

Artificial Intelligence in Marketing: Evidence from Slovak Enterprises

Peter Štetka & Federico Banda

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*A firm-level study of adoption, diffusion, perceived value, and adopter
typologies through TOE and DOI lens*

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Data availability

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Data preparation and statistical analyses were performed using standard scientific software. The authors are responsible for all data, analyses, interpretations and conclusions, and have reviewed and approved the final manuscript; any use of digital assistance was confined to routine support and does not affect the integrity or originality of the scientific content.

Abstract

Artificial intelligence (AI) is entering the marketing function quickly, yet firm-level evidence on how companies adopt AI in marketing, as opposed to how consumers react to a single AI tool, remains thin. The gap is widest for small and medium-sized enterprises (SMEs) and for Central and Eastern Europe (CEE). We address it with the AI-IMPACT Survey Dataset (Slovakia, 2025), an organization-level survey of 816 enterprises, of which 562 already use or pilot AI and 209 have begun implementing or testing AI in Marketing and Sales. Working from the Technology–Organization–Environment (TOE) framework and Rogers's Diffusion of Innovations, the study addresses seven research questions and twelve hypotheses covering the adoption landscape, the use-case architecture of fifteen marketing applications, the correlates of adoption and of use-case breadth, the way firms weigh benefits against risks, the perceived value and employment effects, and a data-driven segmentation of adopters. The design is cross-sectional and the measures are self-reported, so the results describe associations and perceptions in this sample rather than causal effects or population parameters.

Marketing and Sales is the most frequently selected functional area for AI among the AI-using firms surveyed (37.2%), ahead of production, logistics, and finance, though the option bundles marketing with sales and is broader than the single functions it outranks; a paired test confirms it is selected more often than production (McNemar $p = .003$). Adoption is recent (68.4% of marketing adopters dated their first AI project to 2023 or later), which mirrors the recency of enterprise AI generally rather than anything specific to marketing. Across the fifteen use cases, customer-facing automation is furthest along, with chatbots, advertising automation, personalized offers, and price optimization in active use by roughly 40–50% of adopters, while data-intensive analytical applications trail and sit mostly in the planning stages. The breadth of active use is most strongly associated with perceived benefit (negative-binomial IRR = 1.51, 95% CI [1.20, 1.89], $p < .001$); firm size and formal AI maturity show no independent association once benefit is included, although, because benefit and breadth are reported by the same respondent, the association is equally consistent with breadth shaping belief. Benefits and risks do not trade off. Firms that rate benefits highly tend also to rate risks highly (Spearman $\rho = .65$, falling to about .47 once a response-style adjustment is applied), benefits exceed risks only modestly (3.62 vs. 3.46; Wilcoxon $p < .001$, $d_z = 0.28$), and organizational "fear" is essentially unrelated to adoption. More intensive use is associated with more favourable perceived outcomes for revenue, productivity, and customer-service quality ($\rho \approx .27$ –.42, all $q < .001$ after correction). On employment, more adopters report adding or planning AI-related roles (22.5%) than report AI-related layoffs, realized or planned (8.6%), which indicates no sign of marketing-led displacement at this stage rather than a measured net employment effect. A two-segment description, here labelled Advanced Integrators (56%) and Cautious Experimenters (44%), captures most of the structure in the adopter population, though the two groups differ in degree of engagement rather than in kind.

The study offers use-case-level evidence on AI in marketing for an under-examined CEE economy, complementing prior CEE work on general MarTech and digital-marketing adoption; it elaborates how TOE and diffusion ideas apply to the breadth and depth of use rather than to adoption alone; and it gives managers, policymakers, and technology providers a grounded read on where the bottlenecks lie. All numerical results, including the multiple-comparison corrections and common-method-bias diagnostics, are documented in an accompanying Master Results Registry, and all literature claims in a Literature Registry of 108 verified sources.

Keywords: artificial intelligence; marketing; AI adoption; diffusion of innovations; TOE framework; SMEs; Slovakia; Central and Eastern Europe; marketing analytics; technology adoption.

List of abbreviations

AI — artificial intelligence; AUC — area under the receiver-operating-characteristic curve; CEE — Central and Eastern Europe; CI — confidence interval; CRM — customer-relationship management; DOI — Diffusion of Innovations (theory); EFA — exploratory factor analysis; GDPR — General Data Protection Regulation; IRR — incidence-rate ratio; KMO — Kaiser–Meyer–Olkin measure; KPI — key performance indicator; ML — machine learning; NACE — statistical classification of economic activities in the European Community; NLP — natural-language processing; OR — odds ratio; RBV — resource-based view; ROI — return on investment; SME — small and medium-sized enterprise; TAM — Technology Acceptance Model; TOE — Technology–Organization–Environment (framework); UTAUT — Unified Theory of Acceptance and Use of Technology.

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We are equally grateful to the enterprises and their representatives who gave their time to respond. Their willingness to describe, candidly, how they actually use artificial intelligence in their day-to-day work is what gives this study its evidentiary base, and we hope the findings repay that openness.

We thank our colleagues and home institutions for the intellectual environment in which this research took shape, and the reviewers whose questions and corrections improved the manuscript in ways large and small. Any errors that remain are, of course, our own.

Finally, and most personally, we thank our families. Their patience, encouragement, and quiet understanding through the long hours that a project like this demands were a gift we did not take for granted. This book is, in no small part, theirs as well.

Foreword

Artificial intelligence has moved, in only a few years, from a specialist concern to an everyday instrument of management and nowhere inside the firm has it arrived faster than in marketing. Yet most of what we know about AI in marketing describes how individual consumers react to a single tool, not how organizations actually take it up. The evidence is thinnest precisely where it would be most useful: among the small and medium-sized enterprises that make up the bulk of the European economy, and across Central and Eastern Europe. This monograph sets out to close part of that gap.

It draws on the AI-ImpactSK survey of 816 Slovak enterprises, 209 of them already using or testing AI in marketing and sales, and reads the evidence through the Technology-Organization-Environment (TOE) framework and Rogers's Diffusion of Innovations (DOI). Across seven research questions it asks where firms begin, which of fifteen marketing use cases they take up, how far they extend them, how they weigh benefits against risks, and what value and employment effects they perceive.

The picture that emerges is of an early but distinct stage of adoption. Marketing is the function most often chosen for AI; uptake is recent and led by customer-facing automation, while the data-intensive analytical applications still sit largely in planning. How far a firm goes turns out to be tied less to its size or its formal AI maturity than to how beneficial it judges the technology to be; benefits and risks rise together rather than trading off; and adopters report adding marketing roles more often than cutting them.

