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AI – DRIVEN CUSTOMER JOURNEY MAPPING AND PERSONALIZATION IN SMEs: PREDICTING AND PRESCRIBING OPTIMAL TOUCHPOINTS FOR ENHANCED CUSTOMER EXPERIENCE

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Abstract

Small and medium-sized enterprises (SMEs) compete in markets where customers move across an increasing number of digital and physical touchpoints, yet most of these firms still map and manage the customer journey with intuition and fragmented data rather than systematic analysis. This thesis examines, through a structured review of the marketing, information systems and service research literature published mainly between 2016 and 2025, how artificial intelligence (AI) reshapes customer journey mapping and personalization in the specific context of resource-constrained smaller firms. The discussion is organised around four objectives: tracing the evolution of customer journey mapping and personalization in SMEs; analysing how AI improves the analysis of customer behaviour and the visibility of the journey; evaluating how predictive and prescriptive analytics help identify and act on optimal touchpoints; and assessing the opportunities, limitations and ethical implications that accompany AI-driven personalization.

The evidence indicates that AI shifts customer journey mapping from a static, retrospective artefact towards a continuously updated and forward-looking capability, in which machine learning, natural language processing and predictive analytics convert behavioural traces into anticipations of customer needs. Predictive models help SMEs estimate which touchpoints matter and when intervention is most valuable, while prescriptive approaches translate those estimates into concrete recommendations about timing, channel and content. The literature also points towards real constraints for SMEs, including limited data volumes, scarce analytical skills and dependence on external platforms, alongside ethical concerns about privacy, transparency and the risk that personalization is perceived as surveillance. The analysis highlights that the value of AI for smaller firms depends less on the sophistication of individual algorithms than on the integration of data, capabilities and governance around a clearly understood customer journey. The thesis closes by identifying gaps in the current literature and outlining implications for SME customer experience strategy.

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Introduction

Background and motivation

The way customers reach, evaluate and stay loyal to a business has changed substantially over the past two decades. Purchase decisions are no longer the outcome of a small number of isolated interactions but emerge from journeys that unfold across search engines, social media, marketplaces, messaging applications, physical stores and after-sales service, often in non-linear and overlapping sequences (Lemon and Verhoef, 2016). Each of these contacts, commonly described as a touchpoint, contributes to the cumulative experience that shapes satisfaction, repurchase and word of mouth (Verhoef et al., 2009). The proliferation of channels has made the customer journey richer in opportunity but also harder to observe, because the signals a firm needs in order to understand its customers are scattered across systems that were rarely designed to work together.

Two developments give this thesis its motivation. The first is the consolidation of customer experience as a central concern of marketing strategy. Firms increasingly compete not only on products and prices but on the quality and coherence of the journeys they offer, and managing those journeys has become an explicit organisational practice rather than an occasional design exercise (Homburg et al., 2017; Edelman and Singer, 2015). The second is the maturing of artificial intelligence as a practical set of technologies for analysing behaviour at scale. Machine learning, natural language processing and predictive analytics now make it possible to detect patterns in customer data, anticipate intentions and tailor interactions in ways that were previously confined to the largest data-rich organisations (Davenport et al., 2020; Huang and Rust, 2021).

The intersection of these developments is particularly consequential for small and medium-sized enterprises. SMEs account for the majority of firms and employment in most economies, and they frequently rely on close customer relationships and responsiveness as their main competitive assets. At the same time, they face structural disadvantages: limited budgets, scarce specialist skills, smaller data volumes and a strong dependence on third-party digital platforms (Coleman et al., 2016; Taiminen and Karjaluoto, 2015). The promise that AI can help these firms understand and personalize the customer journey is therefore attractive, but it cannot be assumed to transfer automatically from the large-enterprise settings where much of the evidence originates. Understanding how, and under what conditions, AI genuinely improves journey mapping and personalization for smaller firms is the central concern of this work.

Research problem and objectives

Despite a substantial and fast-growing body of research on customer experience, customer journeys and AI in marketing, the literature remains fragmented across disciplines and is dominated by studies of large organisations. Work on customer journey mapping tends to treat the journey as a design and measurement problem, while work on AI in marketing concentrates on technological capabilities and consumer responses, often without addressing the organisational realities of firms that lack data scientists or integrated systems. The specific question of how predictive and prescriptive analytics can help an SME decide which touchpoints to prioritise, and how to act on them, has received comparatively little structured attention. This thesis addresses that gap by synthesising existing knowledge rather than generating new empirical data.

The investigation is guided by four research objectives. The first (O1) is to examine the evolution of customer journey mapping and personalization within SMEs. The second (O2) is to analyse how artificial intelligence improves customer behaviour analysis and journey visibility. The third (O3) is to evaluate how predictive and prescriptive analytics help identify optimal customer touchpoints. The fourth (O4) is to assess the opportunities, limitations and ethical implications of AI-driven personalization for SMEs.

These objectives are expressed as four research questions that the analysis seeks to answer. RQ1 asks how artificial intelligence improves customer journey mapping in SMEs. RQ2 asks how AI can predict customer behaviour and optimise customer touchpoints. RQ3 asks how AI-driven personalization influences customer experience and customer satisfaction. RQ4 asks what opportunities, limitations and ethical challenges SMEs face when implementing AI-driven personalization. Each question is addressed cumulatively across the two main chapters and drawn together in the conclusion.

Scope and significance of the study

This is a literature-based study. It does not rely on surveys, interviews, questionnaires or any primary empirical data, and it does not report new statistical findings. Its contribution lies in organising, interpreting and connecting existing peer-reviewed evidence so that the implications for SMEs become clearer. The sources prioritised here are drawn from established journals in marketing, service research and information management, with an emphasis on work published between 2016 and 2025 and a small number of older, foundational contributions where they remain conceptually central. Any conclusions emerge from the analysis of that literature rather than from independent measurement.

The significance of the study is both academic and practical. Academically, it brings together two literatures that are usually treated separately, the customer journey and AI in marketing, and reads them through the lens of the SME, a setting that is under-represented in both. Practically, it offers SME managers a structured account of what AI can realistically contribute to journey mapping and personalization, what it cannot, and what risks accompany its adoption. By distinguishing prediction from prescription, and by treating data, capabilities and governance as conditions rather than afterthoughts, the analysis aims to support more realistic decisions than the optimistic claims that often surround the topic.

