

Master's Program in Computer, Communication and Information Sciences

Leveraging Large Language Models to Reduce Knowledge Debt-Induced Suboptimal Allocation of Customer Acquisition Budgets in Micro and Small Enterprises

Mitigating Knowledge Debt with Generative Artificial Intelligence to Optimize Resource Allocation

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Abstract

Micro and small enterprises often face challenges in allocating marketing budgets efficiently due to limited access to marketing knowledge, a phenomenon known as knowledge debt. This limitation often results in investment decisions based on intuition rather than data-driven decision making, leading to suboptimal marketing outcomes. For micro and small enterprises with limited resources, this inefficiency can massively impair growth, financial health and competitiveness.

Generative artificial intelligence tools have the potential to reduce the effects of knowledge debt by giving micro and small enterprises cheap access to relevant contextualized marketing support. These tools can assist in marketing content creation, strategies and performance analysis tasks, that typically require expensive specialist knowledge.

This thesis investigates the role of generative artificial intelligence tools in addressing knowledge debt within micro and small enterprise marketing processes. A qualitative study was done through semi-structured interviews with eight companies to explore current marketing challenges and the potential of artificial generative intelligence tools. After, a case study was carried out in a real business context to evaluate if the use of generative artificial intelligence led marketing activities can lead to improvements in return of marketing investment metrics.

The results show that most participating micro and small enterprises suffer from marketing knowledge debt, which has led to ineffective budget allocation and poor marketing outcomes. In the case study the use of generative artificial intelligence tools contributed to a large improvement in the key performance indicators and marketing outcomes. The findings are limited by a small sample size and convenience-based sample selection, but the evidence still suggests that generative artificial intelligence tools can serve as decision support tools for improving marketing budget allocation in micro and small enterprises.

Keywords Generative Artificial Intelligence, Knowledge Debt, Marketing Budget Optimization, Micro and Small Enterprises.

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Mikro- ja pienyritykset kohtaavat usein haasteita markkinointibudjettiensa tehokkaassa kohdentamisessa rajallisen markkinointiosaamisen takia. Tätä ilmiötä kutsutaan osaamisvajeeksi. Tämä vaje johtaa usein investointipäätöksiin, jotka perustuvat intuitioon dataan pohjautuvan päätöksenteon sijasta, mikä aiheuttaa epäoptimaalisia markkinointituloksia. Tämä voi heikentää mikro- ja pienyritysten kasvua, taloudellista vakautta ja kilpailukykyä merkittävästi.

Generatiiviset tekoälytyökalut voivat vähentää osaamisvajeen vaikutuksia tarjoamalla mikro- ja pienyrityksille pääsyn edulliseen markkinointitukeen. Nämä työkalut voivat auttaa esimerkiksi markkinointisisällön luomisessa, strategian laatimisessa ja tulosten analysoinnissa. Nämä ovat tehtäviä, jotka perinteisesti vaativat kallista asiantuntijaosaamista.

Tämä opinnäytetyö tutkii generatiivisten tekoälytyökalujen roolia osaamisvajeen lievittämisessä mikro- ja pienyritysten markkinointiprosessien kontekstissa. Tässä työssä toteutettiin laadullinen tutkimus toteuttamalla puolistrukturoituja haastatteluita kahdeksan yrityksen kanssa nykyisten markkinointihaasteiden ja generatiivisten tekoälytyökalujen mahdollisuuksien selvittämiseksi. Tämän jälkeen toteutettiin tapaustutkimus todellisessa liiketoimintaympäristössä, jonka tarkoituksena oli arvioida, voivatko generatiiviset tekoälytyökalujen johtamat markkinointitoimenpiteet parantaa markkinointi-investointien tuottavuutta.

Työn tulokset osoittavat, että suurin osa osallistuneista mikro- ja pienyrityksistä kärsii markkinointiin liittyvästä osaamisvajeesta, mikä on johtanut heikkoihin tuloksiin. Tapaustutkimuksessa generatiivisten tekoälytyökalujen käyttö johti merkittäviin parannuksiin keskeisissä suorituskykymittareissa ja markkinoinnin lopputuloksissa. Tuloksia rajoittaa pieni otoskoko ja ei satunnainen otanta, mutta tulokset silti viittaavat, että generatiiviset tekoälytyökalut voi toimia päätöksenteon tukena ja auttaa kohdentamaan investointeja.

Avainsanat Generatiivinen tekoäly, osaamisvaje, markkinointibudjetin optimointi, mikro- ja pienyritykset.

Preface

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Table of contents

Abstract	4
Abstract in Finnish	5
Preface.....	6
1 Introduction	9
1.1 Background	9
1.2 Problem statement.....	10
1.3 Research Questions.....	10
1.4 Thesis Structure	11
2 Knowledge Debt in MSE Marketing: State-of-the-Art	13
2.1 Introduction	13
2.2 Knowledge Debt	13
2.2.1 Knowledge-Based View of the Firm	14
2.2.2 Organizational Learning and Absorptive Capacity	15
2.3 Marketing challenges in micro and small enterprises	17
2.3.1 Marketing Efficiency	18
2.3.2 Manifestation of knowledge debt in marketing	19
2.4 Financial Implications of Knowledge Debt in Marketing	21
2.4.1 Inefficient Allocation of Marketing Budgets.....	23
2.5 Role of generative AI in addressing knowledge debt	24
2.5.1 Overview of generative AI in marketing	25
2.5.2 LLMs as an on-demand marketing strategy consultant	26
2.5.3 Using LLMs to create and improve text-based marketing	27
2.5.4 Using image generators to create and improve visual marketing materials	31
2.5.5 Using audio generators to create and improve audio marketing materials.	33
2.6 Limitations, risks, usability and ethical considerations of using AI in MSE marketing	36
2.6.1 Limitations with AI Use in Marketing	36
2.6.2 Risks Associated with AI Use in Marketing	37
2.6.3 Ethical Problems with AI Tools in MSE Marketing.....	39
2.6.4 Usability problems with AI tools in MSE marketing.....	40

3	Research Approach, Data, and Methodology	42
3.1	Research Design.....	42
3.2	Selection of Case Companies	43
3.3	Data Collection Methods	44
4	Results and Analysis.....	47
4.1	Marketing Channel Usage and Data.....	47
4.2	Analyzing knowledge debt's impact on marketing efficiency	49
4.3	Current Use and Perceptions of Generative AI Tools	51
4.4	Case Study	52
4.4.1	Practical Guide for Micro- and Small Enterprises	53
5	Discussion.....	57
5.1	Overview of the results	57
5.1.1	Scientific Impact	58
5.1.2	Practical Impact.....	58
5.1.3	Uncertainty Analysis	59
5.1.4	Further Research	59
6	Conclusion	61
7	References	62

1 Introduction

1.1 Background

Micro and small enterprises (MSEs) play a large role in global economies by driving innovation, creating employment and contributing to GDP growth. In Finland, micro-enterprises make up approximately 95.7% of all businesses and provide around one-fifth of the country's employment (Yrittäjät, 2025). Despite their significant economic impact, these enterprises often experience relatively slow growth rates, revenue stagnation and high failure rates compared to larger companies partly due to substantial challenges in customer acquisition arising from limited resources and expertise (Chundu et al., 2020). Given that MSEs make up most of all companies, their under-performance not only affects their own survival but also has broader implications for a country's economic development and employment.

Micro enterprises often do not utilize advanced marketing tools and methods such as data analytics, marketing automation platforms, or customer relationship management (CRM) systems, because they lack the knowledge, budget or expertise to implement and operate them. The rise of digital marketing channels has introduced complex yet extremely important technologies that require specialized skills, which are often beyond the reach of many micro and small enterprises (Nikunen et al., 2017). As a result, these businesses are often unable to collect or analyze customer data effectively, leading to uninformed decision-making, inefficient marketing and poorly performing sales campaigns. A global survey of over 1000 companies of all sizes found that marketers waste an average of 26% of their budgets on ineffective channels and strategies (Benes, 2018). This inefficiency is often higher in smaller enterprises. A survey of over 800 small and medium businesses discovered that over 50% of them don't know what insights their data could provide (Amazon Web Services, 2022). Additionally, 5 out of 8 companies interviewed for this thesis were unable to effectively collect, understand and utilize their own marketing data. Without the ability to track key performance indicators (KPIs) like Cost Per Lead (CPL) or Customer Acquisition Cost (CAC), companies cannot reliably improve and accurately assess the effectiveness of their marketing efforts (Nikunen et al., 2017). This often leads to suboptimal allocation of marketing budgets.

To combat this problem, many MSEs rely on outside marketing agencies to offset their internal lack of expertise (Nikunen et al., 2017). 4 of the 8 companies interviewed for this thesis have made such arrangements. While this approach frees up internal resources for core business activities, it often does not fix the fundamental problem of limited in-house marketing skills.

Instead, depending on external agencies can create new problems, such as communication gaps, slow feedback loops, and ultimately increase costs, leaving MSEs vulnerable to strategic misalignment and reduced long-term growth (Cueto et al., 2022).

Generative Artificial Intelligence (GenAI), particularly Large Language Models (LLMs) like OpenAI's GPT-4, offer promising solutions to address these challenges faced by MSEs, as these models can assist in simplifying and explaining complex marketing concepts (Deloitte, 2024). As LLMs can be cheaper to operate compared to outside expert help, this could allow MSEs to make data-driven decisions at a lower cost, making effective customer acquisition strategies more accessible and driving growth as AI can be used to create new, more effective business models (Jorzik et al., 2024).

1.2 Problem statement

Micro and small enterprises (MSEs) frequently face challenges in acquiring customers, often because of knowledge debt in marketing and sales. As result, MSEs may misallocate their marketing budgets, waste precious resources and fall short of achieving key growth objectives.

Addressing knowledge debt is essential for MSEs aiming to optimize their marketing activities, use resources more effectively, and foster sustainable growth.

1.3 Research Questions

The primary objective of this thesis is to explore if leveraging Large Language Models can reduce knowledge debt-induced suboptimal allocation of customer acquisition budgets in micro and small enterprises.

To address this challenge, this work aims to equip MSEs with LLMs that enhance their understanding of marketing data and empower them to make informed marketing decisions internally. To accomplish this, the goal of this thesis is to (Research Question 1-3):

1. Identify the key areas where knowledge debt impacts marketing efficiency in MSEs through a study involving 8 micro and small enterprises.
2. Assess the potential of LLMs and other Generative AI tools in mitigating knowledge debt by decision-making and marketing operations.

3. Tests with a case company to see if LLMs and other Generative AI tools can help MSEs to increase the ROI of their marketing investments.

1.4 Thesis Structure

This thesis is structured into six chapters.

Chapter 1: Introduction

Establishes the background, outlines the problem statement, defines the research questions, and provides an overview of the thesis structure.

Chapter 2: Knowledge Debt in Customer Acquisition

Explores the concept of knowledge debt in sales and marketing, its impact on marketing budget allocation in MSEs, and the potential role of Generative AI in addressing these challenges. The chapter concludes with a synthesis of the literature.

Chapter 3: Research Approach, Data, and Methodology

Details the research design, including the selection of case companies, data collection methods (surveys and interviews), and the justification of methods based on existing literature. It also describes the data analysis techniques used.

Chapter 4: Research and Analysis

Presents the findings from the surveys and interviews, analyzes the data in the context of the research questions, and specifies the requirements for integrating Generative AI tools into marketing processes.

Chapter 5: Discussion

Discusses how Generative AI tools can be utilized within a marketing environment to reduce knowledge debt. It explores practical implementation strategies and addresses potential challenges of this thesis.

Chapter 6: Conclusions

Summarizes the key findings, discusses the implications for micro and small enterprises, acknowledges the limitations of the study, and provides recommendations for future research.

2 Knowledge Debt in MSE Marketing: State-of-the-Art

2.1 Introduction

To ground this research, this chapter examines core literature on knowledge debt and explains how these deficits specifically affect marketing practices in micro and small enterprises (MSEs) and how AI might mitigate associated problems. The material is presented in four main sections. Subsection 2.1 defines the foundational elements of knowledge debt, showing how it emerges in marketing and outlining key metrics. Subsection 2.2 covers theoretical frameworks, spanning organizational learning and technology adoption, to clarify why new software can fail to gain traction. Subsection 2.3 introduces the core concepts of generative AI, examining how such tools can help address skill and knowledge gaps. Finally, Subsection 2.4 highlights AI-based solutions designed to alleviate marketing-related knowledge debt within MSEs.

2.2 Knowledge Debt

Knowledge debt refers to the accumulation of outdated, insufficient, or incomplete knowledge within an organization that interferes with informed decision-making (Coker, 2020) that accumulates when an organization fails to continually invest in and update its knowledge base. This is similar to technical debt in software engineering, where neglected code improvements or shortcuts ultimately increases costs over time by postponing essential training, ignoring fundamental gaps in relevant technical understanding, and causing repeated rework (Nord and Ozkaya, 2012).

To understand the concept of knowledge debt, it is important to examine two underlying theoretical perspectives: the knowledge-based view (KBV) of the firm (Grant, 2005), which posits knowledge as the key resource for competitive advantage, and organizational learning theory (Bergh et al., 2025) including the notion of absorptive capacity which explains how firms acquire, retain, and apply knowledge. These frameworks highlight why updating marketing knowledge is essential for maintaining competitiveness, and how low organizational learning capacity can lead to a buildup of knowledge debt that hampers effective decision-making in areas like customer acquisition, ultimately driving up marketing related costs (Ghotbifar, Marjani and Ramazani, 2017).