The study is deliberate about its limits. Its design is cross-sectional and its measures are self-reported, so it describes associations and perceptions in one country at one moment rather than causes or population effects. Within those bounds it offers managers a benchmark and a rough segmentation of their peers, policymakers a read on the binding constraints, and technology providers and educators a map of where adoption currently stops.

We offer it, with its limits stated plainly, as a starting point for the longitudinal, cross-country, and outcome-linked work the subject ultimately requires and in the hope that it proves useful to anyone trying to understand how AI is reshaping the marketing function in practice.

Authors

Table of Contents

Abstract.....	5
List of abbreviations	7
Acknowledgements.....	8
Foreword.....	9
1. Introduction	12
1.1 The marketing function as a frontier of enterprise AI.....	12
1.2 Why Slovakia, and why now	12
1.3 Problem statement and research objectives	13
1.4 Contributions	14
1.5 Structure of the monograph	14
2. Conceptual background and literature review.....	15
2.1 Defining artificial intelligence in marketing	15
2.2 The Technology–Organization–Environment framework.....	15
2.3 Diffusion of Innovations	16
2.4 AI marketing use cases, capability, and diffusion.....	17
2.5 Organizational AI maturity and readiness	17
2.6 Sentiment, acceptance, and the benefit–risk calculus.....	18
2.7 Business value, outcomes, and employment	18
2.8 Barriers to adoption	19
2.9 Synthesis and the research gap	19
3. Research questions and hypotheses	20
4. Data and methods.....	22
4.1 The AI-IMPACT survey and dataset	22
4.2 The marketing subsample and its skip-logic provenance	22
4.3 Measures and derived variables	23
4.4 Analytical strategy	24
4.5 Reliability and validity	25
4.6 Limitations of the data and ethical note.....	25

5. Results.....	26
5.1 The adoption landscape: marketing leads, and it is new	26
5.2 A descriptive profile of marketing-AI adopters.....	31
5.3 The diffusion architecture of marketing AI use cases	32
5.4 Predictors of marketing-AI adoption.....	34
5.5 Maturity, sentiment, and the breadth of use	36
5.6 The benefit–risk calculus: dual salience, not trade-off.....	40
5.7 Perceived value and employment effects.....	44
5.8 A typology of marketing-AI adopters	46
5.9 Summary of results.....	48
6. Discussion	49
6.1 Marketing as a common entry point for enterprise AI	49
6.2 What relates to breadth, and what does not.....	49
6.3 Dual salience: benefit and risk rise together	50
6.4 The ownership association	51
6.5 Value with jobs	51
6.6 What the study contributes, and how far	52
7. Implications.....	53
7.1 For managers and marketing leaders	53
7.2 For policymakers	53
7.3 For technology providers and educators.....	54
8. Limitations and future research	55
9. Conclusion	57
References	58
Appendix A. Codebook of derived variables.....	66
Appendix B. Research questions, hypotheses, and verdicts	68

1. Introduction

1.1 The marketing function as a frontier of enterprise AI

Marketing has taken up the recent wave of artificial intelligence visibly and fast. Its raw material is a good match for what current AI does well. Customer data, language, and images, together with the standing problem of spreading finite attention and budget across more and more channels, line up with pattern recognition at scale, natural-language generation and understanding, prediction of discrete behaviours, and the automation of routine judgement. The conceptual literature saw the fit coming. Huang and Rust (2018, 2021) argued that AI advances through successive "intelligences," mechanical, thinking, and feeling, each substituting for or augmenting a different layer of marketing work, from routine automation through data-driven decisions to interaction with customers. Davenport, Guha, Grewal, and Bressgott (2020) set out a framework spanning the level of machine intelligence, the type of task, and whether AI is embedded in a robot or runs as software, and expected AI to reshape both marketing strategy and customer behaviour. A decade of systematic and scientometric reviews has since mapped a fast-moving field (Verma, Sharma, Deb, & Maitra, 2021; Mariani, Perez-Vega, & Wirtz, 2021; Mustak, Salminen, Plé, & Wirtz, 2021), and a recurring observation in them is that the conceptual writing has run ahead of firm-level evidence.

That imbalance is the point of departure for this study. The marketing literature is rich in consumer-side experiments—how shoppers respond to an anthropomorphic chatbot (Araujo, 2018; Adam, Wessel, & Benlian, 2020), how recommendation systems shape choice (Chinchanachokchai, Thontirawong, & Chinchanachokchai, 2021), how disclosing the use of generative AI affects perceived brand authenticity (Brüns & Meißner, 2024)—but comparatively poor in evidence on the organization as the unit of adoption. We know a great deal about whether a given AI marketing tool works on consumers, and far less about *which firms deploy which portfolios of tools, in what sequence, why, and with what perceived consequences*. The gap is most acute precisely where the economic stakes are largest: among the small and medium-sized enterprises that constitute the overwhelming majority of European firms, and in the Central and Eastern European economies whose digital trajectories cannot simply be assumed to mirror those of Western Europe or the United States.

1.2 Why Slovakia, and why now

Slovakia offers an instructive setting for a firm-level study of AI in marketing. It is a small, open, EU-member economy with a manufacturing-heavy industrial base, a dense population of SMEs, and a digital-transformation agenda shaped by both EU policy and the competitive pressures of

regional value chains. Existing CEE evidence has concentrated on Industry 4.0 in manufacturing and logistics (Richnák, 2022; Valášková, Nagy, Zábojník, & Lăzăroiu, 2022), on the digital transformation of human-resource processes (Čirčová, Berešecká, Borsos, & Capošová, 2025), on e-commerce within the EU Digital Single Market (Wiktor, Dado, & Šimberová, 2021), and on the dynamic capabilities of Visegrád SMEs (Civelek, Krajčík, & Ključnikov, 2023; Belás, Klietk, Dvorský, & Streimikiene, 2025). What this body of work does not yet provide is a dedicated, use-case-level account of how enterprises apply AI *in marketing*—the customer-facing function in which AI's consumer-facing capabilities and a firm's internal data assets meet most directly.