Thesis structure overview

The remainder of the thesis is organised into two main chapters and a conclusion. Chapter 1 establishes the foundations, defining customer journey mapping and personalization, situating them in the SME context, and explaining why traditional methods increasingly require AI support. Chapter 2 turns to AI-driven approaches, examining the core technologies, the enhancement of journey mapping, personalization frameworks suited to smaller firms, the prediction and prescription of optimal touchpoints, and the challenges and ethical considerations that constrain practice. The conclusion synthesises the findings against the four research questions, integrates the discussion of AI-driven journey mapping and personalization, identifies gaps for future study and draws out implications for SME customer experience strategy.

Chapter 1: Foundations of Customer Journey Mapping and Personalization in SMEs

Before AI can be assessed as a tool for smaller firms, the concepts it is meant to support need to be clearly defined. This chapter sets out what customer journey mapping and personalization mean, how they have developed, and why the conditions facing SMEs make them both valuable and difficult to execute. It then explains why traditional, manual approaches to mapping the journey increasingly reach their limits, creating the demand for the predictive and prescriptive methods examined in Chapter 2.

1.1 Concept of Customer Journey Mapping

Definition and evolution of customer journey mapping

The customer journey can be defined as the full sequence of interactions a customer has with a firm and its offering, before, during and after a purchase, together with the perceptions and emotions those interactions generate (Lemon and Verhoef, 2016). Customer journey mapping is the practice of representing that sequence so that an organisation can see the experience from the customer's point of view rather than from the perspective of its internal functions. A map typically identifies the stages a customer passes through, the touchpoints encountered at each stage, the customer's goals and frictions, and the channels involved (Rosenbaum et al., 2017). Its purpose is to make an otherwise invisible and subjective experience explicit enough to be analysed and improved.

The idea has clear intellectual roots in earlier service and experience research. Models of the service encounter and of customer experience formation argued that satisfaction is shaped by accumulated interactions rather than by any single transaction, and that firms therefore need to manage the experience as a whole (Verhoef et al., 2009). The notion of a journey gained particular traction after the diffusion of digital channels, when practitioners and scholars recognised that the traditional purchase funnel no longer captured how customers actually behaved. The widely cited reformulation of the funnel as a circular consumer decision journey, in which evaluation and post-purchase experience feed back into future consideration, marked an important shift away from a linear conception of buying (Court et al., 2009; Edelman and Singer, 2015).

Subsequent scholarship has refined the concept in two directions. First, it has clarified the vocabulary of the journey, distinguishing touchpoints from the broader context in which they occur and from the qualities that customers attribute to them, which helps avoid the loose use of the term touchpoint to mean almost any contact (De Keyser et al., 2020). Second, it has grounded the journey in customer experience theory, treating the journey as the temporal structure through which experience accumulates and emphasising that experience is co-created with the customer rather than simply delivered (Becker and Jaakkola, 2020). A systematic review of the field shows that, although interest has grown rapidly, the literature remains methodologically diverse and only loosely integrated, which is one reason practitioners often work from simplified templates rather than from a settled theory (Følstad and Kvale, 2018). More recent systematic reviews extend this picture, showing that the rapid diffusion of artificial intelligence has begun to reshape the journey itself: data-driven co-creation and predictive analytics now raise personalization and real-time engagement to levels that earlier conceptions did not anticipate, prompting renewed calls to rethink what a customer journey is and how it should be studied (Gouveia and Santos, 2025).

Key stages: discovery, consideration, conversion, loyalty, advocacy

Although every business has its own journey, most maps organise it into a small number of recognisable stages. A common formulation distinguishes discovery, when a customer becomes aware of a need and of the firm; consideration, when the customer evaluates alternatives and weighs options; conversion, when a purchase or commitment is made; loyalty, when repeated interactions and satisfaction sustain the relationship; and advocacy, when satisfied customers recommend the firm to others (Lemon and Verhoef, 2016; Court et al., 2009). These stages are best understood as analytical conveniences rather than fixed steps, because customers frequently move back and forth, abandon journeys, re-enter at different points and pursue several stages in parallel.

Alongside the division into stages, the literature distinguishes touchpoints by who controls them, and this distinction is important for understanding how much influence a firm actually has over the journey. A widely adopted classification separates brand-owned touchpoints, which the firm designs and controls, such as its website and advertising; partner-owned touchpoints, shared with collaborators such as distributors or payment providers; customer-owned touchpoints, which reflect the customer's own actions and thoughts and lie largely outside the firm's reach; and social or external touchpoints, including peer reviews and word of mouth, over which the firm has little direct control but which strongly shape outcomes (Lemon and Verhoef, 2016). Recognising that much of the journey is owned by customers and third parties tempers the assumption that mapping equates to control, and it clarifies why understanding the journey, rather than merely managing the firm's own channels, is the real object of the exercise.

What makes the stage model useful is that different touchpoints and different objectives dominate at each phase. Discovery is shaped heavily by external and brand-owned touchpoints such as search results, social content and advertising, where the firm has partial control. Consideration is influenced by comparison, reviews and peer opinion, which are largely outside the firm's control but strongly affect outcomes (Anderl et al., 2016). Conversion depends on the smoothness of the purchase process and the reduction of friction at the decisive moment. Loyalty and advocacy depend on the post-purchase experience, including service quality and the sense that the relationship is recognised and valued (Homburg et al., 2017). Mapping the journey by stage therefore allows a firm to ask, for each phase, which touchpoints matter most and where effort is best directed.

The literature also stresses that the experience is cumulative and dynamic. A single excellent interaction may not compensate for friction elsewhere, and the relative importance of touchpoints shifts over time and across customer segments (Lemon and Verhoef, 2016). This dynamism is precisely what makes the journey hard to manage with static representations and what later motivates the interest in continuously updated, data-driven mapping.

Customer journey mapping in SME contexts versus large enterprises

The way journey mapping is practised differs substantially between large enterprises and SMEs, and the difference is not only one of scale. Large firms typically possess integrated customer relationship management systems, dedicated analytics teams and the budgets to commission detailed mapping exercises and attribution studies (Wedel and Kannan, 2016). They are able to gather behavioural data across many channels and to model the contribution of different touchpoints to outcomes, even if doing so remains technically demanding. Their challenge is often one of complexity and coordination across functions rather than of basic capability.

SMEs operate under different conditions. They usually hold less data, both because they have fewer customers and because their data is dispersed across disconnected tools such as a website, a social media account, a point-of-sale system and an email provider that do not share information (Coleman et al., 2016). Formal journey mapping, where it exists at all, tends to be informal and intuitive, relying on the owner's or staff's direct familiarity with customers rather than on documented analysis. This intimacy is a genuine asset, because tacit knowledge of customers can substitute to some degree for formal data, but it does not scale and is vulnerable to the loss of key staff (Taiminen and Karjaluoto, 2015).