2.2.1 Knowledge-Based View of the Firm

The knowledge-based view of the firm argues that knowledge is the most critical resource for achieving and sustaining competitive advantage (Bergh et al., 2025). Unlike physical assets which deteriorate or depreciate over time, knowledge tends to appreciate with use (Bergh et al., 2025). In other words, deploying and sharing knowledge increases its value to the firm, as employees and managers refine their expertise and build on each other's insights. Knowledge is also hard to copy by competitors compared to tangible resources, making it a source of differentiation and competitive advantage (Grant, 2005). This perspective extends the resource-based view by emphasizing that intangible knowledge assets, skills, know-how, information and intellectual capital drive innovation and performance more than traditional factors of production.

However, if organizations neglect to invest in renewing and disseminating knowledge, they risk allowing it to become outdated or lost (Nakash and Bouhnik, 2020). The result is knowledge debt, a deficit of relevant know-how that can hinder decision-making and agility. Knowledge debt can be thought of as the organizational drag caused by obsolete understanding, missing skills, or information silos. One industry commentary asks, "*Is your staff up to date with the latest ways of working within their field? Are you allowing them time to grow and offering training?*" (Gould, 2022). These questions underscore that failing to update employee knowledge is a liability for the firm. Just as outdated machinery can slow down production, outdated knowledge can slow down a company's ability to make decisions and compete in fast-changing markets.

In the context of marketing, keeping knowledge current is especially critical. Markets, technologies, and consumer behaviors evolve rapidly, meaning that marketing tactics that worked a few years ago may become far less effective today. A World Economic Forum article (Kasriel, 2017) states that the half-life of a professional skill is about five years implying that roughly half of one's expertise becomes obsolete in that time span without ongoing learning. Indeed, as companies build up digital marketing infrastructure, the skills and knowledge needed to utilize these tools effectively often fall behind (Ghotbifar, Marjani and Ramazani, 2017). Failing to stay current on marketing knowledge can put firms at a competitive disadvantage (Nasir, 2015), whether it be the latest search engine optimization techniques, social media algorithms, or data analytics methods. Falling behind therefore means that customer acquisition budgets might be spent on suboptimal channels or strategies simply because decision-makers or employees doing the actual work are unaware of better alternatives.

2.2.2 Organizational Learning and Absorptive Capacity

While the knowledge-based view of the firm explains why knowledge is central, organizational learning explains how firms build and preserve that knowledge over time. Organizational learning (Argote, 2012) refers to the process by which organizations acquire, create, retain and transfer knowledge to modify their behavior and improve performance over time. It involves not just individual learning, but the embedding of knowledge into organizational processes, culture, and memory and emphasizes that organizations must learn continuously to adapt to changing environments (Argote, 2012). Applied to the marketing context, organizational learning underpins a company's ability to understand evolving customer needs, learn from past campaign outcomes, and refine its marketing strategies accordingly. An organization with strong learning practices will systematically analyze its marketing experiments (successful or not), retain lessons learned, and disseminate that knowledge so that future decisions are better informed.

A key concept in organizational learning is absorptive capacity. It refers to the organization's ability to identify, absorb, and leverage new external knowledge and information for business applications (Harrington and Guimarães, 2005; Cohen and Levinthal, 1990). In simpler terms, absorptive capacity can be thought of as the learning capability of a firm and how its able to absorb new knowledge and utilize it for achieving desired business outcomes. High absorptive capacity allows a company to quickly learn about and implement a novel digital marketing technique or recognize and adapt messaging based on a newly founded shift in consumer behavior based on market research. Absorptive capacity depends on factors like the existing knowledge base (prior related knowledge makes it easier to learn new things), the firm's processes for knowledge sharing, and its culture regarding innovation (Argote, 2012). Companies with knowledgeable leadership and open communication tend to have greater absorptive capacity and thus navigate change more successfully (Garrido-Moreno et al., 2024). By contrast, organizations with strong, hierarchical cultures often resist change, lacking the ability to capture new knowledge from the environment. In such firms, even if the outside world offers new marketing insights or technologies, the organization fails to internalize them, contributing to knowledge debt. Low absorptive capacity thus directly aggravates knowledge debt: the firm cannot readily learn or implement new marketing

tactics, so it sticks with outdated approaches and falls further behind learning organizations (Harrington and Guimarães, 2005).

Organizational learning theory also highlights the importance of knowledge retention, ensuring that what has been learned by individuals or teams remains accessible to the organization in the future (Daghfous, Belkhodja and Angell, 2013). Firms face a continual risk of knowledge loss due to employee turnover, retirement, document loss or simply forgetting over time. If valuable knowledge “walks out the door” or gets lost over the years, the organization may have to relearn hard-won lessons. This not only incurs extra costs but also represents a form of knowledge debt, as past investments in learning yield no lasting benefit. A great example comes from NASA: after the Apollo missions, much of the know-how for travelling to the moon was lost as experts retired and documents were lost (Jennex, 2014), forcing NASA to relearn processes decades later as they are now attempting new lunar missions. Similar scenarios play out when companies fail to document or institutionalize knowledge. Marketing and sales processes are especially vulnerable to the loss of knowledge because they often rely on tacit knowledge such as personal insights into customer relationships or creative know-how in campaign design held by individuals or small teams (Arnett, 2013). Marketing also tends to experience high staff turnover. According to LinkedIn, marketing roles had the fourth highest turnover rate of any field at 12.9 % in 2022. This turnover rate is 21.7 % higher than the overall average (LinkedIn, 2022). This employee churn means that without proper knowledge retention practices, a small enterprise with a limited number of marketing employees could lose key marketing expertise every time an employee leaves (Arnett, 2013).

Effective knowledge retention entails capturing and preserving critical marketing knowledge so that it remains within the firm’s collective memory (Schmitt, Borzillo and Probst, 2012). This can involve creating knowledge repositories (documents, playbooks, databases), encouraging senior marketers to mentor juniors, and fostering a culture of knowledge sharing. Such efforts are not mere administrative overhead; knowledge retention is a critical resource and the cornerstone for sustainable competitive advantage (Levy, 2011). When organizations successfully retain knowledge, they protect themselves from having to constantly reinvent the wheel. For example, a company that maintains a well-documented history of past advertising campaigns (including what worked and what didn’t) can avoid repeating mistakes and can build on prior successes, thereby using its marketing budget more effectively each year.

2.3 Marketing challenges in micro and small enterprises

MSEs face several structural and operational challenges that contribute to the increase of marketing related knowledge debt and overall costs associated with marketing activities. These challenges arise from limited resources, the rapid evolution of marketing technologies, and the change and increasing complexity of consumer behavior (Hendrawan et al, 2024).

MSEs typically operate with restricted budgets that limit their ability to hire specialized marketing professionals or invest in comprehensive employee training (Brush et al., 2019). Instead, they often rely on generalist staff who may lack the necessary in-depth expertise to navigate the complexities of modern marketing (Gilmore, Carson and Grant, 2001). This reliance on undertrained or multitasking employees can lead to ineffective strategies, inefficient allocation of marketing budgets, and missed opportunities for growth. Furthermore, resource limitations make it difficult for MSEs to access high-quality marketing analytics tools, which are often expensive or require high-cost labour to be operated. Without these tools, businesses might struggle to gain insights into key performance metrics such as Cost per Lead (CPL) and Customer Acquisition Cost (CAC).

The marketing industry is continuously evolving, primarily due to the rapid growth of digital marketing channels. Over the past decade, digital advertising has grown rapidly, with global spending increasing from \$108 billion in 2014 to \$545 billion in 2022, accounting for 62% of total media ad spending (Navarro, 2024). This dramatic growth underscores the fast-shifting landscape of consumer engagement and the importance of digital platforms in modern marketing. New platforms, algorithms, and tools are introduced at a high pace, requiring businesses to continually adapt their strategies. For example, social media platforms like TikTok and emerging technologies such as AI-driven personalization and customer communications have quickly become components of highly profitable marketing strategies.

The continuous influx of new marketing tools, channels, and strategies contributes to an environment of information overload. According to (Roetzel, 2019) information overload occurs when the volume of information surpasses an individual's or company's capacity to process and make informed decisions. For MSEs, this is particularly problematic as many lack the required budgets to invest in employee training or in new technologies (Hendrawan et al, 2024), thus making the adaption of new marketing information about new marketing channels and new marketing methods troublesome.

2.3.1 Marketing Efficiency

Small businesses typically operate with limited financial and human resources, which often forces them to adopt simpler, informal, and ad-hoc marketing practices compared to larger firms (Bocconcelli et al., 2016). Many small enterprises, unable to afford dedicated marketing staff, rely on the owner-manager to handle multiple roles (Gilmore, Carson and Grant, 2001). This reliance on a generalist approach often leads to an expertise gap where critical functions, such as market research, strategic planning, and analytics might be underdeveloped or neglected (Oduro and Mensah-Williams, 2023).

Marketing efficiency, defined as the effective allocation and utilization of a marketing budget to maximize outcomes like customer acquisition, retention, and brand building, varies a lot between small and large companies (Oduro and Mensah-Williams, 2023). Larger companies not only command higher budgets (Berthon, Ewing and Napoli, 2008) but are also better aligned to use more data driven marketing capabilities across channels (Morgan, Slotegraaf and Vorhies, 2009). In contrast, small businesses frequently make budgetary decisions based on intuition rather than robust analysis, which can result in under-investment in high-return channels and over-investment in less effective ones (Morris, Schindehutte and LaForge, 2002).

This challenge is compounded by a general lack of confidence among small enterprises. For instance, 37% of MSEs identify the selection of appropriate marketing channels as their top improvement area, while only a small fraction feels confident in their current marketing channel choices (Constant Contact, 2024). Consequently, the limited use of analytics, which is common among small firms, further undermines their ability to refine marketing strategies. While larger organizations invest more heavily in tracking detailed metrics, running A/B tests, and employing dedicated analysts, small businesses often encounter barriers to adopting these data-driven practices (Maroufkhani et al., 2020).

Cost per Lead (CPL) and Customer Acquisition Cost (CAC) are two key metrics that serve as essential tools for assessing the efficiency of marketing efforts (Hormozi, 2023) in small businesses, when resource constraints often limit the ability to invest in extensive analytics. CPL quantifies the average expense incurred to acquire a potential customer's contact information (Hormozi, 2023). For small businesses operating on tight budgets, this metric is critical. A high CPL can indicate that a significant portion of limited marketing funds is being spent on channels that do not yield sufficient prospects (Hormozi, 2023). Without established benchmarks, firms risk overspending on under-performing initiatives, which further restricts their

capacity to invest in more promising marketing opportunities (Hormozi, 2023; Keap, 2019). In essence, CPL provides a first-line indicator of how effectively a company is using its budget to generate leads that could eventually be converted into customers.

CAC measures the total expenditure required to get a paying customer (Hormozi, 2023). This metric is especially important because it includes all costs, such as marketing, sales, and operational that are involved in winning a customer. A sustainable marketing strategy is generally characterized by a CAC that is well below the Customer Lifetime Value (LTV) and for a success standard the commonly accepted target ratio for LTV-to-CAC is between 3:1 and 4:1, meaning that for every dollar spent on acquiring a customer, the firm should expect to generate three to four dollars in revenue over the customer's lifetime (Klipfolio, 2025; Geckoboard, 2025; Hubspot, 2024). A survey of 1,300 small and medium-sized companies found that 73% of small businesses are uncertain about the effectiveness of their marketing strategies, yet 39% plan to increase their marketing related spending (Constant Contact, 2024). This disconnect suggests that without systematic analysis of critical metrics like CPL and CAC, many firms are making decisions based on guesswork rather than evidence. Furthermore, the issue of "knowledge debt" extends to both strategic decisions and day-to-day marketing operations. Small enterprises frequently experiment with new platforms such as TikTok or AI chatbots, often without conducting a meaningful return-on-investment analysis or ensuring long-term strategic alignment (Guerrero, 2023). The rapid adoption of such platforms often overlooks the additional skills required for effective engagement, such as video editing and creative content production, thereby risking ineffective campaigns that fail to resonate with target audiences (Guerrero, 2023).

In summary, the literature and industry data consistently indicate that marketing efficiency is generally lower in small enterprises than in large firms. Even though small businesses can sometimes leverage fast and creative marketing in their niches, limited budgets combined with gaps in marketing expertise, technology, and analytical capability, often leads to suboptimal allocation of resources. Addressing these deficiencies through targeted training or more accessible analytics tools is frequently cited as essential for enhancing the competitiveness of small businesses.

2.3.2 Manifestation of knowledge debt in marketing

Accumulated knowledge debt extends its impact far beyond immediate marketing inefficiencies, manifesting in lower returns on marketing investments and slower overall business growth for micro and small enterprises

(Morgan, Vorhies and Mason, 2009). A narrow understanding of marketing and market orientation contributes to this challenge (Boso, Story and Cadogan, 2017). Many small business owners mistakenly equate marketing solely with advertising or social media, overlooking critical strategic dimensions such as market segmentation, positioning, and customer relationship management (Gilmore, Carson and Grant, 2001). Others might operate under the false assumption that simply establishing an online presence is sufficient to attract customers, neglecting the need for a comprehensive strategy that integrates content planning, search engine optimization, and targeted outreach (Erdmann, Arilla and Ponzoa, 2022). These misconceptions lead to reactive decision-making, where firms persist with familiar but suboptimal tactics rather than embracing innovative, data-driven approaches (Jones and Rowley, 2011).