The timing is also consequential. The diffusion of generative AI from late 2022 onward lowered the threshold of experimentation for marketing teams dramatically, putting content generation, conversational interfaces, and analytical copilots within reach of firms that had never run a formal data-science project. The AI-IMPACT survey was fielded in 2025, capturing enterprises at the inflection point of this wave. As the results below show, the recency is not incidental: more than two-thirds of Slovak marketing-AI adopters date their first AI project to 2023 or later, which means this study documents the early structure of a diffusion process still very much in motion.

1.3 Problem statement and research objectives

The central problem this study addresses can be stated simply: *we lack firm-level, multi-use-case evidence on how enterprises adopt artificial intelligence in marketing, what drives the breadth and depth of that adoption, how firms weigh its benefits against its risks, and what value and employment consequences they perceive—particularly for SMEs and in the Central and Eastern European context.*

From this problem, the monograph pursues six interlocking objectives:

1. **To map the landscape**—to establish how prevalent and how recent AI adoption in marketing is among Slovak enterprises, and how it ranks against other functional areas.
2. **To characterize the diffusion architecture**—to describe which marketing use cases are actively used versus merely planned, and to test whether they form a coherent latent structure.
3. **To identify the determinants of adoption**—to model, within a TOE logic, which technological, organizational, and environmental factors distinguish firms that apply AI in marketing from other AI-using firms, and which factors drive the breadth of use.
4. **To analyse the benefit–risk calculus**—to measure how firms perceive the benefits and risks of marketing AI, whether benefits dominate, and whether the two trade off or co-occur.

5. **To assess perceived value and employment effects**—to test whether more intensive adoption is associated with more favourable perceived outcomes and to characterize the labour-market footprint.
6. **To derive an adopter typology**—to segment marketing-AI adopters empirically into interpretable types that can inform managerial and policy action.

1.4 Contributions

The study makes four contributions. Empirically, it provides one of the first use-case-level portraits of AI in the marketing function for a CEE economy, based on a large and well-documented enterprise survey, complementing prior regional work on general MarTech and digital-marketing adoption. Conceptually, it applies and elaborates the TOE and diffusion frameworks beyond the usual binary question of whether a firm adopts AI, toward the breadth and depth of use and the structure of benefit–risk perception, and it shows that what relates to "whether" and to "how much" are not the same. Methodologically, it brings descriptive analysis, multivariable regression (logistic and negative-binomial), reliability and factor analysis, correlation analysis, cluster-based segmentation, multiple-comparison correction, and common-method-bias checks into one documented chain, with every statistic externally recorded. Practically, it gives managers a benchmark and a rough segmentation, policymakers a read on the binding constraints, and technology providers a map of where adoption currently stops.

1.5 Structure of the monograph

Chapter 2 develops the conceptual background and reviews the literature across the study's analytical angles, culminating in an explicit statement of the research gap. Chapter 3 formalizes the seven research questions and twelve hypotheses and presents the conceptual model. Chapter 4 describes the AI-IMPACT dataset, the marketing subsample and its skip-logic provenance, the measures and derived variables, the analytical strategy, and the limitations of the data. Chapter 5—the empirical core—presents the results in eight sections, moving from the adoption landscape through the diffusion architecture, the determinants of adoption and breadth, the benefit–risk calculus, perceived value and employment, and finally the adopter typology. Chapter 6 discusses the findings against theory and prior evidence; Chapter 7 draws out implications for managers, policymakers, and providers; Chapter 8 states the limitations and a future-research agenda; and Chapter 9 concludes. References follow in APA 7th-edition style, and appendices provide the derived-variable codebook, the hypothesis-verdict table, and the figure index.

2. Conceptual background and literature review

This chapter situates the study within four bodies of scholarship that correspond to its analytical angles: (i) the theoretical apparatus of technology adoption and diffusion; (ii) AI in marketing as a domain of use cases and capabilities; (iii) organizational AI maturity, sentiment, and the perception of benefits and risks; and (iv) the business value, employment effects, and barriers associated with AI. Each section reviews the state of knowledge, and the chapter closes by synthesizing the research gap that the Slovak evidence is positioned to fill. Throughout, the review is deliberately oriented toward firm-level adoption rather than consumer response, because it is the enterprise—not the individual consumer—that is the unit of analysis in this study.

2.1 Defining artificial intelligence in marketing

"Artificial intelligence in marketing" is best understood not as a single technology but as a portfolio of capabilities applied to marketing tasks. Huang and Rust's (2018) service framework distinguishes mechanical intelligence (standardized, repetitive automation), analytical intelligence (learning and reasoning from data), intuitive intelligence (creative, holistic judgement), and empathetic intelligence (recognizing and responding to emotion); their strategic framework for marketing (Huang & Rust, 2021) collapses these into three practically useful stages—mechanical AI for automating repetitive marketing tasks, thinking AI for processing data into decisions, and feeling AI for two-way interaction with customers. Davenport et al. (2020) complement this with a taxonomy organized by intelligence level, task type (analytical vs. interactive), and embodiment. These frameworks specify *what AI can do* for marketing; they are, however, largely silent on the empirical question that animates this study—*which configurations of these capabilities enterprises actually deploy, and how far up the diffusion ladder each configuration has climbed*. Reviews of the field repeatedly note that practitioners are "still searching for best-fit AI solutions for specific marketing problems" (Verma et al., 2021) and that the literature remains dominated by conceptual contributions and single-tool consumer experiments (Mariani et al., 2021; Mustak et al., 2021).

2.2 The Technology-Organization-Environment framework

The dominant theoretical lens for firm-level technology adoption is the Technology–Organization–Environment (TOE) framework, originated by Tornatzky and Fleischer and consolidated by Baker (2011). TOE holds that a firm's adoption of an innovation is shaped by three contexts: the technological context (the characteristics of the technology relative to the firm's existing stack, such as relative advantage, compatibility, and complexity), the

organizational context (size, slack resources, managerial support, culture, structure), and the environmental context (competitive pressure, regulatory regime, partner and customer readiness). Oliveira and Martins (2011) showed in an influential review that TOE, often combined with the diffusion paradigm, outperforms purely individual-level acceptance models for organizational decisions, and that it travels well across technologies, from electronic business to cloud computing (Oliveira, Thomas, & Espadanal, 2014) and RFID (Wang, Wang, & Yang, 2010).