These contrasts matter for the rest of the thesis. The evidence suggests that SMEs are not simply smaller versions of large firms when it comes to journey mapping; they face a qualitatively different situation in which limited and fragmented data coexists with rich relational knowledge. Any account of how AI can support journey mapping in SMEs therefore has to take seriously both the scarcity of structured data and the value of the close relationships that smaller firms already enjoy.

1.2 Customer Personalization in Business Practice

From generic to personalized customer experiences

Personalization refers to the adaptation of a firm's offering, communication or experience to the characteristics, preferences or behaviour of an individual customer or a narrowly defined group (Chandra et al., 2022). It stands in contrast to mass marketing, in which the same message and offer are directed at an undifferentiated audience. The shift from generic to personalized experiences has been driven by the recognition that relevance increases the value customers derive from an interaction and the likelihood that they respond favourably, and by the availability of digital channels that make individualised treatment technically feasible at scale (Kannan and Li, 2017).

Early forms of personalization were essentially rule-based: customers were addressed by name, segmented into broad categories and sent offers based on a small number of attributes. Foundational work on electronic customisation demonstrated that adapting content to inferred preferences could improve outcomes, and that personalization is most effective when it reflects genuine knowledge of the customer rather than superficial tailoring (Ansari and Mela, 2003). Over time, personalization has moved towards finer granularity and greater dynamism, responding to behaviour as it unfolds rather than to fixed profiles. The literature increasingly distinguishes this richer, behaviourally responsive form, sometimes called hyper-personalization, from earlier static approaches, while cautioning that the underlying logic, matching offering to customer, is continuous across both (Chandra et al., 2022). Recent work that situates personalization explicitly within the customer journey reframes it as AI-enabled personalization, a capability that adapts profiling, guidance, nudging and retention to the customer's position in the journey rather than to a fixed profile, which sharpens the contrast between this dynamic form and its rule-based predecessor (Gao and Liu, 2023).

The relationship between personalization and customer experience is not automatically positive. Research on the so-called personalization paradox shows that personalization improves responses when customers trust the firm and understand why their data is being used, but can provoke discomfort and reactance when it appears intrusive or when the collection of data is opaque (Aguirre et al., 2015). Personalization is therefore best understood as a capability that creates value conditionally, depending on relevance, transparency and the customer's sense of control, a theme that becomes more acute once AI intensifies the practice.

Role of data-driven insights and segmentation

Personalization depends on the ability to derive insight from data about customers. At its core lies segmentation, the grouping of customers according to shared characteristics or behaviours so that treatment can be differentiated. Traditional segmentation relied on demographic or geographic variables and on relatively stable categories. The growth of digital interaction has made behavioural and transactional data far more abundant, enabling segmentation based on what customers actually do rather than only on who they are, and supporting more dynamic groupings that change as behaviour changes (Wedel and Kannan, 2016).

The wider movement towards data-driven decision making has reinforced this shift. Evidence from large samples of firms indicates that organisations adopting data-driven approaches tend to perform better on measurable outcomes, which has encouraged investment in analytics across many sectors (Brynjolfsson and McElheran, 2016). In marketing specifically, the analysis of large and varied customer data has been argued to transform how firms understand and respond to consumers, moving from periodic studies towards continuous insight (Erevelles et al., 2016). For personalization, the practical implication is that the quality of the experience offered depends heavily on the quality, integration and interpretation of the underlying data.

This dependence is a double-edged condition for SMEs. On one hand, the techniques of data-driven segmentation are increasingly embedded in affordable platforms, lowering the barrier to entry. On the other hand, smaller firms often lack the integrated data and the analytical skill to exploit these techniques fully, so that the gap between what personalization could achieve and what a given SME can actually do may widen even as tools become cheaper (Coleman et al., 2016). The role of AI, discussed later, is partly to narrow that gap by automating the derivation of insight from data, but the discussion in this chapter establishes that data and capability, not technology alone, are the binding constraints.

A further complication is that personalization across multiple channels requires those channels to be coordinated, an aspiration usually described as omnichannel integration. Customers who move between a website, a social media page and a physical interaction expect to be recognised as the same person throughout, yet most firms, and SMEs in particular, manage these channels through separate systems that do not share a customer identity (Hagberg et al., 2016; Verhoef et al., 2021). The result is that personalization is often channel-bound, relevant within a single touchpoint but incoherent across the journey as a whole. The literature on digital transformation argues that integrating channels and data is one of the central organisational challenges firms face, and that the difficulty is as much about coordination and legacy systems as about technology, which is precisely why it weighs heavily on smaller firms with limited capacity to redesign their systems (Verhoef et al., 2021; Kraus et al., 2022).

1.3 SME Constraints and Opportunities

Resource limitations, data accessibility, and scalability challenges

SMEs face a set of interlocking constraints that shape what is realistic for them in journey mapping and personalization. The most obvious is resource limitation: smaller firms have tighter budgets, fewer staff and little or no specialist analytical capacity, which restricts both the tools they can afford and their ability to use those tools well (Taiminen and Karjaluoto, 2015). Hiring data scientists or building bespoke systems is rarely feasible, so smaller firms typically depend on packaged software and on the analytical features that platform providers choose to offer.

A second constraint concerns data accessibility. SMEs generate data, but it is frequently locked in separate systems that do not communicate, and the volume associated with any individual customer is small. This fragmentation makes it difficult to assemble the integrated view of the journey that mapping and personalization require, and the limited volume can undermine the reliability of statistical or machine learning methods that depend on large samples (Coleman et al., 2016). Dependence on external platforms compounds the problem, because much of the most valuable behavioural data, for example interactions on social media or marketplaces, is held by intermediaries and is accessible to the SME only on the terms those intermediaries set.

A third constraint is scalability. Smaller firms can deliver highly personalized experiences manually when customer numbers are low, but this craft approach does not scale: as the firm grows, the same attentiveness cannot be sustained without systems, and yet the firm may not have crossed the threshold of data and resources at which automated approaches become reliable (Reim et al., 2020). The literature thus describes a characteristic middle ground in which SMEs are too large for purely manual personalization but too small or under-resourced for the data-intensive methods used by large enterprises, a tension that AI is often proposed to resolve.

Strategic advantages of agility and customer intimacy in SMEs

The picture is not solely one of disadvantage. SMEs possess strategic advantages that are directly relevant to the customer journey, and the evidence suggests these advantages can offset some of their resource constraints. The first is agility. Smaller firms have shorter decision chains and less bureaucratic inertia, which allows them to experiment, adjust and respond to customer feedback more quickly than large organisations can (Drydakis, 2022). In a domain where the journey is dynamic and the relevance of touchpoints shifts, the ability to act quickly on what is learned is itself valuable.