A related issue is the absence of long-term strategic planning in marketing (O'Dwyer, Gilmore and Carson, 2009). The pressing demands of daily operations force many MSEs into short-term, reactive approaches that prioritize immediate needs over the development of cohesive, data-driven strategies (Bresciani and Eppler, 2010). This lack of strategic foresight often results in inconsistent messaging, fragmented customer experiences, and inefficient resource utilization (Hausman, 2020), further deepening the expertise gap. Without a deliberate focus on long-term planning, MSEs might be unable to build the robust marketing infrastructure necessary for sustainable growth (Gilmore, Carson and Grant, 2001).

Many MSEs address their internal marketing knowledge debt by outsourcing marketing functions to external agencies or freelancers (OECD, 2019). While this strategy can provide access to specialized expertise and allow the business to concentrate on core competencies (Dibbern et al, 2004), it can simultaneously inhibit the development of in-house marketing capabilities (Park, Lee and Morgan, 2011). Overreliance on external providers often means missing out on daily learning opportunities that are critical for cultivating internal expertise (Fitzgerald and Willcocks, 1994). Agencies, driven by recurring revenue and long-term client retention, may not always prioritize the most cost-effective or self-sustaining strategies (Hormozi, 2023). In some cases, these external partners may even withhold performance data or provide limited transparency regarding their methods (Gilley and Rasheed, 2000), which in turn restricts the internal team's ability to independently manage and adapt marketing strategies. This dynamic not only reinforces existing knowledge gaps but also leaves MSEs less agile when market conditions shift.

The cumulative effect of these factors can increase knowledge debt that critically undermines an MSE's ability to compete (OECD, 2019). Without the necessary expertise to analyse marketing performance, businesses struggle to allocate budgets efficiently, refine their strategies, or capitalize on

emerging trends (Salam et al., 2025). This shortfall not only reduces current performance but also creates a compounding effect, where future challenges become more daunting as the marketing landscape continues to evolve. In some instances, the resulting strategic paralysis and inaction can lead to missed opportunities, eroded profit margins, and an increased dependency on external expertise, further locking MSEs into a cycle of inefficiency.

2.4 Financial Implications of Knowledge Debt in Marketing

This section investigates the financial ramifications of knowledge debt on MSEs, focusing on how it impacts profits, marketing expenditures, and overall business sustainability. As discussed in the previous chapters, when small business owners or marketers lack expertise in key marketing areas, they might execute marketing based on guesswork or habits rather than data-driven strategies (Morgan, Vorhies and Mason, 2009). This can be seen as overspending on familiar but ineffective channels or failing to invest in high-return marketing activities simply because the team isn't aware of them or doesn't have the necessary skills to take advantage of them.

To illustrate the possible scale of this problem, let's assume a situation where an imaginary company overspends on a marketing channel:

Micro-enterprise spends €15,000 annually on customer acquisition, of which €5,000 is invested in SEO optimization. This €5,000 represents one-third of their total customer acquisition budget. The SEO investment is poor due to several factors: the company targets highly competitive keywords with insufficient resources to rank effectively, employs an outdated or poorly executed SEO strategy (e.g., neglecting mobile optimization or quality backlinks), and faces a mismatch with their audience, who prefer direct channels like email over organic search. These inefficiencies result in a high Customer Acquisition Cost (CAC) of €500 per customer via SEO, compared to €150 via email marketing. We will calculate the cumulative effect of this poor SEO investment over five years, assuming for the sake of this example that the company's current CAC and Lifetime Value (LTV) figures remain constant over this period and LTV signifies total revenue generated by a single customer.

Budget Allocation in Year 1:

Email Marketing:

- Annual investment: 10,000€ (two-thirds of the total budget)
- CAC via email marketing: 150€ per customer

- New customers acquired: $10,000\text{€} / 150\text{€ per customer} = 66$ customers
- Net revenue per customer: $600\text{€ (LTV)} - 150\text{€ (CAC)} = 450\text{€}$
- Annual net revenue from email marketing: $66 \text{ customers} * 450\text{€} = 29,700\text{€}$

SEO Optimization:

- Annual investment: $5,000\text{€}$ (one-third of the total budget)
- CAC via SEO optimization: 500€ per customer
- New customers acquired: $5,000\text{€} / 500\text{€ per customer} = 10$ customers
- Net revenue per customer: $600\text{€ (LTV)} - 500\text{€ (CAC)} = 100\text{€}$
- Annual net revenue from SEO optimization: $10 \text{ customers} * 100\text{€} = 1,000\text{€}$

Five-Year Cumulative Effect

Email Marketing:

- Annual net revenue: $29,700\text{€}$
- Five-year net revenue: $29,700\text{€} * 5 \text{ years} = 148,500\text{€}$

SEO Optimization:

- Annual net revenue: $1,000\text{€}$
- Five-year net revenue: $1,000\text{€} * 5 \text{ years} = 5,000\text{€}$

What is the total effect over five years? Let's assume all $15,000\text{€}$ had been invested in efficient email marketing:

- Total investment: $15,000\text{€}$
- CAC via email marketing: 150€ per customer
- New customers acquired: $15,000\text{€} / 150\text{€ per customer} = 100$ customers
- Net revenue per customer: 450€
- Annual net revenue: $100 \text{ customers} * 450\text{€} = 45,000\text{€}$
- Five-year net revenue: $45,000\text{€} * 5 \text{ years} = 225,000\text{€}$

Comparison:

- Five-year net revenue with the current split investment: 148,500€ (email) + 5,000€ (SEO) = 153,500€
- Five-year net revenue without SEO investment: 225,000€
- Lost net revenue due to poor investment: 225,000€ - 153,500€ = 71,500€
- Cumulative growth is not accounted for and we assume all numbers stay the same.

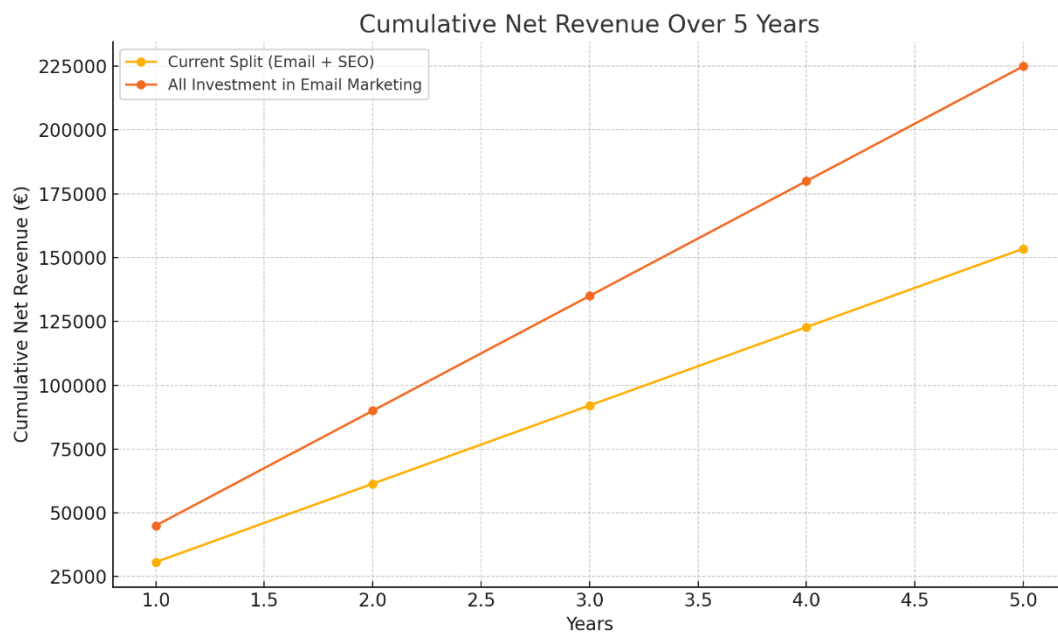


Image 1: Cumulative revenue growth over 5 years

This micro-enterprise loses 71,500€ in net revenue over five years because it allocated one-third of its customer acquisition budget to inefficient SEO optimization. This significant waste of resources slows the company's growth and reduces its total revenue in the long term. Such a misguided investment undermines the company's competitiveness and opportunities in the market.

2.4.1 Inefficient Allocation of Marketing Budgets

A global survey of 1,000 marketers worldwide revealed that marketers waste an average of 26% of their marketing budgets on ineffective channels and strategies (Benes, 2018). For Micro and Small Enterprises (MSEs), this percentage is often higher due to limited expertise and resources required

to effectively optimize marketing activities (Gilmore, Carson and Grant, 2001).

The waste on ineffective marketing expenditure does not contribute to generating new sales. If wasted funds had instead been invested in effective marketing channels with proven return on investment (ROI), substantial additional revenue could have been generated. For example, assuming an average ROI of 5:1 for effective marketing campaigns in small businesses, a marketing budget of €5,000 could have generated €25,000 in revenue. Thus, even minor misallocations can lead to considerable revenue losses for MSEs. Beyond immediate financial losses, wasted marketing spend represents significant opportunity costs, not just in terms of misallocated funds but also in lost opportunities for organizational knowledge growth (Hanssens and Pauwels, 2016). As a result, the knowledge capital within the company can grow slower and the failure to generate expected revenue has a cascading effect on the company's financial health. With lower revenue, the company has less cash flow available for reinvestment in growth opportunities, such as expanding product lines, opening new marketing channels, or improving operational efficiency. Lower revenue in the current period can lead to smaller marketing budgets in future periods, as the company may need to cut back on expenses. This reduction creates a vicious cycle where inadequate marketing spending further hampers the company's ability to reach potential customers and generate sales. The direct consequence of this is a significant slowdown in revenue growth. According to industry reports, businesses grow significantly slower due to suboptimal marketing spend and poor marketing operations. This is highlighted by the fact that proper alignment between sales and marketing teams alone can lead to an annual revenue growth increase of 20% (Mirman, 2025). Additionally, during economic downturns, SMEs are at greater risk of sudden moves in revenue growth compared to larger companies, which are in a better position to absorb cyclical changes in demand. This vulnerability can lead to increased financial distress and challenges in maintaining operational stability. This places MSEs at a considerable disadvantage in competitive markets where larger firms or more agile competitors are more likely to leverage data-driven strategies and modern tools (Maroufkhani et al., 2020) to enhance marketing efficiency and marketing budget optimization (World Bank, 2021).

2.5 Role of generative AI in addressing knowledge debt

Generative AI models, particularly Large Language Models (LLMs) like GPT-4 or similar, offer micro and small enterprises a unique solution to overcoming knowledge debt. One of the most critical knowledge debt related challenge MSEs face is their inability to afford or access the expertise

required to make data-driven marketing decisions (Bell, 2025). LLMs can act as a cost-effective alternative in some cases, delivering insights and education on-demand, making it easier for businesses to close their knowledge gaps. This section focuses on how affordable, Generative AI tools, such as subscription-based ChatGPT and Midjourney, offer a practical solution to overcome these gaps without the need for custom-built systems (Chui et al., 2023).

The decision to center this study around subscription-based Generative AI tools is driven by several pragmatic considerations. First, these tools are relatively inexpensive and do not require significant upfront investments or specialized technical expertise. Unlike custom AI solutions, GenAI SaaS platforms offer plug-and-play integration, making them particularly well-suited for MSEs that typically operate under resource constraints (Alpha, 2025). Furthermore, the subscription-based model ensures that these tools are continuously updated and maintained by the provider, allowing businesses to access the latest features and capabilities without additional overhead (Chui et al., 2023; McKinsey & Company, 2023). This ease of adoption, coupled with their cost-effectiveness, positions subscription-based Generative AI tools as an immediately accessible remedy for MSEs for reducing knowledge debt and enhancing marketing performance for.

2.5.1 Overview of generative AI in marketing

Generative AI represents a rapidly evolving field that has fundamentally reshaped content creation and data analysis across multiple industries. Recent advancements in large language models (LLMs), in voice and image synthesis have accelerated their adoption in business applications, particularly within marketing (McKinsey & Company, 2023). This section outlines the core capabilities of MSE marketing related subscription based generative AI tools, while highlighting AI's growing importance for modern marketing practices.

The evolution of generative AI has been marked by significant breakthroughs in recent history. The introduction of the Transformer model laid the groundwork for processing sequential data through self-attention mechanisms (Vaswani et al., 2017). Subsequent advancements have refined these models, with autoregressive techniques now enabling LLMs to generate coherent and context-sensitive text. The current generation of LLMs can, for example, produce human-like text, generate code and distill large datasets into concise summaries (OpenAI, 2023), thereby expanding the frontier of creative and analytical applications (McKinsey & Company, 2023).Recent

work has also pushed the boundaries in image and audio generation, where models can now produce photorealistic visuals and realistic speech from textual descriptions (Rombach et al., 2022; Wang et al., 2023). These developments reflect an ongoing shift towards more and more sophisticated systems that merge text, speech and visual intelligence, ensuring that generative AI tools remain at the forefront of technological innovation and continue to evolve and shape the future of marketing.