The framework has been applied to AI specifically with increasing frequency. Chatterjee, Rana, Dwivedi, and Baabdullah (2021) built and tested an integrated TAM–TOE model of AI adoption in manufacturing and production firms; Sharma, Singh, Islam, and Dhir (2022) grounded SME chatbot adoption in TOE and found technological and organizational readiness to be decisive; Badghish and Soomro (2024) modelled AI adoption across six Saudi sectors; and Delgado-Sánchez, Calderón, and Herrera (2025) integrated TOE with diffusion attributes to identify ten critical SME AI-adoption factors—precisely the dual framing adopted here. In the public sector, Neumann, Guirguis, and Steiner (2022) and Mikalef et al. (2021) confirmed that the relative weight of technological, organizational, and environmental factors shifts by context, a caution directly relevant to transferring Western or Asian determinant estimates to a CEE economy.

2.3 Diffusion of Innovations

Where TOE specifies which factors matter, Rogers's Diffusion of Innovations (Rogers, with Singhal & Quinlan, 2019) describes how adoption unfolds over time. Rogers's central claim is that the rate of adoption depends on five perceived attributes of the innovation (relative advantage, compatibility, complexity, trialability, and observability) and that adopters distribute along an S-curve from innovators and early adopters through the early and late majority to laggards. Dahlke et al. (2023) showed empirically that AI adoption among firms follows epidemic-type dynamics, in which prior adoption by others raises the probability of subsequent adoption. The diffusion lens fits marketing AI here in part because the instrument records each use case on a five-stage scale from rejection through consideration and planning to piloting and active regular use, which gives Rogers's qualitative stages a measurable form, though only as a cross-sectional snapshot rather than a true adoption-over-time curve. The Technology Acceptance Model (Davis, 1989) and its integrations with TOE (Gangwar, Date, & Ramaswamy, 2015) add the point that perceived usefulness is the belief most proximate to adoption, an idea that the results below speak to, with the caveats about direction that a cross-sectional design imposes.

2.4 AI marketing use cases, capability, and diffusion

Beneath the umbrella frameworks lies a granular literature on specific use cases. Conversational agents and chatbots are the most studied: anthropomorphic design cues increase satisfaction and engagement (Araujo, 2018; Blut, Wang, Wunderlich, & Brock, 2021), AI chatbots can raise user compliance (Adam et al., 2020), and chatbot adoption hinges on compatibility, ease of use, and trust (Mostafa & Kasamani, 2021). Personalization and recommendation form a second cluster: AI enables individualized engagement at scale (Kumar, Rajan, Venkatesan, & Lecinski, 2019), though consumer expertise moderates responses to AI recommendations (Chinchanchokchai et al., 2021), and a bibliometric consolidation maps how AI-enabled personalization reduces information overload (Chandra, Verma, Lim, Kumar, & Donthu, 2022). Advertising and pricing constitute a third: AI underpins programmatic advertising and "programmatic creative" (Chen, Xie, Dong, & Wang, 2019; Ford, Jain, Wadhwani, & Goyal Gupta, 2023), even as automated advertising heightens privacy concerns (Palos-Sánchez, Saura, & Martín-Velicia, 2018). A fourth cluster covers analytics and segmentation: machine-learning models predict purchasing behaviour in non-contractual settings (Martínez, Schmuck, Pereverzyev, Pirker, & Haltmeier, 2018), interpretable models segment customers from reviews (Joung & Kim, 2023), online sentiment analysis informs marketing research (Rambocas & Pacheco, 2018), and—most directly relevant here—Hossain, Agnihotri, Rushan, Rahman, and Sumi (2022) show that *marketing-analytics capability* is positively associated with AI adoption and competitive advantage. Generative AI now spans content creation and sentiment analysis (Kshetri, Dwivedi, Davenport, & Panteli, 2023; Krugmann & Hartmann, 2024), with new questions about authenticity disclosure (Brüns & Meißner, 2024).

For the present purpose, the few studies that examine the adoption of these tools tend to treat one tool at a time, or to remain provider-centric. Reviews of MarTech-stack adoption in SMEs (Mou, 2025) and of MarTech antecedents (Veghes et al., 2023; Anning-Dorson, 2026) note that firms adopt stacks rather than single tools, yet empirical work rarely measures the portfolio. Pollák and Markovič (2021) show that business-unit size influences SMEs' willingness to adopt digital marketing in Central Europe, and Huňady (2025), using Flash Eurobarometer micro-data on more than 19,000 firms, links AI adoption among EU SMEs to missing skills and other firm-level factors. Neither maps marketing use cases at the level of detail attempted here.

2.5 Organizational AI maturity and readiness

A firm's capacity to deploy AI is captured by the literature on AI maturity and readiness. Jöhnk, Weißert, and Wyrski (2020) conceptualize organizational AI readiness along five factors including strategic alignment, resources, and culture; Holmström (2021) frames an AI-readiness model across data, technology, organization, and strategy dimensions; and Uren and Edwards (2022) show empirically that *people, process, and data readiness* are jointly required. These

dimensions correspond closely to the seven maturity items measured in the AI-IMPACT survey (culture, data, ethics, organization, privacy, strategy, and technology). The maturity literature tends, however, to treat readiness as an enabler of whether a firm adopts AI; it says less about whether maturity predicts the breadth of use once a firm has begun—an open question this study tests directly. In the Slovak context, Valášková et al. (2022) document advanced Industry 4.0 capabilities in the automotive sector, suggesting pockets of high readiness coexisting with a broader population of less-prepared firms.

2.6 Sentiment, acceptance, and the benefit–risk calculus

Adoption is not a purely rational calculation; it is mediated by attitudes. A multilevel review by Bankins et al. (2023) shows that organizational discourse about AI is "sharply divided," with proponents emphasizing efficiency and opponents emphasizing threat. That ambivalence is one reason this study measures enthusiasm and fear separately. Reviews of AI acceptance find behavioural intention driven by performance expectancy, effort expectancy, and facilitating conditions (Kelly, Kaye, & Oviedo-Trespalacios, 2022; Maldonado-Canca, Cabrera-Sánchez, González Robles, & Casado Molina, 2024), while studies of automation perceptions show owners and employees diverging in how they appraise AI (Gómez Gandía, Gavrilá Gavrilá, de Lucas Ancillo, & del Val Núñez, 2024). A parallel stream documents algorithm aversion: decision-makers discount algorithmic advice after seeing it err (Prah & Van Swol, 2017), a tendency reviewed by Burton, Stein, and Blegind Jensen (2019) and Mahmud, Islam, Ahmed, and Smolander (2021) and counterbalanced by work on the antecedents of trust in AI (Kaplan, Kessler, Brill, & Hancock, 2021). On the benefit side, tertiary reviews catalogue drivers and barriers (Čubrić, 2020), and ethics scholarship maps the risk landscape of privacy, accountability, bias, and transparency (Hagendorff, 2020; Corrêa et al., 2023), with corporate digital responsibility emerging as a marketing-specific concern (Kunz & Wirtz, 2023; Al Haj Eid et al., 2024). What this literature has not settled is how benefit and risk perceptions relate at the firm level: whether they trade off, or whether more engaged firms simply register both. The present study takes up that question.