The second advantage is customer intimacy. Because they serve fewer customers and often interact with them directly, SME owners and staff frequently hold detailed, tacit knowledge of their customers' preferences, histories and circumstances. This relational knowledge is a form of personalization that large firms struggle to replicate, and it can substitute, within limits, for the formal data that smaller firms lack (Becker and Jaakkola, 2020). The strategic question for an SME contemplating AI is therefore not only how to compensate for weaknesses but how to amplify these existing strengths, using technology to extend agility and intimacy across a larger base rather than to replace them.

Framing the situation in this way reframes the role of AI for smaller firms. Rather than positioning AI as a means of imitating large-enterprise analytics, the literature increasingly suggests that its most plausible contribution to SMEs is to make their native advantages scalable: to capture and reuse the relational knowledge that currently resides in individuals, and to support rapid, informed responses to customers without requiring the firm to become data-rich in the manner of a large corporation (Reim et al., 2020; Drydakis, 2022). The most recent work on generative artificial intelligence reinforces this reading, arguing that the latest tools can democratise scalability and creativity for firms with little technical expertise or capital, allowing smaller firms to streamline routine work and widen their reach without the specialist infrastructure on which larger competitors depend (Rajaram and Tinguely, 2024).

1.4 The Need for AI in Customer Journey Optimization

Limitations of traditional customer journey mapping methods

Traditional journey mapping, whether the elaborate version practised by large firms or the intuitive version common in SMEs, suffers from limitations that become more pronounced as customer behaviour grows more complex. The first is that a map is usually a static artefact. It captures the journey at a moment in time and is updated infrequently, yet the journey itself is continuous and changing, so the map quickly diverges from reality (Følstad and Kvale, 2018). The second is that maps are often built from assumptions and from selective evidence rather than from systematic observation of actual behaviour, which means they may encode what managers believe customers do rather than what they actually do (Rosenbaum et al., 2017).

A third limitation concerns attribution. Because customers interact through many touchpoints, it is difficult to know which contacts genuinely influence outcomes and which merely accompany them. Manual mapping rarely resolves this, and even formal attribution modelling is technically demanding and contested (Anderl et al., 2016). For SMEs, the difficulty is sharper: with fragmented data and no analytical staff, they typically cannot trace the path that leads to conversion or loss, and so cannot confidently identify which touchpoints to improve. The result is that effort is allocated on the basis of intuition or of the most visible channels, rather than of demonstrated importance.

These limitations are not arguments against journey mapping but against treating it as a one-off, assumption-driven exercise. They point towards a need for mapping that is continuously informed by behavioural data, that distinguishes influential from incidental touchpoints, and that can keep pace with change. This is the gap that AI-based methods are claimed to fill, and assessing that claim is the task of the next chapter.

Emerging demand for predictive and prescriptive approaches

The constraints of traditional mapping have generated demand for two related but distinct analytical capabilities. The first is prediction: the use of historical and current data to estimate what a customer is likely to do next, such as which product they may want, whether they are at risk of abandoning the journey, or which channel they are likely to use (Shmueli and Koppius, 2011). Prediction shifts mapping from a backward-looking description towards a forward-looking anticipation, allowing a firm to prepare for the next stage of the journey rather than only to record the last one.

The second capability is prescription: moving from estimating what is likely to happen to recommending what the firm should do about it. Prescriptive approaches use the outputs of predictive models, together with rules and objectives, to suggest concrete actions, such as the timing, channel and content of an intervention at a particular touchpoint. The distinction matters because a prediction has no value unless it informs an action, and translating predictions into well-judged actions is a separate and often harder problem (Davenport et al., 2020). The literature on analytics maturity treats predictive and prescriptive capability as more advanced stages that build on descriptive foundations, and notes that many organisations, especially smaller ones, remain at the descriptive level (Wedel and Kannan, 2016).

For SMEs, the appeal of predictive and prescriptive approaches lies precisely in their potential to compensate for the firm's limitations: to extract more value from limited data, to direct scarce resources towards the touchpoints that matter, and to act with the speed that smaller firms can uniquely offer. Whether AI delivers on this potential, and through which technologies and frameworks, is examined in Chapter 2, which moves from these foundations to the specific mechanisms by which artificial intelligence predicts and prescribes optimal touchpoints.

Chapter 2: AI-Driven Approaches to Predicting and Prescribing Touchpoints

Chapter 1 established that traditional journey mapping and personalization reach their limits where behaviour is complex, data is fragmented and resources are scarce, and that this gap creates demand for predictive and prescriptive capabilities. This chapter examines how artificial intelligence is claimed to meet that demand. It begins with the core technologies and their role in customer experience, then considers how AI enhances journey mapping, what personalization frameworks suit SMEs, how optimal touchpoints can be predicted and then prescribed, and finally the technological limitations and ethical concerns that qualify the whole enterprise.

2.1 Artificial Intelligence in Customer Experience

Core AI technologies: machine learning, NLP, predictive analytics

The term artificial intelligence covers a family of technologies rather than a single tool, and distinguishing among them is necessary to understand what AI can contribute to customer experience. Machine learning, the most relevant branch for this discussion, refers to methods that learn patterns from data rather than following explicitly programmed rules, and that improve as more data becomes available (Davenport et al., 2020). Supervised learning uses labelled examples to predict outcomes such as whether a customer will churn, while unsupervised learning identifies structure in unlabelled data, for example by grouping customers into segments. These methods underpin most of the predictive capability discussed later in the chapter.

Natural language processing (NLP) enables systems to interpret and generate human language, which is central to customer experience because so much interaction occurs through text and speech. NLP supports the analysis of reviews, messages and social media to infer sentiment and intent, and it powers conversational interfaces such as chatbots and virtual assistants that interact with customers directly (Adam et al., 2021). Predictive analytics, finally, is less a distinct technology than an application of statistical and machine learning methods to forecasting, and it is the capability that converts accumulated behavioural data into estimates of future behaviour (Shmueli and Koppius, 2011). A useful way to organise these technologies is to see them as performing tasks of increasing complexity, from recognising patterns, to predicting outcomes, to engaging customers and even shaping their decisions, a progression that mirrors how AI moves from mechanical to more thinking and feeling tasks (Huang and

Rust, 2018). A more recent development, generative artificial intelligence, has moved quickly from research into practice since 2023 and extends this set of capabilities by producing new content, such as text, images and tailored messages, rather than only classifying or predicting; because its outputs are generated rather than retrieved, it opens fresh possibilities for customer communication while raising new questions about accuracy and the degree of human oversight required (Grewal et al., 2025).