Subscription based generative AI tools such as ChatGPT (LLM), Midjourney (image generator), and Elevenlabs (speech generator) have emerged as accessible solutions, significantly reducing barriers of cost and complexity associated with leveraging AI technologies (OpenAI, 2025; Midjourney, 2025; Elevenlabs, 2025). Subscription-based platforms democratize access to advanced AI capabilities, allowing even resource-constrained businesses to enhance their marketing capabilities quickly and affordably (Bell, 2025).

Generative AI tools can substantially mitigate knowledge debt by delivering affordable, on-demand marketing and content creation help and expertise (Maryam and Westerman, 2023). For instance, a MSE can utilize a LLM such as ChatGPT GPT-4o to rapidly obtain insights, recommendations, and strategic guidance traditionally acquired through costly marketing consultants. A marketing consultant might cost between \$75–\$200 per hour (Cemoh, 2025), whereas a personal ChatGPT subscription ranges from \$20–\$200 per month (OpenAI, 2025). This relatively low cost of AI solutions allows MSEs to ask for help and outsource some marketing activities to it, gain capabilities they might not otherwise have and over time save substantial amounts of money, depending on the extent of AI use and marketing needs. For the purposes of covering the capabilities offered by Generative AI solutions, let's address the key capabilities and tools for MSEs in 4 sections (this is not an exhaustive list of use cases for MSEs): using LLMs as an on-demand marketing strategy consultant, using LLMs to create and improve text based marketing materials, using image generators to create and improve visual marketing materials and using audio generators to create and improve audio marketing materials.

2.5.2 LLMs as an on-demand marketing strategy consultant

Large-language models (LLMs) such as GPT-4 and O3 are now available through conversational interfaces (e.g., ChatGPT) and deliver expert-level reasoning across professional domains (OpenAI, 2023). For micro and small enterprises, which typically operate under severe human- and financial-resource constraints, these models represent a readily accessible decision-support layer. A recent systematic review of AI adoption in small-

business contexts confirms that generative AI tools are increasingly deployed to compress planning cycles and offset skill gaps (Schwaeke et al., 2024). Case-study evidence further shows that ChatGPT can be embedded in SME workflows to structure sustainability road-mapping, stakeholder engagement, and KPI tracking (Fonseca et al., 2024). When supplied with firm-specific inputs such as historical campaign data, customer-lifetime values, or channel-level cost information, LLMs can flag emerging trends and generate multiple “what-if” scenarios in natural language and in different visualizations (OpenAI, 2024). Taken together, the evidence indicates that, provided with high-quality, context-specific data, LLM-based advisory systems can deliver strategic guidance that rivals traditional consultancy services. For MSEs this translates into a scalable, always-on, and cost-effective alternative, one capable of converting raw performance logs into concrete recommendations on budget allocation, channel sequencing, and KPI tracking while continuously incorporating new market information.

2.5.3 Using LLMs to create and improve text-based marketing

This section provides an examination of how large language models, such as ChatGPT, can be utilized by MSEs to create and improve text-based marketing materials and communication, as of March 17, 2025. The analysis focuses on their transformative impact, practical applications, and benefits, particularly in the context of addressing resource constraints and enhancing marketing efficiency.

Tools like ChatGPT can help MSEs with the actual text based marketing activities they might do on a daily basis. One of the main ways LLMs facilitate this is by helping users create “a first draft” (Dwivedi et al., 2023). For instance, consider an MSE specializing in sustainable consumer products that lacks a dedicated marketing team. To boost its online presence, the firm requires a search engine optimized blog post that not only highlights the benefits of its eco-friendly cleaning products but also ranks well in search engine results. However, they don’t know how to do SEO, nor how to write a compelling blog post. Using ChatGPT, the company can initiate the content creation process by providing a prompt such as:

How can I help?

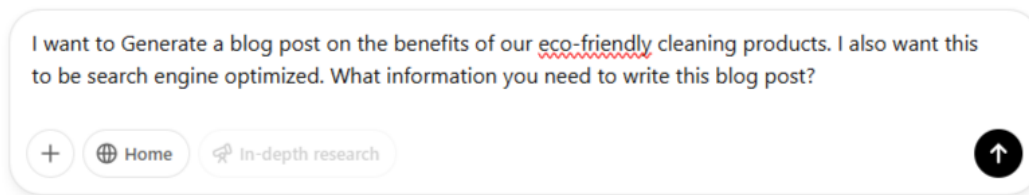


Image 2: Prompting ChatGPT

In response to this prompt, ChatGPT asked for additional information needed to write a search engine optimized blog post:

To create a compelling, SEO-optimized blog post, I would need several pieces of information:

- **Product Details:**
 - Specific eco-friendly cleaning products you offer (names, variants, etc.)
 - Key features and benefits (e.g., ingredients, performance, sustainability certifications)
 - Unique selling propositions and any scientific data or studies supporting the claims
- **Brand and Story:**
 - Brand background and core values
 - Your brand's environmental mission and any certifications or eco-labels that enhance credibility
- **Target Audience:**
 - Who you're addressing (e.g., environmentally conscious consumers, households, commercial clients)
 - Year of
- **SEO & Content Strategy:**
 - Primary and secondary keywords or phrases you'd like to rank for
 - Competent
 - Preferred call-to-action and overall blog post structure (headings, meta description, etc.)
- **Additional Information:**
 - Any customer testimonials or case studies
 - Details on pricing, promotions, or special offers
 - Visual assets or guidelines for image use, if applicable

Image 3: ChatGPT asks for information

Said MSE has answers to most questions and additional information asked by ChatGPT, but they don't employ anyone who knows how to do search engine optimization. Therefore, they are unable to answer SEO related questions. However, ChatGPT can assist them when provided with a prompt such as:

i have answers to all other things but I dont know how to do SEO. How do i figure out "Primary and secondary keywords or phrases you'd like to rank for" and "Preferred call-to-action and overall blog post structure (headings, meta description, etc.)"

Concluded in 6 seconds >

Here's a breakdown of how you can determine effective keywords and structure your blog post for optimal SEO:

Identifying Primary and Secondary Keywords

1. Brainstorm Core Terms:

Start by listing words and phrases directly related to your eco-friendly cleaning products. For example, terms like "eco-friendly cleaning," "green cleaning products," and "sustainable cleaning solutions" could be your core ideas.

2. Utilize Keyword Research Tools:

- **Google Keyword Planner, SEMrush, or Ahrefs:**
These tools help you find related keywords, search volume data, and competition levels. You can input your core terms to get suggestions and variations.
- **Google Trends:**
Check the popularity of your keywords over time and see if there are any seasonal trends.

3. Analyze Competitor Content:

Image 4: ChatGPT guides user with SEO

Every time the answer contains something the MSE doesn't have answers to or doesn't know how to do, they can just ask ChatGPT to assist with a prompt such as:

how to do this: Google Trends:
Check the popularity of your keywords over time and see if there are any seasonal trends.

Concluded in 6 seconds >

Here's how you can use Google Trends to check keyword popularity and identify seasonal trends:

1. Access Google Trends:

Go to [Google Trends](#).

2. Enter Your Keyword:

In the search bar at the top, type in the keyword or phrase related to your eco-friendly cleaning products (e.g., "eco-friendly cleaning products").

3. Set the Region and Time Range:

Image 5: ChatGPT helps with keywords

This cycle of answers and questions can be repeated until the required answer to the original question, the keywords the MSE would like to use in its blogpost, are obtained. This therefore allows the MSE to write the first draft of the blog post with SEO keywords within it. They can now accomplish this independently, something they previously couldn't do on their own or would have needed to outsource to an external agency. Over time, this increases the internal marketing knowledge of the MSE and reduces knowledge debt and dependency on outside factors. Even if the MSE knows how to do search engine optimized blog posts themselves, ChatGPT and similar tools can help them with other marketing tasks or improve the quality of writing and allows for faster blog post creation. ChatGPT-3.5, an older model of ChatGPT released in 2022, has been shown to decrease the time required for writing tasks by 40 percent, and improve output quality by 18 percent (Shakked et al., 2023). These quality and efficiency improvements can be seen in the real world. For example, in a recent case study, an e-commerce platform, with an existing dedicated marketing team, was able to increase its traffic by 40% by using generative AI to help with content creation and SEO related tasks (Jasper, 2025).

In one recent investigation, the performance of ChatGPT was compared with that of physicians in addressing 195 patient inquiries sourced from an online forum. Three healthcare experts evaluated each response using a five-point scale for both information quality and empathy. The findings indicated that ChatGPT's responses were rated as "good" or "very good" in quality in 78% of cases, whereas physician responses received same ratings only 22% of the time. For empathy, ChatGPT achieved empathetic ratings in 45% of its responses, in contrast to 4.6% for the doctors. Additionally, the average answer length from ChatGPT was 305% longer than that from the doctors at 211 words and 52 words respectively (Shmerling, 2024). These findings suggest that AI can generate detailed, compassionate responses consistently. Although this study focused on medical inquiries, similar principles apply to customer service, inbound lead management and social media management. Klarna's LLM powered AI assistant handled 2.3 million conversations and managed two-thirds of Klarna's customer service chats, performing the equivalent work of approximately 700 full-time personnel after just one month of operation (Klarna, 2024). The AI assistant delivered responses that matched human agents in customer satisfaction ratings and contributed to a 25% reduction in repeat inquiries. Notably, it resolved customer issues in under two minutes on average, compared to 11 minutes previously (Klarna, 2024).

Despite the well-known tendency of large language models to hallucinate (Dwivedi et al., 2023), meaning to generate inaccurate or nonfactual or just plain wrong outputs, these findings demonstrate that AI can reliably

produce detailed, accurate, and empathetic responses without the fatigue or inconsistency inherent to human responders. LLM systems are also improving at a very fast pace, and the number of wrong outputs is likely to reduce in the future, given increasing accuracies in benchmark tests (Phan et al., 2025). Therefore, it's possible that beyond the use in marketing related customer service, SMEs can leverage similar LLM solutions for social media and organic content management in several key areas (list is not exhaustive):

1. Quickly and consistently respond to customer queries and feedback on social media platforms like Facebook and YouTube.
2. Monitor and address both positive and negative comments, maintaining a steady, empathetic brand voice.
3. Assist in creating high-quality, engaging posts that resonate with diverse audiences.
4. Offer real-time, multilingual responses to broaden reach and enhance customer experience across global markets.
5. Generate prompt, well-crafted email responses to customer inquiries, ensuring efficient and courteous communication.

Rapid response times are critical for marketing success, yet companies don't respond fast enough to potential clients. An average company has a lead response time of 46 hours and 53 minutes and only 27% of leads get contacted at all (Krogue, 2012). The odds of contacting a potential customer drop by over 10 times and qualifying one by over 6 times within the first hour if responses are delayed. In contrast, contacting a lead within 5 minutes increases the likelihood of reaching them by 100 times compared to waiting 30 minutes, and the odds of qualifying the lead are 21 times higher.

These statistics show the potential for large language models to revolutionize text-based marketing. By generating high-quality, empathetic, and detailed responses almost instantaneously, AI can enhance lead management, customer service efficiency and improve the overall quality of written communications (Klarna, 2024; Shmerling, 2024). For SMEs, integrating LLM use into social media, email support, and lead management processes could dramatically boost engagement and conversion rates, thus improving the effectiveness of marketing activities.

2.5.4 Using image generators to create and improve visual marketing materials

This section provides an examination of how text-to-image tools, such as DALL-E 3 and Midjourney, can be utilized by MSEs to create and improve

visual marketing materials, as of March 17, 2025. The analysis focuses on their transformative impact, practical applications, and benefits, particularly in the context of addressing resource constraints and enhancing marketing efficiency.

Text-to-image generators are transforming visual marketing practices by allowing businesses to produce high-quality imagery quickly and at a fraction of the traditional cost of creating images (Hartmann, Exner and Domdey, 2024). Image generators like DALL-E 3 and Midjourney let users create visuals simply by typing a description of what they need. A user could add information that can include details like mood, color scheme, composition, and style. Technical aspects of the output image such as the aspect ratio can also be adjusted (Midjourney, 2025).

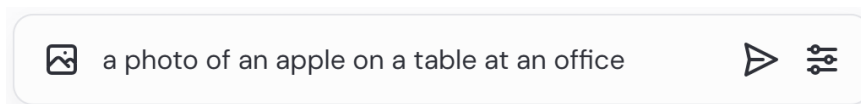


Image 6: A prompt typed into Midjourney's web application

Systems such as Midjourney work interactively. If the first image generated isn't exactly what you envisioned, you can tweak your prompt and try again or edit an output image until you achieve the desired result (Midjourney, 2025). This iterative process makes it relatively easy for even non-designers, such as MSE owners, to produce customized, high-quality images that align with their brand identity and marketing goals.



Image 6: Output from Midjourney using the prompt shown in Figure 5

When compared to human-produced images, AI-generated marketing visuals can achieve superior ratings in quality, cost efficiency and aesthetics based on extensive human evaluations. Image generators have been shown

to increase productivity in visual creative tasks by 25% based on a dataset of over 4 million artworks from 50,000 users (Zhou et al., 2024). In the field of marketing, a study with over 173,000 ad impressions, banner ads created using DALL-E 3 attained click-through rates that were over 50% higher than those of professional human-made stock photos (Hartmann, Exner and Domdey, 2024). Additionally, the cost per image is dramatically lower at approximately \$0.03 - \$0.05 per AI-generated image (Midjourney, 2025) versus around \$5 - \$10 for average individual human-created images from stock image banks (iStock, 2025). Moreover, if MSEs hire an outside marketing agency for a custom photo shoot, the price tag can easily rise to thousands or tens of thousands of dollars (Bark, 2025). This substantial cost efficiency offered by text to image generators allows companies to produce thousands of images for the price of a single traditionally taken professional visual photo asset. This empowers many MSEs that previously lacked the resources to enhance their marketing and other materials with high-quality visuals, which is a critical capability in terms of marketing efficiency. With human perception being predominantly visual, businesses must leverage images, videos, and other forms of visual media to maximize engagement and marketing effectiveness. People process visual information significantly faster than text (Potter et al., 2014), making it an efficient tool for capturing attention and delivering messages. Digital advertisements with visuals receive on average 94% more views and twice as many comments and 67% of consumers place greater importance on clear, detailed images than on customer reviews and product descriptions (MDG, 2025).