2.7 Business value, outcomes, and employment

The promise of AI is ultimately a promise of value. Resource-based and dynamic-capabilities studies show that AI and analytics capability improve firm performance (Wamba et al., 2017; Mikalef & Gupta, 2021; Wamba-Taguimdje, Fosso Wamba, Kala Kamdjoug, & Tchatchouang Wanko, 2020), and firm-level econometric evidence from Germany links AI adoption to innovation (Rammer, Fernández, & Czarnitzki, 2022). In marketing specifically, AI is associated with customer-facing gains—from AI sales "coaches" (Luo, Qin, Fang, & Qu, 2021) to B2B knowledge creation (Bag, Gupta, Kumar, & Sivarajah, 2021)—even as a meta-analysis of 45 studies documents a "dark side" of adverse customer reactions (Barari et al., 2024). On

employment, the macro literature ranges from occupation-based displacement estimates (Frey & Osborne, 2017) to task-based corrections that find far lower at-risk shares (Arntz, Gregory, & Zierahn, 2016), to robot-exposure studies showing local labour-market displacement (Acemoglu & Restrepo, 2019, 2020) and vacancy-based evidence that AI-exposed establishments restructure their hiring (Acemoglu, Autor, Hazell, & Restrepo, 2022). Field evidence on generative AI finds productivity gains concentrated among less-experienced workers (Brynjolfsson, Li, & Raymond, 2023; Dell'Acqua et al., 2023). Almost none of this work examines *the marketing function specifically*: which marketing tasks are automated versus augmented, and whether AI-adopting marketing organizations create or destroy roles on balance. This study supplies direct, if perceptual, firm-level evidence on both value and employment.

2.8 Barriers to adoption

Finally, a substantial literature catalogues the barriers that slow AI adoption, particularly among SMEs: limited financial and human resources, weak technical competencies, poor data quality and availability, difficulty integrating AI with legacy information systems, and regulatory uncertainty (Čubrić, 2020; Bhalerao, Kumar, Kumar, & Pujari, 2022; Oldemeyer, Jede, & Teuteberg, 2024; Závodná, Überwimmer, & Frankus, 2024). For digital marketing specifically, Enshassi, Nathan, Soekmawati, and Ismail (2025) find perceived usefulness and ease of use to be the dominant drivers among Malaysian SMEs, with barriers moderating intention. This evidence is, again, overwhelmingly Western, Asian, or Gulf in origin; CEE SMEs—differing systematically in digital maturity, data availability, and talent supply—are largely absent.

2.9 Synthesis and the research gap

Three gaps converge precisely where this study contributes. First, AI-in-marketing scholarship is dominated by conceptual frameworks and single-use-case consumer experiments; firm-level, multi-use-case adoption—the portfolio and its position on a diffusion ladder—is under-studied. Second, adoption theory (TOE, Diffusion, TAM/UTAUT) is mature but is typically applied to the binary question of whether a firm adopts, and disproportionately to manufacturing, large firms, and non-European settings; the determinants of breadth and depth of use, and the structure of benefit–risk perception, remain open, as does the joint role of maturity and sentiment. Third, the geographic base is skewed away from Central and Eastern Europe; Slovakia in particular appears mainly through Industry-4.0, logistics, e-commerce, and HR-digitalization studies rather than dedicated firm-level analyses of AI in marketing. The AI-IMPACT dataset allows all three gaps to be addressed at once: it provides country-level, multi-use-case evidence from a CEE economy; it permits the determinants of adoption and of breadth to be estimated separately; and it foregrounds the neglected marketing function. The next chapter translates these gaps into explicit research questions and hypotheses.

3. Research questions and hypotheses

The study is organized around seven research questions (RQ1–RQ7). Three of them (RQ2, RQ4, RQ5/RQ6) carry formal hypotheses, because they make directional claims that can be tested against the data; the remaining questions are descriptive or structural and are answered with diffusion, factor, and cluster analyses. The conceptual model treats the TOE contexts and Diffusion attributes as antecedents of two distinct outcomes—whether a firm adopts AI in marketing, and, conditional on adoption, *how broadly and deeply* it does so—and treats benefit–risk perception both as an outcome of engagement and as a driver of breadth.

RQ1: The adoption landscape. *How prevalent and how recent is AI adoption in the marketing function among Slovak enterprises, and how does marketing rank against other functional areas?* This question is descriptive and establishes the empirical stakes.

RQ2: Correlates of adoption. *Among AI-using firms, which technological and organizational factors, and which firmographics, are associated with adopting AI specifically in marketing?* A note on the framework is needed here. TOE places firm size and resources in the organizational context and reserves the environmental context for competitive pressure, regulation, and partner or customer readiness; the survey contains no direct measure of that environmental context, so the model tests technological and organizational factors and treats sector and ownership as the nearest available environmental proxies. Four hypotheses follow:

H1 (Technology). Firms with higher AI maturity and technological intensity are more likely to adopt AI in marketing.

H2 (Organization, engagement). Firms with greater overall AI-use intensity are more likely to adopt AI in marketing. Because overall intensity is derived from the same item that defines the marketing-adoption outcome, this is partly mechanical and is examined as an engagement control rather than a clean organizational driver.

H3 (Organization, size). Larger firms are more likely to adopt AI in marketing.

H4 (Environment proxy, ownership). Ownership type is associated with the likelihood of adopting AI in marketing.

RQ3: The diffusion architecture. *Which marketing use cases are actively used versus planned, and do the use cases form a coherent latent structure?* This question is answered with the five-stage diffusion ladder and exploratory factor analysis.

RQ4: Drivers of breadth. *Do organizational AI maturity, pro-AI sentiment, and perceived benefit drive the breadth of active marketing-AI use?* Four hypotheses follow:

H5. Higher AI maturity is associated with greater breadth of use.

H6. Greater enthusiasm (pro-AI sentiment) is associated with greater breadth of use.

H7. Higher perceived benefit is associated with greater breadth of use.

H8. Greater organizational fear/skepticism inhibits breadth of use.