Building on this view, a strategic reading of AI in marketing distinguishes several kinds of intelligence that differ in what they can do for the customer relationship. Mechanical intelligence performs standardised, repetitive tasks such as routing enquiries or sending scheduled messages; analytical or thinking intelligence processes data to learn, reason and predict, which is the form most relevant to journey analysis and touchpoint optimization; and more advanced intuitive and empathetic intelligence would adapt to context and respond to emotion, capabilities that remain only partially realised in practice (Huang and Rust, 2021). The value of the distinction for SMEs is that it separates what AI reliably does today, mechanical automation and analytical prediction, from what is still aspirational, namely genuine empathy and judgement, and so guards against the assumption that adopting AI delivers the relational sensitivity on which smaller firms depend. The evidence suggests that the empathetic dimension of customer experience continues to rest largely with people, and that AI contributes most where analytical and mechanical tasks can be offloaded to free human attention for the interactions that matter (Huang and Rust, 2018; Wirtz et al., 2018).

AI's role in enhancing service delivery and personalization

Across these technologies, the contribution of AI to customer experience can be understood through a small number of recurring roles. The first is scale: AI allows the kind of individualised attention that was previously possible only in small numbers to be extended across large customer bases, automating tasks such as segmentation, recommendation and response that would otherwise be infeasible (Huang and Rust, 2021). The second is speed: AI can analyse behaviour and respond in real time, enabling interventions at the moment a customer is engaged rather than after the fact (Hoyer et al., 2020). The third is anticipation: by predicting needs and intentions, AI shifts service from reactive to proactive, allowing firms to address customers before problems arise or opportunities pass.

Empirical and conceptual work agrees that these roles can improve experience, but it also stresses that the effect is not uniform. Consumers respond to AI-mediated interactions in complex ways, sometimes valuing the convenience and relevance, sometimes resenting the loss of human contact or feeling that they are being watched or manipulated (Puntoni et al., 2021). The experiential perspective on AI argues that the same capability can be perceived very differently depending on whether the customer feels served or surveilled, exploited or empowered, which means that the design and framing of AI-mediated experiences matter as much as the underlying technical performance (Puntoni et al., 2021; Ameen et al., 2021). For SMEs, this is a reminder that adopting AI is not only a technical decision but a relational one, with direct consequences for the trust on which smaller firms particularly depend.

2.2 AI-Enhanced Customer Journey Mapping

How AI tools anticipate and respond to consumer behaviour

AI changes journey mapping most fundamentally by altering what a map is. Where a traditional map is a static representation built from assumptions and periodic research, an AI-enhanced map is continuously updated from behavioural data, so that it reflects how customers are actually moving through the journey at a given time (Hoyer et al., 2020). Machine learning models can identify the paths customers commonly take, detect where they hesitate or drop out, and recognise patterns that human analysts would not see in fragmented data. This converts the map from a design artefact into a living analytical capability that tracks the journey as it unfolds.

Beyond observation, AI allows the journey to be anticipated. By learning from past journeys, models can estimate where a given customer is likely to go next and what they are likely to need, enabling the firm to prepare or trigger an appropriate response (Davenport et al., 2020). Natural language processing extends this to the large volume of unstructured signals customers produce, such as enquiries, reviews and messages, allowing the firm to infer intent and sentiment and to fold these into the picture of the journey (Adam et al., 2021). The combination of behavioural prediction and language understanding means that AI-enhanced mapping is not only more current than its manual predecessor but also forward-looking in a way that manual mapping cannot be. Studies of adoption add an important qualification: introducing AI tools into the journey does not by itself enhance it, because the same tools can either smooth a customer's progress or, by adding steps and heightening privacy concerns, make the journey more complex, so the value AI creates depends on how its adoption is managed rather than on the technology alone (Dhiman et al., 2023).

The evidence suggests this addresses several of the limitations identified in Chapter 1. Continuous updating counters the staleness of static maps; learning from actual behaviour counters the reliance on assumption; and pattern detection across channels begins to address the attribution problem by revealing which sequences of touchpoints precede desired and undesired outcomes (Anderl et al., 2016). These improvements respond directly to RQ1, indicating that AI improves journey mapping in SMEs principally by making it continuous, behaviourally grounded and anticipatory rather than periodic, assumption-led and retrospective, provided the firm can supply and integrate the necessary data.

Predictive analytics for touchpoint optimization

Within enhanced mapping, predictive analytics has a specific role: estimating the value and likely effect of individual touchpoints so that the firm can decide where to concentrate effort. Rather than treating all touchpoints as equally important, predictive models can estimate the probability that a given contact, at a given stage, contributes to progression towards conversion or loyalty, drawing on the historical association between touchpoint sequences and outcomes (Anderl et al., 2016; Wedel and Kannan, 2016). This is the analytical basis for touchpoint optimization, the redirection of resources from touchpoints that look busy but do little towards those that demonstrably move customers forward.

The literature on marketing analytics emphasises that this is more than measuring channel performance in isolation. Because touchpoints interact, the contribution of any one of them depends on the others around it, and predictive attribution methods attempt to capture these interactions rather than crediting outcomes to a single last contact (Anderl et al., 2016). For SMEs, full attribution modelling may exceed available capability, but even simpler predictive approaches embedded in marketing platforms can indicate, for example, which messages or moments are associated with continued engagement, giving smaller firms a more evidential basis for allocating effort than intuition alone provides. The point that the analysis highlights is that prediction reframes touchpoints as a portfolio to be optimised rather than a list to be maintained.

A further consequence concerns timing. Because much customer behaviour now unfolds in digital channels where activity can be observed as it happens, the value of a prediction depends partly on how quickly it can be acted upon (Hoyer et al., 2020). Models that estimate, in the moment, whether a visitor is likely to abandon a basket or respond to a prompt allow the firm to intervene while the journey is still in motion rather than reconstructing it afterwards. The literature on enhanced mapping increasingly treats this orchestration of touchpoints in close to real time as the distinguishing feature of AI-supported journeys, since it is the capacity to respond within the customer's own timeframe, rather than the sophistication of any single model, that separates a living map from a static diagram (Chung et al., 2016; Becker and Jaakkola, 2020).

2.3 Personalization Frameworks for SMEs

Key elements: data integration, dynamic segmentation, personalized offers, real-time support

Translating AI capability into personalization requires a framework that connects data to action, and several elements recur in the literature as constitutive of effective AI-driven personalization. The first is data integration. Because personalization depends on a coherent view of the customer, and because SME data is typically fragmented, integrating data from the website, transactions, communications and service interactions into a usable whole is a precondition rather than an optional refinement (Coleman et al., 2016; Kannan and Li, 2017). Without it, AI operates on partial signals and produces partial personalization.