These statistics show the potential for text to image generators to greatly assist MSEs in visual marketing activities. By generating high-quality, brand aligned, and situation customized images, image generators can improve click and conversion rates, thus improving the effectiveness of marketing activities. Text to image generators are especially helpful in situations where traditional photo production is not an option. For instance, consider an MSE specializing in sustainable consumer products that needs a photo of a happy person on one of their landing pages, but they lack a brand friendly model for this purpose. An image generator can be used to create a photo of a person or fine-tuned brand ambassador, as faces made with Image generators are highly photorealistic and a 2022 paper shows they are nearly indistinguishable from real faces and are judged more trustworthy than real people (Nightingale and Farid, 2022).

2.5.5 Using audio generators to create and improve audio marketing materials.

This section provides an examination of how generative AI audio tools, such as ElevenLabs and Suno, can be utilized by MSEs to create and improve

audio marketing materials, as of March 17, 2025 (Elevenlabs 2025; Suno, 2024). The analysis focuses on their transformative impact, practical applications, and benefits, particularly in the context of addressing resource constraints and enhancing marketing efficiency.

The rapid evolution of generative AI in audio production is reshaping how businesses, especially MSEs, approach audio marketing. These tools convert text inputs into high-quality, natural-sounding audio, primarily speech and music, offering a cost-effective alternative to traditional audio production methods (Elevenlabs 2025; Suno, 2024). This is particularly relevant for MSEs, which often face audio production challenges such as limited budgets and lack of specialized skills.

AI audio generators operate by allowing users to input text descriptions or scripts, which the platform then converts into audio. For speech generation, platforms like Elevenlabs offer a library of pre-trained voices with various accents, genders, and styles. Users customize outputs by adjusting parameters such as pitch, speed, and emphasis, ensuring alignment with brand identity (Elevenlabs, 2025). Even voice cloning is possible, if the user chooses and has the necessary recording equipment to provide the AI model with high quality training data (Elevenlabs, 2025). For music generation, tools like Suno enable users to describe the desired music style or mood (e.g., "upbeat pop song with guitars and drums") or type full lyrics and the AI generates corresponding tracks (Suno, 2024). These audio creation processes are relatively user-friendly and designed for non-experts, which is crucial for MSEs lacking technical skills. This accessibility reduces the knowledge gap in audio production, allowing small businesses to produce professional-grade content without extensive training or hiring specialized staff. AI audio generators offer a wide range of applications for MSE marketing, enhancing their ability to compete in digital and traditional media (this list is not exhaustive):

- 1) MSEs can generate narrations for promotional videos or social media content, replacing the need for expensive voice actors. For instance, a small e-commerce business can create product demo videos with AI-generated voiceovers, aligning with their brand tone.

- 2) These tools facilitate the production of radio ads or audio ads on digital platforms, at a fraction of the cost of traditional recording sessions. This is particularly beneficial for MSEs looking to expand their reach through audio advertising.

- 3) AI can generate intro/outro music or background sounds, making it easier for small businesses to launch or maintain branded high quality digital

audio and video-based content without significant investment in audio production.

4) Voice generators allow MSEs to generate voiceovers in multiple languages, enabling them to reach international markets without hiring multilingual voice actors. For example, a small business selling eco-friendly products can create audio ads in English, Spanish, and French, expanding their global presence.

The real-world benefits of these tools are substantial, weaving together rapid production, cost savings, customization, and ease of use into a cohesive solution that provides a solution to the many audio needs of small businesses. One of the standout advantages of AI audio generators is their ability to enable rapid production and iteration of audio assets. These tools allow companies to quickly create multiple versions of voiceovers or music tracks, making it possible to test different styles and scripts based on real-time feedback (LuciHub, 2024). This speed is a game-changer in marketing, where the ability to refine campaigns swiftly can dramatically boost performance. Imagine an MSE crafting several variations of an audio ad, testing them across platforms like social media or podcasts, and pinpointing the most engaging version all in a matter of hours rather than weeks. This iterative approach ensures small businesses can stay agile and responsive without being bogged down by lengthy production timelines.

Equally compelling is the cost efficiency these platforms deliver. Traditional audio production can be prohibitively expensive for MSEs, with costs piling up from hiring professional voice actors, ranging from around \$100 to \$1500 per recording session, according to Speechify (Speechify, 2025), to pay for composers, recording equipment, and studio time. In stark contrast, AI audio generators slash these expenses to a fraction of the cost. For example, a \$5 per month plan from ElevenLabs provides 30,000 characters, translating to roughly 30 minutes of audio at just \$0.16 per minute (ElevenLabs, 2025). These dramatic savings mean MSEs can produce professional grade audio content without draining their limited budgets. Instead, they can redirect those funds to other critical marketing areas. Beyond speed and savings, AI audio generators offer customization and brand alignment (ElevenLabs, 2025), a vital edge for small businesses looking to stand out. This consistency is key to building trust and recognition. Whether it's a warm, friendly voice for a local bakery or a crisp, professional tone for a tech startup, AI platforms ensure the audio reflects the company's unique style. This level of personalization, once the domain of big-budget firms with access to expert producers, is now within reach for MSEs, amplifying their branding efforts without added complexity or cost.

Perhaps the most transformative is the accessibility for non-experts that AI audio generators provide. Small businesses often lack the in-house expertise and equipment needed for traditional audio production, leaving them reliant on costly external help or subpar DIY solutions. AI platforms change that by simplifying the process, requiring no specialized skills to produce high quality audio content. Generalist staff like a marketing assistant or owner of the business can jump in and create polished voiceovers or soundtracks with ease. This democratization of audio production directly addresses the knowledge debt many MSEs face, helping to level the playing field and allowing MSEs to compete in the digital marketplace with professional-grade audio materials.

2.6 Limitations, risks, usability and ethical considerations of using AI in MSE marketing

This section provides an examination of the limitations, risks, and ethical problems associated with using artificial intelligence in marketing for micro and small enterprises, particularly in the context of addressing knowledge debt and resource constraints.

2.6.1 Limitations with AI Use in Marketing

One of the primary limitations of AI in marketing for MSEs lies in its accuracy and reliability. Large language models, such as ChatGPT, can generate outputs that appear convincing yet are factually incorrect, a phenomenon often termed "hallucinations" (Dwivedi et al., 2023). Such inaccuracies necessitate human oversight to ensure marketing content and strategies remain trustworthy. This necessity of human oversight to mitigate inaccuracies introduces a profound challenge, particularly in the context of MSEs' reliance on AI to combat knowledge debt. If AI outputs require validation to ensure trustworthiness, how can MSEs, already constrained by limited marketing expertise, determine when the technology is providing incorrect or inappropriate answers? The effective use of AI presupposes a level of understanding that many MSEs might not possess. Without this expertise, small businesses may fail to spot errors or biases in AI-generated content, creating a paradox: the tool intended to reduce knowledge debt may instead perpetuate it if errors go unchecked.

This limitation extends to data dependency. The quality of AI outputs depends on the quality of input data. MSEs, constrained by resources, often cannot curate comprehensive, accurate, or unbiased datasets (Hendrawan et al., 2024). For example, an LLM analyzing incomplete sales data might recommend investing in suboptimal marketing channels. These skewed

outputs can reduce marketing effectiveness, deepening rather than alleviating knowledge debt.

Strategic complexity further limits AI utility. While Chapter 2.5 emphasized AI's prowess in routine tasks, e.g., drafting text (2.5.3), generating images (2.5.4), or producing audio (2.5.5), the Marketing AI Institute (2021) notes its shortcomings in nuanced, industry-specific planning. MSEs in niche markets require tailored marketing strategies that AI struggles to devise without human input, a gap that persists despite tools like ChatGPT's analytical capabilities. Technical integration also poses barriers, as integrating AI with existing systems demands infrastructure and expertise MSEs often lack. Subscription costs, though lower than custom solutions, can remain a hurdle, with Marketing Insider Group (2019) identifying this as a persistent challenge for budget-constrained MSEs.

2.6.2 Risks Associated with AI Use in Marketing

Beyond limitations, AI adoption introduces multifaceted risks that threaten MSEs' operational and reputational stability. Data security and privacy are critical, given AI's reliance on customer data. (KPMG, 2024) stresses the need for robust security and (Sullivan, 2023) warns that AI systems are possible cyberattack targets. A breach at an AI provider, that is outside of MSEs control, could expose internal or customer data, leading to legal trouble or even penalties and trust erosion. Moreover, MSEs might inadvertently misuse data, violating regulations like GDPR and incurring fines they cannot afford. Copyright and intellectual property risks are particularly acute with generative tools. Chapter 2.5.3 highlighted Midjourney and DALL-E 3's ability to create visuals, and 2.5.4 showcased ElevenLabs and Suno's audio generation. These tools, which rely on vast datasets potentially containing copyrighted music, voices, or other materials (Rivaux, Fink, and Perez, 2024), expose MSEs to legal and ethical vulnerabilities beyond their control. For example, critical concerns arises from the clauses in Suno's Terms of Service (Suno, 2025), which state (as of 18.3.2025):

"you agree to defend, indemnify, and hold harmless Suno, its affiliates, and its and their respective officers, employees, directors, service providers, licensors, and agents (collectively, the "Suno Parties") from any and all losses, damages, expenses, including reasonable attorneys' fees, rights, claims, actions of any kind, and injury (including death) arising out of or relating to your use of the Service, any Content or use thereof, your connection to the Service, your violation of these Terms of Service, or your violation of any rights of another, including through your generation or use of any Output."

This means that if a copyright holder sues over AI-generated music mimicking a protected track, the MSE, not Suno, bears full responsibility for legal

costs and damages. For MSEs, which typically lack the budget to engage attorneys or settle disputes, even unintentional infringement could impose crippling financial strain.

Further example compounding risk comes from the non-unique nature of Suno's outputs. The Terms explicitly note (as of 18.3.2025):

"Due to the nature of machine learning, Output may not be unique across users and the Service may generate the same or similar output for a third party."

This implies that music generated for an MSE might not only resemble another user's output but could also inadvertently mimic copyrighted works. If an MSE uses such music in marketing materials, it again risks infringement lawsuits. These risks and similar ones posed by other AI SaaS services, produce potentially massive legal risks for MSEs using said services. Beyond legal costs, future negative PR from public backlashes, like accusations of unethical content sourcing—could devastate MSEs' reputations as scrutiny of AI ethics intensifies. Additionally, this non-uniqueness could dilute brand identity if competitors deploy similar tracks, weakening the MSE's market differentiation.

Over-reliance on AI poses an additional, equally critical risk to MSEs. Over-reliance on AI risks reducing human cognitive capacities, a concern directly relevant to MSEs' efforts to mitigate knowledge debt. Previous research indicates that excessive dependence on automated systems can lead to deskilling, where critical thinking and creative skills atrophy due to underuse. According to a recent study (Ahmad et al., 2023), AI's augmentation of tasks can inadvertently diminish human capabilities if individuals delegate complex problem-solving entirely to technology (Ahmad et al., 2023). Similarly, the Journal of Applied Psychology highlights "automation-induced complacency," where reliance on AI tools reduces attention and decision-making proficiency, especially in strategic marketing contexts requiring nuanced judgment (Papagiannidis et al, 2023). The Organisation for Economic Co-operation and Development further warns that without concurrent investment in reskilling, workers risk becoming overly dependent on AI, losing the ability to innovate independently (OECD, 2023). In marketing, where creativity and adaptability are paramount, this deskilling effect could leave MSEs less equipped to respond to market shifts. Thus, over-reliance may not only fail to bridge knowledge gaps but could widen them, making MSEs "stupider" in their marketing acumen over time.

Evidence from the marketing industry supports these findings. For example, human-authored content still often outperforms AI-generated equivalents in attracting sustained traffic, a critical metric for marketing success. An analysis of content performance found that human-generated blog posts generally rank higher in search engine results and drive more visits,

attributing this to their ability to offer unique perspectives and emotional resonance (Patel, 2025). By analyzing 744 articles across 68 websites, it was discovered that while AI tools like ChatGPT can produce a blog post in about 16 minutes compared to 69 minutes for a human, human content significantly outperforms in traffic generation, getting on average 5.44 times more monthly page visits after 5 months. Moreover, when factoring in efficiency—visitors per minute of effort—human content yields 4.10 visitors per minute spent, compared to AI’s 3.25. This suggests that AI, despite its speed, may be less cost-effective in the long run, as the initial time savings do not translate into proportional traffic gains. They attribute this edge to human writers’ ability to weave context and emotion into their work, elements AI struggles to replicate authentically (Patel, 2025).