RQ5: The benefit–risk calculus. *How do firms perceive the benefits and risks of marketing AI, do benefits dominate, and do the two trade off?* Two hypotheses follow:

H9. Perceived benefits exceed perceived risks on average.

H10. Perceived benefits and risks trade off (are negatively correlated across firms).

RQ6: Perceived value and employment. *Is more intensive marketing-AI use associated with more favourable perceived outcomes, and what is the employment footprint?* Two hypotheses follow:

H11. Greater breadth/intensity of marketing-AI use and higher perceived benefit are associated with more favourable perceived financial and customer outcomes.

H12. More adopters report adding AI-related marketing roles than cutting them (a firm-level perception, not a measured net employment effect).

RQ7: Adopter typology. *Can marketing-AI adopters be segmented into interpretable types?* This question is answered with cluster analysis and a strategic positioning map.

The hypotheses are deliberately a mix of conventional expectations (H1, H3, H9, H10) and propositions that the diffusion and benefit-belief logic suggests may diverge from convention (H2, H7, the negation of H8). As Chapter 5 shows, several of the conventional expectations are not supported, and it is precisely those divergences that carry the monograph's analytical "story."

4. Data and methods

4.1 The AI-IMPACT survey and dataset

The empirical basis is the AI-IMPACT Survey Dataset (Slovakia), an organization-level survey of artificial-intelligence adoption and use among enterprises operating in the Slovak Republic, fielded in 2025 and released under a CC BY 4.0 licence. The publicly available analytical dataset contains responses from 816 organizations across 621 variables, organized into thematic blocks that follow the questionnaire's logic: company and respondent characteristics; a multidimensional AI-maturity battery; corporate sentiment toward AI; the status and intensity of AI adoption; functional areas of application and their detailed evaluation; and perceived barriers. The instrument integrates several variable types—categorical firmographics, ordinal maturity items, Likert-type significance and agreement scales, and binary indicators derived from multiple-choice questions—supplemented by technical metadata. The raw export comprises 1,086 complete cases; the analytical dataset used here is the deduplicated version (N = 816), in which duplicate company representations have been removed so that each organization appears once.

4.2 The marketing subsample and its skip-logic provenance

The unit of analysis for most of the study is the enterprise that has begun implementing or testing AI in Marketing and Sales. The relevant survey item ("In which areas of the company have you started implementing or testing AI?", multiple choice, "select all that apply") was displayed only to respondents who had previously indicated that their firm uses or is piloting AI, that is, who answered the gating item *Aluse* with "we use AI in multiple areas," "we use AI in several specific processes," or "we are testing/piloting AI." The skip logic is clean and fully verified: exactly the 562 AI-using or piloting firms saw the functional-area question, and the 254 non-users and future-intenders did not. Of those 562, **209 firms (37.2%) selected Marketing and Sales**, and these 209 are the principal analytical subsample. A second item set, the dedicated Marketing-and-Sales module measuring fifteen specific use cases, sixteen perceived positive impacts, and fourteen perceived risks, was in turn shown only to these 209 firms, all of whom completed it (209/209 on the use-case ladder, the positive-impact battery, and the negative-impact battery). Two comparison groups are used: the **353 "other AI adopters"** (AI users who did not select marketing) and, where relevant, the full sample of 816. One wording note: the survey option is the combined "Marketing and Sales," and the text uses that label, shortening it to "marketing AI" only for brevity. A second: the gate item asks where firms have "started implementing or testing" AI, while the use-case module asks where they "use" it, so an

adopter can still mark individual use cases as not used or not planned, which is why active breadth (5.42 of 14) sits well below the maximum.

It should be noted that the parallel "planned-use" item (MarSalplan) was, by the questionnaire's routing, shown to firms that did not already report marketing as an implementation area; consequently none of the 209 adopters answered it (0/209), and planned use is therefore not analysed for the adopter subsample. This is a property of the instrument's design rather than item non-response, and the five-stage use-case ladder already encodes each firm's position from rejection through planning to active use, making a separate planned-use measure unnecessary for the adopter population.

4.3 Measures and derived variables

The analysis uses both native survey items and composite indices constructed from them. The **AI-maturity index** is the mean of seven ordinal items (culture, data, ethics, organization, privacy, strategy, technology), each measured on a five-stage scale from absent to industry-leading (Cronbach's $\alpha = .908$ in the full sample). **Corporate sentiment** is measured by eight agreement items; because four are positively and four negatively worded, an "enthusiasm" subscale (four positively worded items) and a "fear/skepticism" subscale (four negatively worded items) are computed separately, a decision validated by the low reliability of a combined bipolar composite ($\alpha = .586$) and the near-zero correlation between the two subscales—evidence, discussed below, that enthusiasm and fear are distinct, coexisting dimensions rather than opposite poles.

The **marketing use-case ladder** comprises fifteen use cases, each rated on a five-stage diffusion scale (1 = do not use and do not plan; 2 = considering for the more distant future; 3 = plan within two years; 4 = piloting/occasional; 5 = active regular use). From the fourteen substantive use cases (excluding "Other"), three firm-level measures are derived: *active breadth* (the count of use cases at stage ≥ 4), *use intensity* (the mean stage across the fourteen), and *pipeline breadth* (the count at stage ≥ 3). **Perceived benefit** and **perceived risk** are the means of sixteen positive-impact and fourteen negative-impact items, each rated 1–5 for significance (1 = not significant at all, 5 = very significant); these are ratings of how significant firms judge each effect to be, not measured magnitudes. *Net benefit* is their difference. Additional composites capture **adoption drivers** (nineteen items, 1–5 importance), **KPI usage** (eight items, where the scale runs from "do not use and have no plans to" through "rarely," "considering," and "occasionally" to "regularly," so it captures use-or-intent rather than pure usage; the derived "KPI breadth" counts items at level ≥ 4), **barriers** (twenty items, one of which is a government-financing item that earlier processing mislabelled as free text and which is retained here), **AI technology-type intensity** (seven items), and **perceived financial/operational impact** (thirteen items, 1–5 from significant decrease to significant increase). The financial-impact stem asks firms that have used AI for at least twelve months to report the realized change and asks

the rest to give an expectation, so for this recently-adopting cohort the measure is largely expectational and is read that way throughout. Firmographics, namely company size (four classes), net sales (six classes), ownership (four types), firm age (three bands), industry (eighteen NACE sections), and respondent managerial level, are used as native categorical variables and, where modelled, as standardized or dummy-coded predictors.