The second element is dynamic segmentation. AI enables groupings that update as behaviour changes, rather than fixed categories defined once and left in place, allowing the firm to treat a customer differently as their situation evolves through the journey (Wedel and Kannan, 2016; Chung et al., 2016). The third is the generation of personalized offers and content, in which recommendation systems and adaptive messaging match the offering to the inferred preferences of the individual; foundational and contemporary work alike shows that such matching improves response when it reflects genuine relevance (Ansari and Mela, 2003; Chandra et al., 2022). The fourth element is real-time support, typically delivered through conversational interfaces that respond to customers at the moment of need and that can themselves gather data feeding back into the other elements (Adam et al., 2021).

Read together, these elements describe a cycle rather than a checklist: integrated data supports dynamic segmentation, which informs personalized offers and real-time support, which in turn generate further data. For SMEs, the practical implication is that personalization frameworks should be assembled from accessible platform capabilities organised around this cycle, rather than acquired as a single sophisticated system, because the binding constraint is integration and coherence rather than algorithmic novelty (Reim et al., 2020).

The real-time support element merits particular attention in the SME context because it is where AI most visibly enters the customer's experience. Conversational agents and chatbots have moved from scripted question-and-answer tools towards systems able to interpret intent and sustain a degree of dialogue, and the service literature treats them as a way of extending availability and responsiveness without a proportional increase in staffing (Wirtz et al., 2018; Adam et al., 2021). For a small firm this is significant, because it allows a level of presence at the point of need that would otherwise require resources the firm does not have. The same literature is careful to note the limits: customers value the speed of automated support but resent it when it obstructs access to a person for problems that warrant one, so the design question is less whether to automate contact than how to combine automated and human response so that each is used where it serves the customer best (Wirtz et al., 2018). A recent systematic review of AI-empowered conversational agents confirms both the appeal and the limits: adoption is driven by convenience and constant availability, but it is shaped strongly by whether customers trust the agent and feel understood, which keeps the design of these tools, and not merely their deployment, central to the value they create (Mariani et al., 2023).

AI-driven tactics: profiling, navigation, nudging, retention

Within such a framework, AI supports a set of tactics that map onto different phases of the journey. Profiling uses behavioural and transactional data to build and continuously refine a picture of each customer, which underpins all subsequent personalization (Chandra et al., 2022). Navigation refers to guiding customers through the journey, for example by surfacing relevant products or content that reduce the effort of search and choice; interactive decision aids of this kind have long been shown to improve the quality and ease of online decision making (Häubl and Trifts, 2000).

Nudging applies insights about choice architecture, using the timing and framing of prompts to encourage particular actions without removing the customer's freedom to choose (Thaler and Sunstein, 2008). In an AI-driven setting, nudges can be personalized and triggered by predicted behaviour, for example a reminder when a model estimates that a customer is about to abandon a journey. Retention tactics use predictive models to identify customers at risk of disengaging and to direct attention or incentives towards them before they are lost, which is particularly valuable for SMEs given the high relative cost of acquiring new customers. The literature treats these tactics as complementary rather than alternative, and notes that their legitimacy depends on whether customers perceive them as helpful or manipulative, an issue returned to in the discussion of ethics (Puntoni et al., 2021).

2.4 Predicting Optimal Touchpoints

Models for touchpoint prediction based on customer behaviour patterns

Predicting optimal touchpoints means estimating, for a given customer and moment, which contact through which channel is most likely to advance the relationship. The models that support this draw on patterns in past behaviour: sequences of interactions, responses to previous contacts, timing, and contextual signals. Supervised learning can be trained on historical journeys in which outcomes are known, learning the association between touchpoint patterns and results such as purchase, repeat purchase or churn (Shmueli and Koppius, 2011; Ngai and Wu, 2022). Graph-based and sequence-based attribution methods specifically model the journey as a path, capturing the order and interaction of touchpoints rather than treating them as independent (Anderl et al., 2016).

The quality of such prediction depends heavily on data, and this is where the SME context imposes real limits. Models that excel with the large, integrated datasets of major firms may be unreliable when trained on the smaller, fragmented data typical of smaller firms, because patterns estimated from few observations are unstable (Coleman et al., 2016). The literature on machine learning in marketing accordingly cautions against assuming that predictive performance transfers across settings and stresses the importance of matching model complexity to the available data (Ngai and Wu, 2022). For SMEs, the realistic prospect is not bespoke, highly accurate models but the predictive features increasingly built into affordable marketing and e-commerce platforms, which apply learning across many firms' data and so partly overcome the small-data problem of any single firm.

In concrete terms, the predictions most relevant to touchpoint optimization fall into a few recurring types. Propensity models estimate the likelihood that a customer will take a desired action, such as making a first purchase or responding to a particular offer, allowing effort to be concentrated where it is most likely to pay off. Churn or disengagement models estimate the probability that a customer will lapse, supporting timely retention efforts before the relationship is lost (Ngai and Wu, 2022). Recommendation systems predict which products or content an individual will find relevant, drawing on the behaviour of similar customers, and have become one of the most visible applications of predictive personalization (Ansari and Mela, 2003; Chandra et al., 2022). Each of these tasks can in principle inform which touchpoint to activate, but each also illustrates the cold-start problem that affects smaller firms: when a customer or a firm has little history, predictions are weak, which is one reason platform-pooled models that borrow strength from many firms' data are often more workable for an SME than models built on its own data alone.

Phases of customer journey mapping addressed by AI: discovery, value-adding, conversion, loyalty, advocacy

Predictive touchpoint models can be related to the journey phases introduced in Chapter 1, because the most valuable prediction differs by phase. In discovery, prediction concerns reaching the right prospects through the right channels, and AI supports this by identifying which audiences and content are likely to generate qualified awareness (Kannan and Li, 2017). In the value-adding stage of consideration, prediction concerns which information, comparisons or reassurances a customer needs in order to move forward, allowing the firm to supply relevant content at the moment of evaluation (Häubl and Trifts, 2000).

At conversion, prediction focuses on identifying customers who are close to deciding and on the interventions most likely to reduce friction at the decisive moment, including the timing of a prompt or an offer. In loyalty, prediction shifts to anticipating disengagement and to recognising opportunities for repeat purchase, while in advocacy it concerns identifying satisfied customers most likely to recommend the firm and the moments at which encouragement to do so is well received (Lemon and Verhoef, 2016). Organising prediction by phase in this way clarifies that touchpoint optimization is not a single model but a set of phase-specific estimations, and it directly addresses RQ2 by showing that AI predicts behaviour and optimises touchpoints differently across the journey rather than uniformly.