Although smaller traffic numbers and over-reliance on AI may not present an immediate issue for MSEs that currently engage in little to no marketing, where any progress is better than none, establishing a pattern of dependency and adopting suboptimal habits from the start, such as over utilizing LLMs in blog content creation, could result in undesirable long-term consequences.

2.6.3 Ethical Problems with AI Tools in MSE Marketing

This subchapter examines distinct ethical challenges that arise from AI use in MSE marketing. These include privacy concerns beyond mere security, bias and fairness, job displacement separate from skill erosion, and the spread of misinformation. For marketing purposes, navigating these issues is essential to maintain ethical integrity and consumer trust while leveraging AI to mitigate knowledge debt.

While Section 2.6.2 addressed data security risks like cyberattacks, a broader ethical issue lies in how AI tools handle data with respect to consent and usage. AI systems often require detailed information to personalize marketing outputs, raising questions about whether MSEs obtain informed consent and use data responsibly. The General Data Protection Regulation (GDPR) mandates explicit permission and clear data policies (European Commission, 2025), yet MSEs, with their limited legal expertise, may struggle to comply fully. Mishandling data, not just breaches but overuse or lack of transparency, can violate consumer autonomy, erode trust, and invite regulatory penalties. (Clark, 2024) notes that ethical data practices are vital for maintaining customer relationships, a priority for MSEs reliant on loyalty in competitive markets.

AI tools may unintentionally reinforce biases present in their training data, resulting in marketing practices that lack fairness (Akter et al., 2022). MSEs need to avoid biased marketing that could limit MSEs’ customer base and profitability: if Midjourney generates visuals or ChatGPT crafts messages

that favor certain demographics, MSEs risk excluding others, damaging inclusivity and reputation. Biased algorithms can "lead to unequal treatment of certain groups," a significant ethical lapse in diverse markets. MSEs, often unaware of these biases due to limited technical oversight (Soudi and Bauters, 2024), must ensure their AI-driven campaigns reflect fairness, a challenge compounded by their resource constraints.

While Section 2.6.2 explored deskilling from over-reliance, a related yet important issue is job displacement. AI automation of tasks like content creation or strategy could eliminate roles within MSEs (Chen, Srinivasan and Zakerinia, 2024). The OECD warns that AI adoption without reskilling investments risks unemployment, particularly in small firms with tight budgets (OECD, 2023). Ethically, MSEs must weigh efficiency gains against the societal impact on employees, ensuring AI enhances rather than supplants human contributions, aligning with sustainable business practices.

Solving these issues and the possible adoption of guidelines emphasizing consent, fairness, transparency, and accountability presents a complex challenge for MSEs constrained by tight budgets (Zavodna, Ueberwimmer and Frankus, 2024). While such principles are important to ensure AI tools like ChatGPT and Midjourney do not harm consumer trust or exclude potential markets, implementing them requires resources that small firms often lack, such as legal expertise. Collaborative efforts with industry bodies or regulatory frameworks offer a practical solution, providing affordable access to standardized ethical practices without demanding significant internal investment. Scalable guidelines from external partners might help align AI use with ethical norms, a critical consideration for MSEs aiming to avoid reputational damage that could erode revenue. This approach reflects a duty to prioritize consumer welfare and market inclusivity over unchecked efficiency, enabling MSEs to responsibly harness AI's marketing potential.

2.6.4 Usability problems with AI tools in MSE marketing

Usability barriers significantly undermine AI's potential for MSEs, particularly given resource constraints. AI tools frequently lack adaptive interfaces, systems that dynamically adjust to users' expertise or needs (Fischer, 2000). For instance, ChatGPT's interface assumes a baseline proficiency in prompt engineering and system understanding, requiring users to iteratively refine inputs to achieve marketing-relevant outputs. The challenge lies in the user's proficiency in providing text commands that AI programs can detect (Beyan, 2023). For MSE with minimal AI exposure, this introduces a steep learning curve. Midjourney exemplifies this further. Its previous reliance on Discord (Midjourney, 2025) as a delivery platform introduces an additional layer of interface complexity, requiring users to navigate a social media-like environment to access AI functionalities. For MSEs without prior Discord experience, this non-intuitive setup fragments

workflows, as they must master two systems instead of one. The failure to tailor interfaces to users' operational contexts, which in MSEs' case includes limited staff, time constraints and multitasking demands, can slow down tool adoption and utilization.

In addition to this, Generative AI tools often obscure their decision-making processes, a phenomenon termed automation opacity in HCI research (Norman, 1990). Trust, very important factor in marketing, relies on understanding AI processes if MSEs use them for marketing purposes, yet MSEs using tools like Suno or ChatGPT may not themselves grasp the decision-making logic. This lack of transparency disconnects users from understanding how inputs translate to outputs. For example, when ChatGPT produces a vague or off-brand response, users receive no insight into why the model interpreted their prompt that way, leaving them unable to adjust effectively. This opacity increases cognitive disconnect, where users cannot mentally model the system's behavior (Woods et al., 2002), forcing MSEs into inefficient trial-and-error cycles.

3 Research Approach, Data, and Methodology

This chapter details the research approach, data collection methods, and analytical techniques used to address the research questions outlined in Chapter 1.3. The study investigates how knowledge debt affects marketing efficiency in micro and small enterprises, the potential of Large Language Models to mitigate these issues, and the practical effectiveness of an LLM-based solution in improving marketing return on investment (ROI). The methodology is designed to be replicable, providing a clear description of the steps taken to ensure reliability and validity in achieving the thesis goals.

3.1 Research Design

This study uses mixed-methods research design, using quantitative and qualitative approaches to provide a comprehensive understanding of knowledge debt and the role of LLMs in MSE marketing. A mixed-methods approach is particularly suitable for this exploratory research, as it allows for both the breadth of data across multiple enterprises and the depth of insight from a case study (Creswell, 2009). The design consists of two distinct but interconnected phases:

Phase 1: Survey and interviews with 8 MSEs

This phase addresses research questions 1 and 2: identifying key areas where knowledge debt impacts marketing efficiency and assessing the potential of generative AI tools. Data was collected from 8 MSEs to establish a baseline of current marketing practices, ROI, and AI usage.

Phase 2: In-Depth Case Study with One MSE

This phase answers research question 3: testing a Gen AI-based solution to enhance marketing ROI and evaluating its effectiveness. An in-depth case study with one company allowed for an examination of the implementation and outcomes of the Gen AI-driven intervention.

The choice of 8 MSEs in Phase 1 balances the need for sufficient data to identify patterns with the practical constraints of an exploratory study as multiple industry interviews or case studies enhance the robustness of findings through replication logic (Yin, 2014). The single in-depth case study in Phase 2 provides contextual data to evaluate the Gen AI practical impact, aligning with research design that emphasize depth for testing interventions.

3.2 Selection of Case Companies

The selection process for the case companies was guided by the research research questions and practical considerations.

The 8 MSEs were selected using a convenience sampling approach, targeting companies that were accessible and willing to participate. While convenience sampling lacks the rigor of random selection, it is acceptable for exploratory research where the goal is to generate insights rather than generalize broadly (Etikan, Musa and Alkassim, 2016). The inclusion criteria were:

- Classified as micro or small enterprises per the European Commission's definition (fewer than 50 employees and annual turnover under €10 million).
- Engaged in some form of marketing, even if very limited.
- Willing to participate and share marketing data.

These companies were identified through personal networks, online business directories, and contacted by cold calls and emails if they met the selection criteria. This resulted in a diverse sample across industries, with participating 8 companies operating in 6 different fields.

For Phase 2, one company was selected from the initial 8 based on additional criteria:

- Demonstrated enthusiasm for improving marketing efficiency.
- Possessed sufficient marketing and industry data to support the Gen AI intervention.
- Willing to implement LLM-generated recommendations.

The company selected operates in the consulting sector and was chosen due to its proactive engagement during Phase 1 and its readiness to participate in the intervention. Specific identifying details are withheld to maintain confidentiality as agreed with the company.

3.3 Data Collection Methods

Data collection was tailored to each phase of the research design, using a combination of questionnaires, interviews, and a Gen AI-based intervention. During phase 1, data was collected through in-person or online meetings with representatives from each of the 8 MSEs, typically the owner or a marketing decision-maker. Interviews were conducted between 6/2024 and 3/2025.

Prior to the start of the questionnaire, participants received verbal information detailing the study's purpose and procedures. Verbal informed consent was obtained from all participants. With the participants' permission, interviews were audio-recorded to ensure accurate data capture. Recording the interviews allowed for full interviewer engagement during the conversation (Braun and Clarke, 2013). The audio recordings were listened to when going over notes written during the interviews to make sure of correct capture of the participants' responses. To ensure data security and confidentiality, participant names and company identifiers were not collected. All digital files were stored on a password-protected computer. Data was retained for the length of the data-analysis conducted for this study in accordance with data protection regulations.

Each meeting included a semi structured questionnaire to gather quantitative and qualitative data on marketing practices and AI usage. The questionnaire comprised 15 questions detailing marketing and AI related financial and capability information. An informal discussion was held during the same meetings after the questionnaire to deepen understanding on the topic. No formal interview guide was used during the discussions, but key topics mirrored the questionnaire, such as current marketing strategies and challenges, experiences with AI tools and perceptions of marketing effectiveness. Questionnaire and informal discussions with participating companies lasted from 23 minutes to 134 minutes, providing enough time to delve into topics while respecting the participants' time commitments. The dual approach of questionnaires and discussions provided both standardized data for comparison and nuanced insights into knowledge debt's impact.

Data collection for the in-depth case study, phase 2, was a multi-step process built on the data gathered in phase 1, supplemented with industry-specific information and post-intervention evaluation. The primary data source for this deeper case study was the responses from the questionnaire completed by the selected company during phase 1. This questionnaire provided in-depth information on marketing budgets, channels used, ROI metrics, and perceived inefficiencies, offering a comprehensive view of the

company's marketing practices. To contextualize the company's data, industry-specific information, including market trends, competitor activities, and current marketing methods, was collected. This industry data was drawn from the company's own insights, shared during the Phase 1 meeting, and was manually enriched with publicly available information from online industry reports, SEO reports and market analyses.

With the participating company's consent, the detailed questionnaire data was anonymized and combined with the industry information to form a dataset. This dataset served as the foundation for a custom ChatGPT-based setup created using the OpenAI API platform. The purpose of this setup was to enable ChatGPT to have a deeper understanding of the company's specific marketing situation, surpassing the insights it could derive from its own training data alone. Once the dataset was integrated, the model was prompted with questions such as:

"Given the provided data, what recommendations do you have for improving marketing ROI?"

The model analyzed the inputs provided for it and generated tailored recommendations aimed at enhancing the company's marketing performance such as (this is a real response with real data substituted out):

"You're investing €5,000 annually in social media ads, yet the return on investment stands at only 1.2:1, suggesting that the channel isn't being used efficiently. According to industry research, alternative strategies like thought leadership, blogging, and webinars can generate greater engagement and improved ROI. In fact, one industry paper reports that thought leadership achieves an average ROI of over 7:1 by leveraging expertise to build trust and attract leads. Consider examining your social media funnel for bottlenecks or reallocating part of your budget towards these more effective methods."

The recommendations produced by ChatGPT highlighted specific inefficiencies in the company's current marketing approach and proposed actionable solutions. For instance, here the model identified an over-reliance on digital channels, such as pay per click social media advertising, which delivered a low ROI, and suggested reallocating resources to other strategies, like targeted thought leadership, which industry data indicated could yield higher engagement. From these suggestions, one recommendation that ChatGPT deemed most likely to succeed, given the company's current situation, was selected for implementation. With the help of ChatGPT, a marketing plan was then developed, detailing steps such as audience targeting, content creation, and a timeline for execution. Then I worked closely with the company

to create and implement this plan, providing guidance while the company handled the operational execution.

Following the implementation, post-intervention data was gathered to assess the effectiveness of the marketing campaign recommended and part created by ChatGPT. This included updated performance metrics, such as ROI, Cost Per Lead for the new campaign. The ROI of the previous marketing methods was then compared to the ROI of the new approach, revealing the tangible impact of the intervention. This comparison demonstrated how the Gen AI-based solution addressed inefficiencies and improved marketing outcomes, providing a practical evaluation of its effectiveness.

4 Results and Analysis

This chapter presents and analyzes the findings gathered through the mixed-methods research approach detailed in Chapter 3. Specifically, this chapter will first outline the results obtained from Phase 1, which involved surveys and semi-structured interviews with 8 micro and small enterprises (MSEs). It will then present the findings from Phase 2, detailing the in-depth case study conducted with one selected MSE, including the outcomes of the practical intervention using a generative AI.

The analysis throughout this chapter will connect the findings directly to the three research questions established in Chapter 1.3. By doing so, this chapter seeks to showcase the impact of knowledge debt on MSE marketing efficiency, assess the potential of generative AI tools in this context, and evaluate the tested effectiveness of Gen AI made intervention to improve marketing return on investment.