4.4 Analytical strategy

The analysis proceeds in five stages, matched to the research questions. First, descriptive and diffusion analysis characterizes the landscape (RQ1) and the use-case architecture (RQ3), reporting stage distributions, active-use shares, and item means with dispersion. Second, group comparison contrasts marketing adopters with other AI adopters using the Mann–Whitney U test for ordinal/continuous measures (with rank-biserial effect sizes and Benjamini–Hochberg false-discovery-rate correction across the family of tests) and the chi-square test with Cramér's V for categorical measures. Third, multivariable models estimate determinants: a logistic regression of marketing-AI adoption on standardized TOE predictors among the 562 AI users (reported as odds ratios with 95% confidence intervals, with model fit summarized by McFadden's pseudo- R^2 and the area under the ROC curve), and a count model of active use-case breadth among the 209 adopters. Because the breadth variable is over-dispersed (mean = 5.42, variance = 20.16; Poisson dispersion ≈ 2.2), a negative-binomial model is used and reported as incidence-rate ratios. An ordinary-least-squares model of net perceived benefit complements the count model. The Benjamini–Hochberg false-discovery-rate correction is applied not only to the group comparisons but to every declared family of tests, including the regression coefficients and the use–outcome correlations, with adjusted q-values reported where they change an inference. Fourth, measurement and structure are examined through Cronbach's α for all multi-item scales and exploratory factor analysis (principal-axis extraction, promax rotation; adequacy assessed by the Kaiser–Meyer–Olkin measure and Bartlett's test) for the use-case, benefit, and risk batteries, alongside a Spearman correlation matrix of the key constructs. Because all constructs come from one respondent per firm, common-method variance is assessed directly, through Harman's single-factor test, a straightlining check, and a response-style adjustment of the benefit–risk correlation. Fifth, an adopter typology is derived by k-means and Ward clustering on standardized engagement and perception features, with the number of segments chosen by the silhouette criterion and validated by Kruskal–Wallis tests across segments; a complementary two-by-two map crosses adoption intensity (median split) with the sign of net benefit. All analyses were conducted in Python (pandas, SciPy, statsmodels, scikit-learn, factor-analyzer); every reported statistic is catalogued in the accompanying Master Results Registry, and every literature claim in the Literature Registry.

4.5 Reliability and validity

The multi-item scales have high internal consistency: AI maturity $\alpha = .908$; marketing use-case ladder $\alpha = .926$; perceived benefits $\alpha = .941$; perceived risks $\alpha = .919$; adoption drivers $\alpha = .920$; barriers $\alpha = .942$; AI technology intensity $\alpha = .900$; KPI usage $\alpha = .891$. The exception is the bipolar sentiment composite ($\alpha = .586$); its low value is the reason enthusiasm and fear are modelled separately, though a low reliability for a mixed-worded reverse-scored composite can also reflect careless or acquiescent responding, so the split is treated as a measurement decision supported, but not proven, by the data. The use-case, benefit, and risk batteries each load on a single dominant factor with high sampling adequacy (KMO = .934, .948, .920), which supports the mean composites but, for single-source data, is also consistent with a degree of method variance; the discriminant question, whether benefit and risk are distinct, is tested in Chapter 5 with a joint factor analysis that separates them. The common-method diagnostics give a mixed but usable picture: a first unrotated factor across the sixty-three Likert items explains 32.8% of the variance (below the 50% mark at which a single method factor is judged to dominate), about 15.3% of adopters straightlined at least four-fifths of the thirty benefit-and-risk items, and adjusting the benefit–risk correlation for a general response-style tendency lowers it from .65 to roughly .47. Method variance is therefore present and is flagged where it matters, but it does not account for the main results on its own.

4.6 Limitations of the data and ethical note

The main limitations are previewed here and developed in Chapter 8. The design is cross-sectional and the measures are self-reported by one informant per firm, so use–outcome associations are correlational, the "impact" items are perceptions rather than audited results, and shared method variance is a live concern (assessed above). The sample is not a probability sample: there is no stated sampling frame, the analytical file contains no micro-firms and skews toward larger enterprises, and prevalence figures should be read as properties of these respondents rather than as economy-wide rates. The dependent variable is self-labelled, and at a moment dominated by recent adoption and chatbots, some reported "AI in marketing" may be relabelled rule-based automation. Two handling notes are worth recording. A documentation discrepancy was resolved conservatively: the deduplicated CSV is authoritative at $N = 816$ (matching the README), whereas the parallel SPSS/Jamovi "clean" file is malformed at 1,514 rows and was not used; labels are drawn from the well-formed raw SAV metadata. And a scale-documentation inconsistency, in which the sentiment and barrier batteries are documented as six-point but are five-point in the data, was resolved in favour of the data. The findings describe one country at one early moment and should be read as a snapshot, not a steady state. Ethically, the public dataset is anonymized, with direct identifiers and potentially identifying free-text responses removed, and is reused here under its CC BY 4.0 licence with attribution.

5. Results

5.1 The adoption landscape: marketing leads, and it is new

The first and most consequential descriptive result is that artificial intelligence has already reached a large minority of Slovak enterprises, and that within those enterprises *marketing is the leading point of entry*. Among the 816 surveyed firms, 68.9% use or are piloting AI: 16.5% report using AI in multiple areas, 26.5% in several specific processes, and 25.9% are testing or piloting. The remaining 31.1% comprises 16.1% that do not yet use AI but plan to (within one, two, or three-plus years) and 15.1% that neither use it nor plan to. The distribution (Figure 1) describes a population near the steep middle of a diffusion S-curve: the early majority is already engaged, a substantial planning cohort sits immediately behind, and only one firm in seven is a committed non-adopter.