2.5 Prescribing Actionable Touchpoints

From prediction to prescription: AI recommendations for touchpoint timing and content

Prediction estimates what is likely; prescription recommends what to do, and the move between them is where AI begins to act on the journey rather than only to describe it. A prescriptive system takes the outputs of predictive models, combines them with the firm's objectives and constraints, and recommends a specific action: which message to send, through which channel, with what content, at what time (Davenport et al., 2020). In practice this often takes the form of automated recommendation and orchestration, in which the system selects the next best action for each customer based on their predicted state, and adapts as new behaviour is observed (Chung et al., 2016).

The literature is careful to note that prescription is harder and riskier than prediction. A prediction can be evaluated against what subsequently happens, but a prescription embeds a judgement about what is desirable and about cause and effect, and a recommendation that is accurate as a forecast may still be wrong as an action if it ignores context or the customer's tolerance (Davenport et al., 2020; Puntoni et al., 2021). Prescription also raises the stakes of error, because the system acts on the customer rather than merely informing the firm. For SMEs, prescriptive automation is attractive because it promises to convert limited analytical capability directly into action without requiring expert interpretation at each step, but the same automation reduces the human oversight that has traditionally protected smaller firms' close relationships, which makes the design of when to automate and when to defer to a person a central question.

A recurring expression of prescription in practice is the idea of a next best action, in which a system continuously selects, for each customer and moment, the intervention expected to be most valuable given the customer's predicted state and the firm's objectives. Adaptive approaches go further by learning from the response to each action and adjusting future recommendations accordingly, so that personalization becomes a feedback loop rather than a fixed rule, an approach demonstrated in work on adaptive personalization that updates as it observes outcomes (Chung et al., 2016). The appeal for SMEs is that such systems can orchestrate the journey across touchpoints without constant manual decision making. The caution that the literature attaches is that adaptive optimisation tends to pursue whatever objective it is given, so that a system optimised narrowly for short-term conversion may erode longer-term trust if the objective does not also reflect the quality of the relationship (Puntoni et al., 2021). Defining the objective well, and not only the algorithm, is therefore part of prescribing responsibly.

Enhancing customer satisfaction, retention, and engagement through hyper-personalization

The intended outcome of moving from prediction to prescription is a more relevant, timely and coherent experience, often described as hyper-personalization, in which each interaction is adapted to the individual customer's current context rather than to a broad segment (Chandra et al., 2022). The argument, supported across the customer experience literature, is that greater relevance increases satisfaction, that satisfied customers are more likely to remain and to engage further, and that AI makes this degree of relevance achievable at a scale beyond manual effort (Hoyer et al., 2020; Homburg et al., 2017). Evidence on online customer experience indicates that experiences which are coherent and responsive to the individual tend to produce stronger engagement and loyalty (Bleier et al., 2019).

This is the substance of RQ3, and the evidence indicates a conditional answer. AI-driven personalization can enhance satisfaction, retention and engagement when it is genuinely relevant and is perceived as helpful, but the same intensity of personalization can depress these outcomes when it crosses into intrusion or when customers feel manipulated, the personalization paradox in a sharper form (Aguirre et al., 2015; Puntoni et al., 2021). The relationship between hyper-personalization and customer experience is therefore not linear; beyond a point, more personalization may reduce rather than increase value. For SMEs, whose principal asset is trust, the discussion points towards a measured use of prescription that preserves the relational character of the firm rather than an unconditional pursuit of maximal personalization.

If prescription is to be used responsibly, it has to be evaluated, and the literature suggests that this is where smaller firms have an underappreciated advantage. Because a prescriptive system acts, its effects can in principle be tested: an action can be applied to some customers and withheld from comparable others, and the difference in outcome observed, which turns personalization from an assertion into something that can be checked against evidence (Wedel and Kannan, 2016). Large organisations conduct such testing at scale, but the underlying logic is not expensive, and platform tools increasingly make lightweight comparison available to firms without analytical teams. The value for an SME is twofold: it disciplines the objective, by forcing an explicit statement of what a touchpoint is meant to achieve, and it guards against the quiet drift in which an automated system continues to act long after the behaviour it was built to exploit has changed. The analysis highlights that the firms most likely to benefit from prescription are not those with the most sophisticated models but those that treat each prescribed action as a claim to be verified rather than a setting to be left running.

2.6 Challenges and Ethical Considerations

Technological limitations of AI in brand–customer relationships

Several technological limitations qualify the contribution AI can make, and they bear especially on SMEs. The first is data dependence: AI methods require data of sufficient quantity and quality, and the fragmented, limited data of smaller firms can render models unreliable, biased or simply inapplicable (Coleman et al., 2016; Ngai and Wu, 2022). The second is the difficulty of integration and skills: deploying AI is not only a matter of algorithms but of connecting systems, maintaining them and interpreting their output, capabilities that smaller firms frequently lack and that platform providers supply only partially (Reim et al., 2020; Drydakis, 2022).

A third limitation concerns the relationship between AI and the human element of brand–customer relationships. Research on consumer responses to AI shows that customers sometimes prefer human interaction and may resist algorithmic involvement in tasks they regard as personal or important, a tendency described as algorithm aversion (Dietvorst et al., 2015; Castelo et al., 2019; Longoni et al., 2019). For SMEs whose advantage rests on personal relationships, substituting AI for human contact can therefore erode the very intimacy that distinguishes them, even where it improves efficiency. The analysis suggests that AI is best positioned as an augmentation of the relationship rather than a replacement, supporting staff and extending their reach rather than removing them from the customer's experience (Huang and Rust, 2021).

Privacy concerns and perceived surveillance in AI-driven personalization

The ethical centre of AI-driven personalization is the use of personal data, and the tension it creates is well established: personalization requires knowledge of the customer, but acquiring and using that knowledge can violate the customer's expectations of privacy. Research on data privacy in marketing shows that customers care not only about what data is collected but about how transparently and fairly it is used, and that perceived violations damage trust and firm performance (Martin and Murphy, 2017; Martin et al., 2017). When personalization feels like surveillance, its benefits are offset or reversed, returning to the personalization paradox identified earlier (Aguirre et al., 2015).

Broader work on privacy and behaviour adds that customers' privacy preferences are unstable and context-dependent, so that the same practice may be welcomed in one setting and resented in another, which makes simple rules inadequate and places a premium on transparency and control (Acquisti et al., 2015). The literature on the ethics of AI in consumer markets frames these issues as genuine paradoxes rather than problems with clear solutions, noting that AI simultaneously offers consumers value and exposes them to risks of manipulation, exclusion and loss of autonomy (Du and Xie, 2021; Puntoni et al., 2021). Regulatory developments, most prominently data protection regimes, formalise some of these expectations, but compliance is a floor rather than a guarantee of trust. Recent evidence on AI-enabled personalization sharpens this tension, showing that highly personalized offers can advance or set back the relationship much like a game of snakes and ladders, depending on whether customers read them as helpful or intrusive, and that the same offer may be welcomed or rejected according to context and the perceived sensitivity of the data involved (Canhoto et al., 2024).