4.1 Marketing Channel Usage and Data

The results from Phase 1 reveal a predominant reliance on digital marketing channels. Image 7 summarizes the marketing channels used either currently or within the past two years by the 8 MSEs:

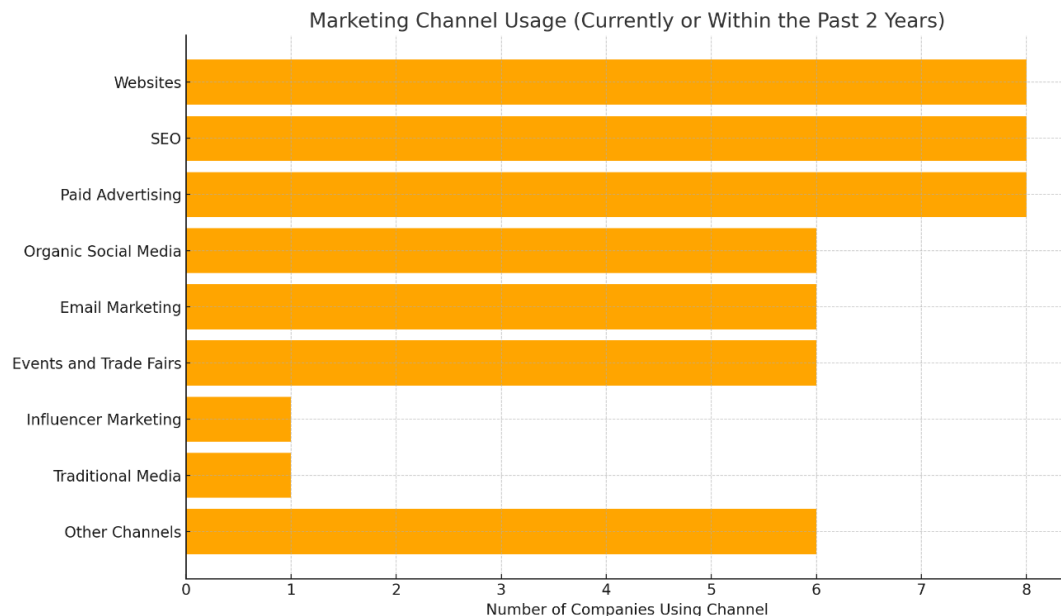


Image 7: Marketing channels used by case companies

Website and SEO: All 8 MSEs maintained websites and engaged in basic search engine optimization (SEO).

Paid advertising: 8 MSEs ran or experimented with pay-per-click (PPC) campaigns.

Organic social media: 6 MSEs utilized platforms like Facebook or LinkedIn for organic traffic creation.

Events and trade fairs: 6 MSEs participated in webinars, trade fairs, or similar events.

Other Channels: 6 MSEs explored avenues like sponsoring sports teams, with only 1 using influencer marketing and 1 using traditional media channels.

Despite this variety, assessing resource allocation proved difficult due to inconsistent data tracking. Only one MSE provided detailed expenditure and results data, while six offered partial insights (e.g., ad spending or agency fees). The eighth lacked any relevant records. Much of the marketing effort stemmed from untracked internal time investments, often described vaguely as “partners doing some marketing on their own time” or estimated loosely (e.g., 8–16 hours/month for social media). This absence of systematic tracking prevented precise calculations of metrics like return on investment (ROI) or Customer Acquisition Cost (CAC) for seven out of eight companies.

Financially, four MSEs maintained entry-level contracts with digital marketing agencies (around 500-1000€/month), which typically covered 5–15 hours of work per month, meaning buying basic services like website upkeep rather than comprehensive marketing support. These contracts were supplemented by annual ad budgets ranging from thousands to tens of thousands of euros. Additional costs included creative services (e.g., graphic design) and event-specific expenses (e.g., promotional materials).

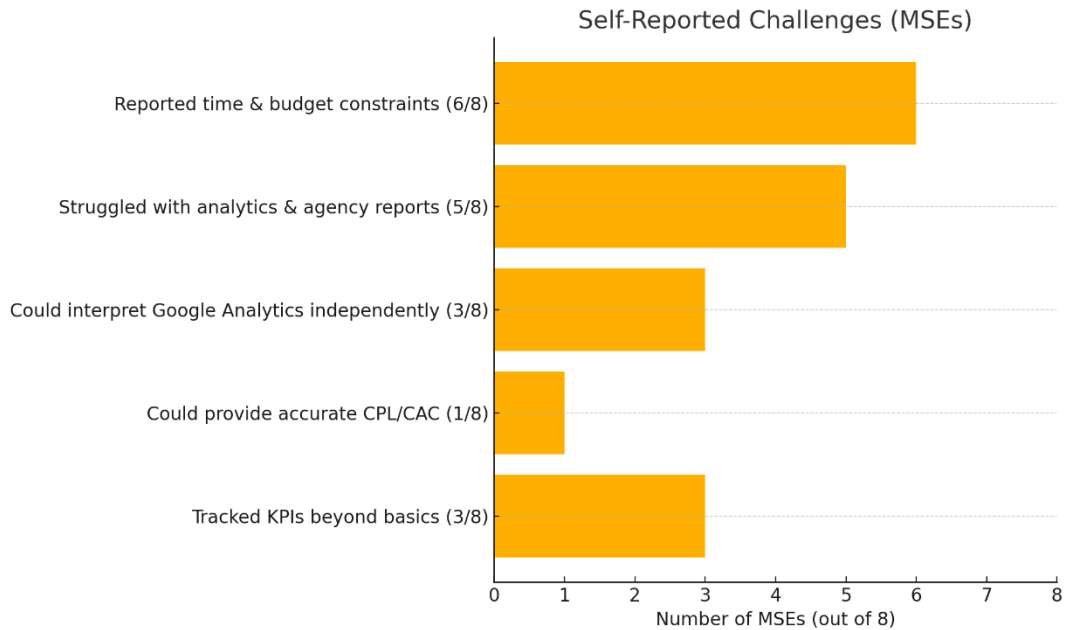


Image 8: Self-reported marketing challenges by case companies

Only 3/8 MSEs tracked key marketing performance indicators (KPIs) beyond basic sales, website visits or conversions, and just 1/8 could provide accurate CPL and CAC data for their marketing channels. Although tools like Google Analytics were available, only 3/8 could interpret them independently, 5/8 could not interpret them beyond the very basics independently and struggled even with marketing agency reports. One key reason for these problems, reported by 6 of the MSEs, was time and budget constraints. This gap in data-driven decision-making underscores a broader knowledge deficiency, setting the stage for the analysis of knowledge debt in Section 4.2.

4.2 Analyzing knowledge debt's impact on marketing efficiency

This section focuses on how knowledge debt, a term defined in Chapter 2.2 as accumulated gaps in expertise due to limited training and resources, affects marketing efficiency in micro and small enterprises (MSEs). It addresses Objective 1 by identifying specific areas where knowledge debt undermines effective marketing.

The data reveals several distinct ways knowledge debt impacts MSEs' marketing efforts, extending beyond the general challenges noted in Section 4.1. Seven out of the eight companies were not happy with the results their marketing efforts were producing. Five MSEs reported uncertainty about

implementing marketing strategies effectively, a sentiment encapsulated by one participant's comment: "I'm not sure how our company can use webinars as a marketing method." This lack of know-how had led to poorly executed campaigns in the case of all participating companies at least once in their histories. For instance, one MSE produced social media videos with low production quality (e.g., poor audio and editing), achieving an average watch time far below industry benchmarks for engagement. This reflects a gap in practical skills that diminishes campaign effectiveness. The four MSEs paying monthly fees to agencies often received minimal output (e.g., basic website upkeep). One company allocated a minuscule daily budget to Google Ads, insufficient for generating actionable insights or results. These misallocations stemmed from a lack of understanding of the scale, quality and best practices required for effective marketing, exacerbating financial inefficiencies.

Section 4.1 noted that only three MSEs could independently navigate analytics tools, and five struggled with them and marketing agency reports. A specific example illustrates this further: one MSE ran a LinkedIn ad campaign, achieving a very good cost per lead (CPL) on one ad creative, but abandoned the channel deeming it ineffective. Industry benchmarks suggest their CPL using this ad creative was well cheaper than on average within their industry, which is highly favorable and can turn into a competitive advantage, yet the company lacked the expertise to recognize this, missing an opportunity to iterate, optimize and scale the campaign. All MSEs reported experimenting with different marketing methods and campaigns but abandoning them when initial efforts were deemed underperforming. One participant noted, "We tried ads, but they didn't work, so we stopped", without stating why the ads didn't work. Many of these marketing decisions were therefore based on under-resourced trials and hunches rather than strategic evaluation, perpetuating a cycle of wasted effort.

These manifestations of knowledge debt directly impair marketing efficiency, as measured by metrics like ROI and CAC. Inefficient budget use and poor campaign execution (e.g., low-quality videos) resulted in minimal returns, the reason why seven out of eight MSEs were not happy with the current state of their marketing. For example, one MSE had switched marketing agencies several times within a short time period, only to buy the same entry level service again and again, expecting different outcomes and blaming the low results on the agencies instead of exploring the root causes. One other MSE had ran paid ads with a considerable budget for years without realizing their campaign was extremely ineffective. Practically speaking, this company was wasting money. With only one MSE accurately tracking CPL and CAC, most lacked insight into customer acquisition costs, marketing effectiveness and the root causes of their results respectively.

Suboptimal campaigns and abandoned channels inflate overall CAC, as resources are spent without yielding proportional customer or revenue gains. The inability to leverage data or sustain channel use limits MSEs' ability to compete with data-driven small and large firms, aligning with Chapter 2.3.1's discussion of MSEs' ad-hoc marketing practices. These examples confirm that knowledge debt compounds the challenges identified in Section 4.1, creating a significant barrier to efficient customer acquisition and sustainable growth.

4.3 Current Use and Perceptions of Generative AI Tools

This section addresses assessing the potential of generative AI tools (e.g., Large Language Models like ChatGPT) to mitigate knowledge debt. It examines current usage and perceptions among the 8 MSEs.

Adoption of companywide generative AI tools was low amongst the participating companies. All companies had tried at least one LLM, 7 had tried using at least one image-generator and 2 had tried audio generation. Only one MSE reported a structured approach, having made a basic AI strategy. The other seven MSEs reported unstructured use, for example the occasional use by individuals for tasks like email writing or creating pictures, lacking any companywide strategic implementation or standard practices. This mirrors the limited use of marketing technologies noted in Section 4.1.

The MSE with an AI strategy viewed these tools positively, appreciating their potential to save time and enhance work quality. They had reasonable understanding of the potential risks associated with generative AI and practices to mitigate these risks. The other seven MSEs expressed curiosity and reported ad hoc use, meaning that some staff were using generative AI, but no standard practices were made. 4 companies also reported skepticism, with comments like,

“I don't see how ChatGPT can help me in my work. I've used it to write emails and reports. Those were okay but that's pretty much it.”

Time and budget constraints, cited by six MSEs, also hinder Gen AI adoption. Learning new tools requires an upfront investment of time and money that many of the participating companies feel reluctant or are unable to make. Additionally, the lack of awareness about practical Gen AI applications and use cases reflects a broader knowledge debt around the topic, necessitating education solutions prior to the adaptation of Gen AI tools. The findings highlight a clear opportunity for generative AI to alleviate knowledge debt. However, this potential requires overcoming adoption barriers, a challenge to be explored further in Section 4.4's case study.

4.4 Case Study

The selected MSE maintains an annual marketing budget of approximately 20,000 euros. This company was chosen due to its willingness to participate in the Gen AI-driven intervention and its flexibility in allowing me to implement the proposed strategy at a manageable pace. These characteristics positioned it as a suitable candidate for evaluating the practical impact of LLM-based solutions on marketing performance.

To begin the intervention, an executive summary of the MSE's current marketing situation was compiled. Due to the company's limited internal tracking, precise Customer Acquisition Cost (CAC) and Cost Per Lead (CPL) figures were unavailable. These metrics were estimated based on available data, determining that the company's CPL was approximately 2.5 times higher than the industry average, which is a clear indicator of marketing inefficiency.

The GPT-4o model was prompted to analyze the anonymized executive summary and suggest options for improving marketing ROI. The model provided a list of potential strategies, including content marketing, social media campaigns, and webinars. It also suggested improving the current marketing methods. When further prompted to identify the easiest-to-implement option given the MSE's constraints, it recommended webinars as the most feasible approach. It then generated a brief outline for hosting a successful webinar, which served as the blueprint for the subsequent implementation.

The webinar strategy was executed based on the models' recommendations, with me acting as a facilitator. The MSE's staff exhibited initial skepticism toward AI tools, reflecting a knowledge gap and adoption barriers discussed earlier. Consequently, I assumed responsibility for operationalizing the AI's guidance. Key implementation steps included:

- **Platform Configuration:** A webinar platform was selected and set up, complete with automated email reminders and a registration link to streamline participant management.
- **Promotional Efforts:** Marketing focused on email campaigns and social media outreach with the help of an image generator (DALL-E3), tailored to the company's existing audience and industry context.

- **Event Execution:** The webinar was scheduled for three weeks after the initial setup and delivered with content designed to address the target market's needs.

While the company contributed 100% of the webinar's content, showcasing their subject matter expertise, it relied heavily on the proposed marketing strategy by gpt-4o for technical setup and strategic execution.

The webinar proved highly effective in improving marketing efficiency. Post-event data revealed a dramatic reduction in CPL, decreasing by a factor of 30 compared to the company's previous marketing methods. This shift, from a CPL 2.5 times above the industry average to a significantly lower figure, demonstrates the potential of LLM-recommended strategies to optimize resource use and enhance customer acquisition outcomes. However, the intervention's success comes with caveats. Unlike scalable methods such as digital advertising, webinars face capacity constraints (e.g., limited audience size and frequency), suggesting that the observed CPL reduction may not be replicable at larger scales. Additionally, my role in executing the strategy indicates that the results were not entirely AI-driven, as human intervention was critical to the implementation process.

