprising time availability, external support access, organizational readiness, and realistic expectation framing, moderates whether intentions translate into sustained behavior. When implementation capability is low, even strong intentions fail to produce sustained use. When implementation capability is high, moderate intentions can translate into successful implementation.

Proposition 1: In resource-constrained SME contexts, the relationship between behavioral intention and actual usage behavior is moderated by implementation capability, including time availability, external support access, organizational readiness, and realistic expectation framing.

Furthermore, our findings reveal that perceived ease of use evolves dynamically during implementation. TAM treats perceived ease of use as a relatively stable pre-adoption assessment (Davis, 1989). However, we observed perceptions shifting dramatically as users discovered complexity hidden behind simple interfaces. Tools appearing simple in demonstrations proved complex in practice, requiring prompt engineering skill, output evaluation capability, and workflow integration knowledge. Failed cases experienced this evolution as expectation violation; successful cases anticipated it.

Proposition 2: Perceived ease of use in AI adoption is not a stable pre-adoption perception but a dynamically evolving assessment that transforms during implementation as users discover the gap between interface simplicity and implementation sophistication.

Extending Resource-Based View (RQ2): Our findings extend RBV by demonstrating temporal dynamics of how resource constraints operate as implementation barriers rather than merely adoption barriers. Resource constraints often appear manageable at the intention stage but become prohibitive during implementation for three reasons: implementation costs exceed anticipated expenses as organizations discover hidden costs of learning and workflow adaptation; time demands compete with operational priorities while SMEs lack organizational slack to absorb both simultaneously; and knowledge gaps become apparent only during implementation when abstract understanding confronts practical reality.

Proposition 3: Resource constraints operate as implementation barriers rather than merely adoption barriers, preventing intention-to-behavior translation rather than intention formation itself, with this effect mediated by temporal dynamics where constraints appear manageable pre-adoption but become prohibitive during implementation.

Introducing the Intention-Expansion Gap (RQ1, RQ2): Case 6 reveals a previously undertheorized failure mode. Initial adoption succeeds with measurable value (40 to 50 percent time savings). Strong expansion intentions exist, repeatedly expressed and clearly articulated. Yet expansion persistently fails despite clear recognition of unrealized value, absence of technical barriers, and availability of resources.

This pattern challenges Innovation Diffusion Theory's assumption that successful initial adoption enables broader organizational diffusion (Rogers, 2003). We identify satisficing dynamics as the mechanism sustaining this equilibrium. Initial success creates a "good enough" state that reduces urgency for improvement. Time saved is absorbed into other activities.

5.2 Practical Contributions (RQ3)

Our findings suggest that the intention-behavior gap in AI adoption is not primarily a technology problem but an organizational readiness and implementation support problem. The practical implications follow accordingly, differentiated by SME profile.

For early-stage adopters (Cases 1-3 profile (low to medium digital maturity, first AI attempt): The priority is expectation calibration. Assume implementation will require two to three times the effort suggested by vendor materials. Frame AI as augmentation requiring human expertise rather than autonomous replacement.

6 Limitations and future research

This study has several limitations. With six cases drawn predominantly from Danish service-sector SMEs, findings provide rich contextual insights but limited statistical generalizability. Future research should examine whether similar mechanisms appear in manufacturing, retail, or other national contexts.

The retrospective nature of data collection means we capture participants' recollections rather than real-time processes. Recruitment through professional networks likely selected for more digitally aware organizations. The challenges identified here may be more pronounced in less digitally oriented SMEs, suggesting that findings represent a lower bound on implementation difficulty for the broader SME population.

Finally, AI marketing tools are rapidly evolving. Some barriers identified, particularly around interface complexity and learning curves, may diminish as tools improve. Longitudinal research tracking how implementation challenges evolve as technologies mature would be valuable.

7 Conclusion

This study investigated why Danish SMEs that recognize AI marketing tools' value and express strong intentions to adopt them nonetheless fail to implement successfully. Through qualitative analysis of six cases representing failed, successful, and partial implementation outcomes, we identified five mechanisms underlying the intention-behavior gap: expectation-reality mismatches, time paradoxes, organizational structure constraints, tool proliferation complexity, and support vacuums.

Successful cases differed from failed cases not in initial enthusiasm but in four organizational characteristics: realistic expectations about implementation scope; strategic resource commitment including protected time; access to contextually relevant external support; and structured implementation approaches rather than ad hoc experimentation.

We make three theoretical contributions. First, we extend TAM by demonstrating that implementation capability moderates the intention-behavior relationship and that perceived ease of use evolves dynamically during implementation. Second, we extend RBV by revealing temporal dynamics of resource constraint effects. Third, we introduce the intention-expansion gap as a theoretically distinct phenomenon requiring different mechanisms than those enabling initial adoption.

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