Two further concerns deserve mention because they are easy to overlook in smaller firms. The first is bias and fairness: because machine learning reproduces the patterns in its training data, personalization can inadvertently disadvantage some customers, for example by systematically showing them fewer opportunities or less favourable treatment, and the firm may not notice because the logic is opaque (Du and Xie, 2021). The second is accountability under data protection regulation, which in many jurisdictions grants individuals rights over their data and expects firms to justify automated decisions; for an SME with no legal or technical specialists, meeting these expectations is itself a capability problem rather than a mere formality (Martin et al., 2017; Acquisti et al., 2015). Neither concern argues against AI, but both reinforce the conclusion that responsible personalization requires deliberate governance, including attention to what data is collected, how decisions are explained, and whether outcomes are fair, rather than trusting that an automated system will be benign by default.

For SMEs the ethical dimension is not peripheral but strategic. Because their competitive position depends on close and trusting relationships, a breach of privacy expectations is more damaging to a smaller firm than to a large one whose relationships are already more impersonal. The discussion points towards responsible personalization, in which SMEs collect only the data they need, are transparent about its use, give customers meaningful control, and reserve human judgement for sensitive decisions, as not merely an ethical obligation but a condition of realising the benefits of AI without undermining the trust on which those benefits depend. This provides the substance of RQ4, indicating that the opportunities of AI-driven personalization are inseparable from limitations of data and capability and from ethical challenges of privacy, transparency and the preservation of the human relationship.

Conclusion

Summary of key literature findings

This thesis set out to understand how artificial intelligence reshapes customer journey mapping and personalization in SMEs, drawing on a structured reading of marketing, service and information systems research. The analysis supports four broad findings. First, customer journey mapping has evolved from a static, design-oriented artefact into a continuously updated, behaviourally grounded capability, and AI is the principal driver of that shift, addressing RQ1 by making mapping current, evidential and anticipatory rather than periodic and assumption-led. Second, AI improves the analysis of customer behaviour by detecting patterns across fragmented signals and by predicting what customers are likely to do, which addresses RQ2 by enabling touchpoints to be optimised differently across the phases of the journey rather than treated as a uniform list.

Third, the evidence on personalization indicates that its effect on customer experience is conditional rather than automatic. AI-driven personalization can raise satisfaction, retention and engagement when it is genuinely relevant and is perceived as helpful, but the same intensity of personalization can reduce these outcomes when it is experienced as intrusive or manipulative, which gives a qualified answer to RQ3 and identifies the personalization paradox as a central constraint. Fourth, the opportunities of AI for smaller firms are inseparable from real limitations of data and capability and from ethical challenges of privacy, transparency and the preservation of human relationships, which addresses RQ4 and frames responsible personalization as a condition of value rather than an external obligation.

Integration of AI-driven customer journey mapping and personalization for SMEs

Read as a whole, the literature suggests that journey mapping and personalization should not be treated as separate activities that AI happens to support, but as two halves of a single cycle. Mapping supplies the understanding of where customers are and what they need; personalization acts on that understanding; and the results of action feed back into the map. AI strengthens both halves and tightens the loop between them, converting observation into prediction, prediction into prescription, and prescription into fresh data. For SMEs the integrating insight is that the value of AI depends less on the sophistication of any individual model than on the coherence of this cycle: on integrated data, on capabilities matched to the firm’s scale, and on governance that protects trust.

This reframes the strategic role of AI for smaller firms identified in Chapter 1. Rather than imitating the data-intensive analytics of large enterprises, the more plausible path for an SME is to use accessible, platform-embedded AI to make its native advantages of agility and customer intimacy scalable, capturing relational knowledge that currently resides in individuals and acting on it quickly across a larger base. The discussion points towards augmentation rather than substitution: AI that extends the reach of people who already know their customers, rather than AI that removes them from the relationship.

Research gaps identified for future study

The analysis exposes several gaps that the current literature leaves open. The most striking is the scarcity of evidence specific to SMEs; much of the work on both customer journeys and AI in marketing is based on large organisations, and its transfer to resource-constrained firms is assumed more often than demonstrated. There is a corresponding need for research that takes seriously the small-data condition of SMEs and that evaluates which AI approaches remain reliable when data is limited and fragmented. The most recent reviews of artificial intelligence in the customer journey reach a similar conclusion, mapping a literature that is expanding quickly yet remains thinly populated with studies of smaller firms, and work specifically on generative AI in SMEs likewise treats their distinctive conditions as promising but under-examined (Gouveia and Santos, 2025; Rajaram and Tinguely, 2024). A second gap concerns the boundary between prediction and prescription: the literature theorises the distinction but offers little guidance on when prescriptive automation is appropriate for smaller firms and when human judgement should be retained, particularly given the relational basis of SME competition.

A third gap lies in the measurement of effects. Because this thesis is literature-based, it can establish what the evidence suggests but not quantify outcomes for SMEs specifically, and the field would benefit from empirical studies that measure how AI-driven journey mapping and personalization affect satisfaction, retention and performance in smaller firms under realistic conditions. A fourth gap concerns the ethics of personalization at the scale of the SME, where the consequences of privacy breaches for trust may differ from those in large firms but have received little dedicated study. These gaps mark natural directions for empirical research that would build on the synthesis offered here.

Implications for SME customer experience strategy

For practice, the analysis yields several implications that follow from the evidence rather than from advocacy. SMEs should treat data integration as the foundation of any AI-driven approach, because coherent personalization is impossible without a coherent view of the customer, and fragmentation rather than algorithmic limitation is usually the binding constraint. They should match their ambitions to their data and capabilities, favouring accessible, platform-embedded AI that pools learning across many firms over bespoke systems that small data cannot support. They should distinguish prediction from prescription and decide deliberately where to automate action and where to keep a person in the loop, protecting the relational intimacy that is their distinctive asset.

Finally, SMEs should approach personalization as a matter of trust as much as of relevance, collecting only the data they need, being transparent about its use, giving customers meaningful control, and treating responsible personalization as a source of advantage rather than a compliance cost. The overall implication is measured rather than promotional: artificial intelligence offers smaller firms a genuine opportunity to understand and personalize the customer journey at a scale previously beyond them, but the realisation of that opportunity depends on data, capability and governance, and on using technology to amplify the human relationship at the heart of the SME rather than to replace it.

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