This case study underscores the capability of LLMs like ChatGPT to address knowledge debt in MSEs by delivering actionable, context-specific marketing strategies. The intervention directly tackled the company's inefficiencies (high CPL and suboptimal marketing approaches) by providing a clear, executable plan that leveraged existing resources effectively. The results also highlight AI's role in compensating for expertise shortages within MSEs. GPT-4o's webinar recommendation and execution outline bridged a gap in the company's internal capabilities, enabling it to adopt a strategy it might not have otherwise pursued. However, the reliance on me implementing the suggestions points to a key limitation: while LLMs can reduce knowledge debt by offering insights, MSEs may lack the capacity to act on those insights independently. GPT-4o's strategy also included parts where the use of image generators was necessary. The case company didn't possess the ability to use these generators without education on the topic.

4.4.1 Practical Guide for Micro- and Small Enterprises

The case study in Section 4.4 demonstrates that generative AI tools, such as ChatGPT, can significantly enhance marketing efficiency in MSEs by addressing knowledge debt and recommending high-ROI strategies. In this instance, the intervention led to a 30-fold reduction in cost-per-lead (CPL)

through a webinar campaign, far outperforming the company's prior ad-hoc approaches. However, the true value of this research lies in its replicability. This subsection provides a step-by-step guide for MSE owners or managers to independently apply a similar AI-driven process. The guide assumes access to affordable subscription-based tools like ChatGPT Plus (€20/month as of July 2025) and requires no advanced technical skills, aligning with MSE resource constraints. It emphasizes iterative human-AI collaboration to ensure outputs are tailored and verified.

Step 1: Collect and Organize Baseline Data

Begin by gathering internal data to establish a clear picture of your current marketing performance. This step mitigates knowledge debt by forcing a structured review of existing practices. If you don't know how, ask the LLM for help.

- **Collect Key Performance Indicators (KPIs):** Review the last 6-24 months of data (or best estimates if records are incomplete). Include total marketing budget, channels used (e.g., social media, SEO, paid ads), number of leads generated per channel, conversions to customers, and revenue attributed to each.
- **Benchmark Against Industry Standards:** Research industry averages for CPL and CAC using free resources on the internet or ask the LLM to create a report for you. For example, if your industry median CPL for email marketing is €50, note this for comparison.
- **Document Constraints and Gaps:** Anonymize sensitive data and note limitations, such as budget (€X/month), staff hours available (e.g., 10 hours/week), goals (e.g., 20% ROI increase), and any uncertainties (e.g., "Unsure of exact ad spend breakdown").

This step typically takes 2–4 hours and creates a 1–2 page briefing document, which serves as input for the AI.

Step 2: Set Up and Brief the Generative AI Tool

Select an accessible LLM like ChatGPT, which excels at analyzing data and generating recommendations without custom coding.

- **Choose and Configure the Tool:** Use ChatGPT or a similar platform. Create a new chat or "custom GPT" for continuity. Upload your briefing document if the tool supports it.

- Provide a Clear Initial Prompt: Start with: "Here's an anonymized summary of our current marketing data: [paste briefing]. Analyze our performance, identify inefficiencies (e.g., high CPL channels), and suggest 2–3 alternative channels or strategies likely to improve ROI under our constraints. Base recommendations on industry benchmarks and explain projected CPL/CAC improvements."
- Refine Iteratively: If outputs are vague, follow up with prompts like: "Explain why [suggested channel] would lower our CPL compared to our current [channel]. Provide a step-by-step implementation plan."

This interaction simulates hiring a consultant but at minimal cost, reducing reliance on external agencies.

Step 3: Evaluate and Select Recommendations

Critically assess AI suggestions to avoid over-reliance and ensure alignment with your business.

- Validate Feasibility: Cross-check suggestions with free online sources (e.g., Google searches for "[industry] webinar success stories"). Test for risks, such as ethical issues (e.g., AI-generated content biases).
- Incorporate Human Judgment: Adjust for unique factors, like your audience preferences or seasonal trends, which the AI might overlook.

Step 4: Implement, Monitor, and Iterate

- Execute the selected strategy while tracking results to build internal knowledge.
- Develop an Action Plan: Use the AI to generate specifics, e.g., "Create a 4-week plan for a webinar, including content outline, promotion tactics, and budget breakdown."
- Execute with Support Tools: Leverage complementary tools (e.g., DALL-E for visuals, Canva for design) if needed. In the case study, this involved platform setup, email promotion, and content creation.
- Measure Outcomes: After 4–8 weeks, recalculate CPL/CAC and compare to baselines.

- Iterate: If results underperform, refine with new prompts incorporating lessons learned.

Potential Challenges and Tips

- Overcoming Usability Barriers: If prompting feels intimidating, start with simple queries and use online tutorials (e.g., "ChatGPT for marketing beginners").
- Ethical Considerations: Always review AI outputs for accuracy and originality to avoid plagiarism or biases.
- Scalability: For MSEs with very limited time, allocate 5–10 hours initially; benefits compound as you gain familiarity.

By following this guide, MSEs can systematically reduce knowledge debt, reallocate budgets to high-ROI channels, and achieve outcomes like the case study's CPL reduction. This process empowers non-experts. Future iterations could incorporate emerging tools, such as multimodal AI for video/audio, to further enhance applicability.

5 Discussion

This chapter is structured to address the study's aims while critically reflecting on its limitations, particularly the small sample size and methodological shortcomings. Subsection 5.1 provides an overview of the results and hypothesizes their implications. Subsections 5.2 and 5.3 discuss the scientific and practical impacts, respectively, introducing new perspectives on AI's role in MSEs. Subsection 5.4 conducts an uncertainty analysis, addressing the study's flaws. Finally, Subsection 5.5 proposes avenues for future research to extend the thesis's findings.

5.1 Overview of the results

The goal of this thesis was to explore whether Gen AI can reduce knowledge debt in MSE marketing, thereby improving customer acquisition efficiency. Secondary aims included identifying areas of knowledge debt, assessing generative AI's potential, and testing its effectiveness in a practical setting. The results, detailed in Chapter 4, largely achieved these aims but are tempered by significant limitations. The survey of eight MSEs (Chapter 4.2) revealed that knowledge debt manifests in poor campaign execution (e.g., low-quality media), inefficient budget allocation (e.g., running unprofitable ads), limited analytics use (only one MSE tracked CPL and CAC accurately), and premature channel abandonment (e.g., dismissing LinkedIn despite favorable CPL). These findings confirm that knowledge debt hinders MSEs' ability to optimize marketing resources, leading to high CPL and low ROI. The case study (Chapter 4.4) demonstrated that an LLM-driven webinar strategy reduced CPL by a factor of 30, suggesting that AI can bridge expertise gaps by recommending high-ROI strategies tailored to MSE constraints.

However, the results also highlight challenges. Low AI adoption (only one MSE had a structured AI strategy) indicates barriers like time constraints and interface complexity. The case study's success relied on external facilitation, suggesting MSEs may struggle to implement AI independently. These outcomes suggest that LLMs can mitigate knowledge debt, but their effectiveness depends on overcoming adoption hurdles and ensuring human oversight. The poor analytics use and channel abandonment may stem from MSEs' reactive, short-term focus, prioritizing immediate operations over strategic planning. The case study's success with webinars, a strategy unfamiliar to the case MSE, implies that LLMs can introduce unused approaches that MSEs might not otherwise consider, expanding their strategic repertoire. However, the reliance on external support raises questions about whether MSEs can sustain AI-driven strategies without ongoing assistance,

a point explored further in Subsection 5.4. In addition, the focus on LLMs and image generation means the results offer no insights, audio generators, limiting the study's contribution to the broader generative AI landscape.

5.1.1 Scientific Impact

This study contributes to the field of AI applications in small business marketing by examining LLMs in resource-constrained MSEs, an underexplored context compared to large firms. The identification of specific knowledge debt areas clarifies how expertise gaps manifest in MSE marketing, adding specificity to prior broad discussions of knowledge debt. While the case study's 30-fold CPL reduction suggests that LLMs may offer strategic guidance in certain MSE contexts, the result is based on a single intervention and should not be interpreted as representative of broader outcomes. Unlike studies on AI for content creation and increasing worker efficiency, this work emphasizes strategic decision-making, showing that LLMs can guide MSEs toward untested channels like webinars. However, the small sample size (eight MSEs) and single case study limit the study's ability to generalize these contributions. The findings are exploratory, offering a foundation for future research rather than definitive conclusions. The lack of longitudinal data also restricts claims about AI's long-term impact on knowledge debt, underscoring the need for further investigation.

5.1.2 Practical Impact

The results have significant implications for MSEs seeking to improve marketing within resource constraints. The case study's success suggests that LLMs can democratize access to strategic expertise, enabling MSEs to adopt high-ROI strategies without costly consultants or agencies. This affordability, generative AI tools costing around 10-200 euros/month versus \$500–\$1000/month or 60-200€/h for entry level agency services that often fail to produce concrete results, makes AI a viable alternative for MSEs. A practical contribution is “AI-guided experimentation.” The case study's webinar strategy introduced a channel the MSE had not previously utilized, suggesting that LLMs can expand MSEs' marketing horizons by proposing novel, low-risk experiments. This approach could help MSEs overcome their tendency to stick with familiar but often suboptimal channels, fostering agility in dynamic markets. This capability has potential for enabling some MSEs to compete more effectively, though further studies with broader samples are required to confirm scalability and consistency of impact. The low companywide AI usage (Chapter 4.3) and case study's external facilitation indicate that MSEs need support to integrate LLMs effectively into their operations.

5.1.3 Uncertainty Analysis

The study's findings must be interpreted with caution due to several methodological shortcomings, which are openly acknowledged to ensure objectivity. The small sample size of eight MSEs in Phase 1 and one in Phase 2, selected via convenience sampling, severely limits generalizability. This sample, drawn from accessible networks, may not reflect diverse MSE industries or regions, potentially skewing the identified knowledge debt areas and AI adoption patterns. Data quality poses another concern. The reliance on self-reported marketing budgets and performance metrics (Chapter 4.1) might introduce inaccuracies, as seven MSEs lacked precise CPL or CAC data. This vagueness, coupled with inconsistent tracking (e.g., unquantified staff time), undermines the precision of knowledge debt's impact assessment. The case study's estimated CPL (2.5 times industry average) further reflects this uncertainty, as baseline metrics were estimated with the available data, which was partly incomplete. Methodological biases also arise. The single case study's focus on webinars may overstate effectiveness, as other marketing methods and strategies were not tested. The external facilitation in Phase 2 might inflate the intervention's success, as MSEs without such support may struggle to replicate results. Additionally, the study did not assess AI output biases or ethical risks potentially overlooking critical barriers to adoption. These limitations suggest that the findings are preliminary, serving as a proof-of-concept rather than robust evidence. The study's exploratory nature and resource constraints justify these flaws, but they necessitate cautious interpretation and further validation.

5.1.4 Further Research

The study's limitations and exploratory findings open several avenues for future research, building on its contributions. These proposed directions could refine this thesis's insights, addressing its methodological gaps and advancing the field of AI-driven marketing for small businesses.

1. Studies with broader, randomized samples across industries and regions could validate the identified knowledge debt areas and Gen AI adoption barriers and enhance generalizability.
2. Investigating LLM generated strategies long-term impact on MSE marketing performance (e.g., revenue growth, customer retention). This would clarify their sustainability and potential deskilling effects.

3. Exploring Gen AI's role in niche MSE markets (e.g., consulting) could uncover tailored strategies, addressing the study's generic approach.
4. Developing MSE-specific Gen AI interfaces with simplified prompts and tutorials could lower adoption barriers, testing whether usability improvements enhance uptake.
5. Formalizing the proposed "Gen AI-guided experimentation" concept through controlled trials could establish a replicable framework for MSEs to test new channels systematically.

6 Conclusion

This thesis makes several contributions. It provides an understanding of knowledge debt in MSE marketing, specifying areas where expertise gaps hinder efficiency. It positions LLMs as tools for strategic innovation, capable of suggesting new marketing channels like webinars that MSEs might not otherwise consider. Additionally, it highlights the gap between LLMs' affordability and their practical adoption, underscoring the need for education and user-friendly design tailored to MSEs. These insights provide a preliminary contribution to the relatively underexplored context of Gen AI and MSE marketing, though findings should be interpreted cautiously due to the study's limited scope. The study's limitations are significant. The small sample size of eight MSEs in Phase 1 and one in Phase 2, selected via convenience sampling limits generalizability. Vague, self-reported data (e.g., imprecise CPL metrics) and untracked staff time compromise data quality. The case study's dependence on external facilitation suggests MSEs may struggle to implement LLMs independently. The exclusive focus on LLMs, despite a broader generative AI aim, means the study offers no insights into image, audio, or video generators. The lack of statistical analysis, short intervention timeline, and absence of ethical risk assessments (e.g., GDPR, copyright) further weaken reliability. The findings lay a foundation for studying generative AI in small business contexts, highlighting adoption barriers and strategic applications. Future research should explore image, audio, and video generators to address the study's LLM-centric gap, use larger and more diverse samples and conduct longitudinal studies to assess long-term impacts. Additional directions include investigating sector-specific AI applications and ethical frameworks for responsible adoption.

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