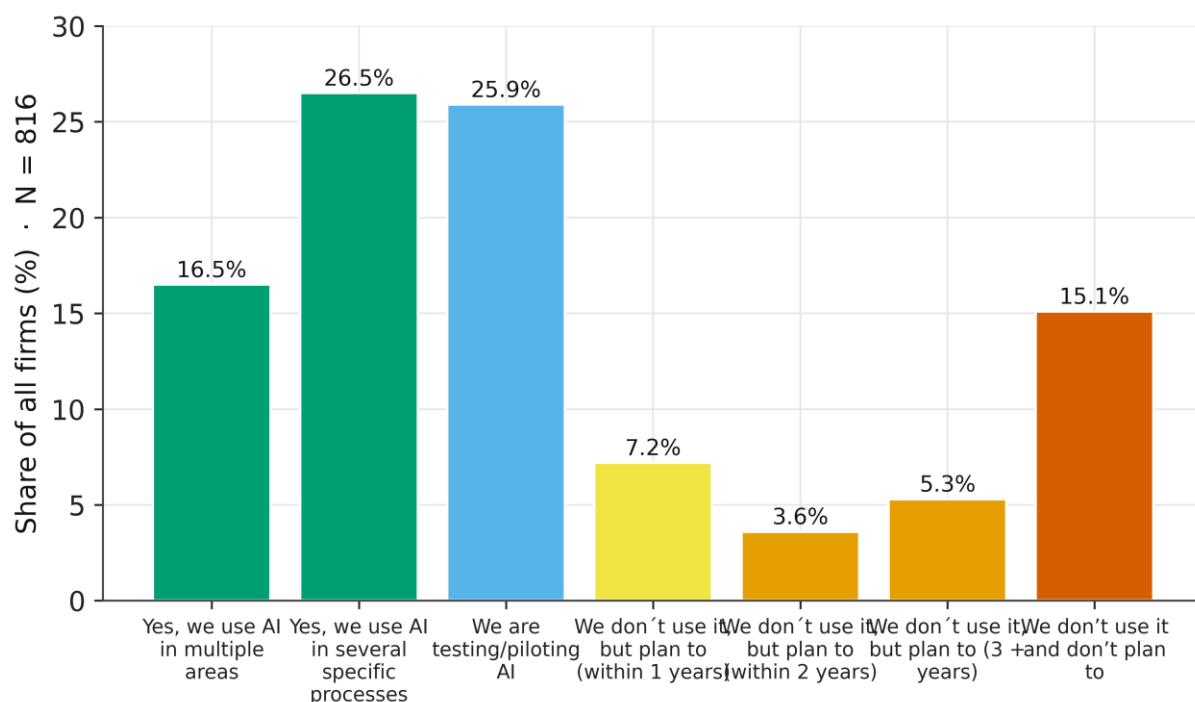


Figure 1. Distribution of AI-use status across surveyed enterprises (N = 816).

Of the 562 firms that use or pilot AI, **209 (37.2%) have begun implementing or testing AI in Marketing and Sales** (Figure 2). That makes Marketing and Sales the most frequently selected functional area, ahead of Production and Operations (27.9%), Logistics (25.3%), Research, Development and Innovation (21.5%), Human Resources (17.8%), Management (16.2%), ICT security (13.9%), and Finance (13.3%). The ranking deserves two qualifications. The survey option combines marketing with sales and is therefore broader than several of the single

functions it outranks, so part of its lead reflects category width. And because firms could select multiple areas, the shares overlap; a paired McNemar test nonetheless confirms that Marketing and Sales is chosen significantly more often than the second-ranked area, Production and Operations ($\chi^2 = 8.8$, $p = .003$). Among the surveyed firms, then, one in four (25.6%) is already applying AI in its marketing function. This is worth noting because regional research on enterprise digitalization in Slovakia and its neighbours has concentrated on the operational core, on Industry 4.0 in manufacturing and logistics (Richnák, 2022; Valášková et al., 2022); marketing turns out to be a comparably common, and in this sample more common, entry point. The pattern fits the argument that AI's language- and data-centric capabilities map readily onto marketing tasks (Huang & Rust, 2021; Davenport et al., 2020), though the sample is not a probability sample of Slovak firms (see Section 4.6) and the figure should be read as a property of these respondents, not an economy-wide rate.

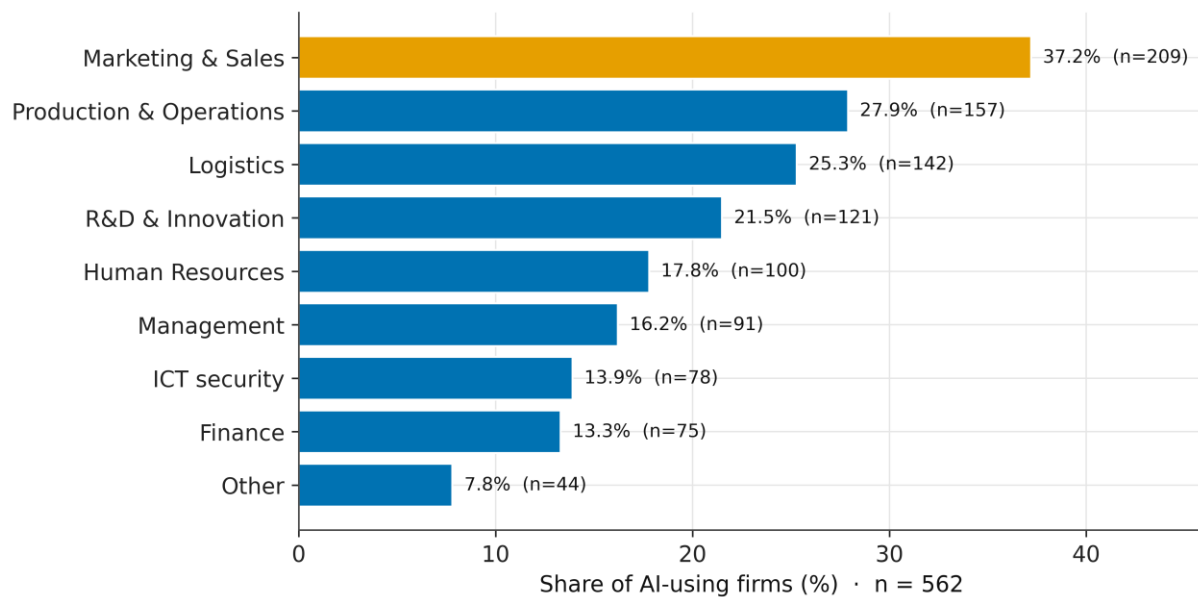


Figure 2. AI adoption by functional area, as a share of AI-using firms ($n = 562$). Marketing and Sales leads all functions.

Adoption is also recent. Among marketing adopters who dated their first AI project, the median start year is 2024, and 68.4% began in 2023 or later (Figure 3), in the window following the public release of generative-AI tools. This recency is not specific to marketing: non-marketing AI adopters are, if anything, slightly more recent (74.2% since 2023). What the data capture, therefore, is an early phase of enterprise AI adoption generally, of which marketing is one prominent part.

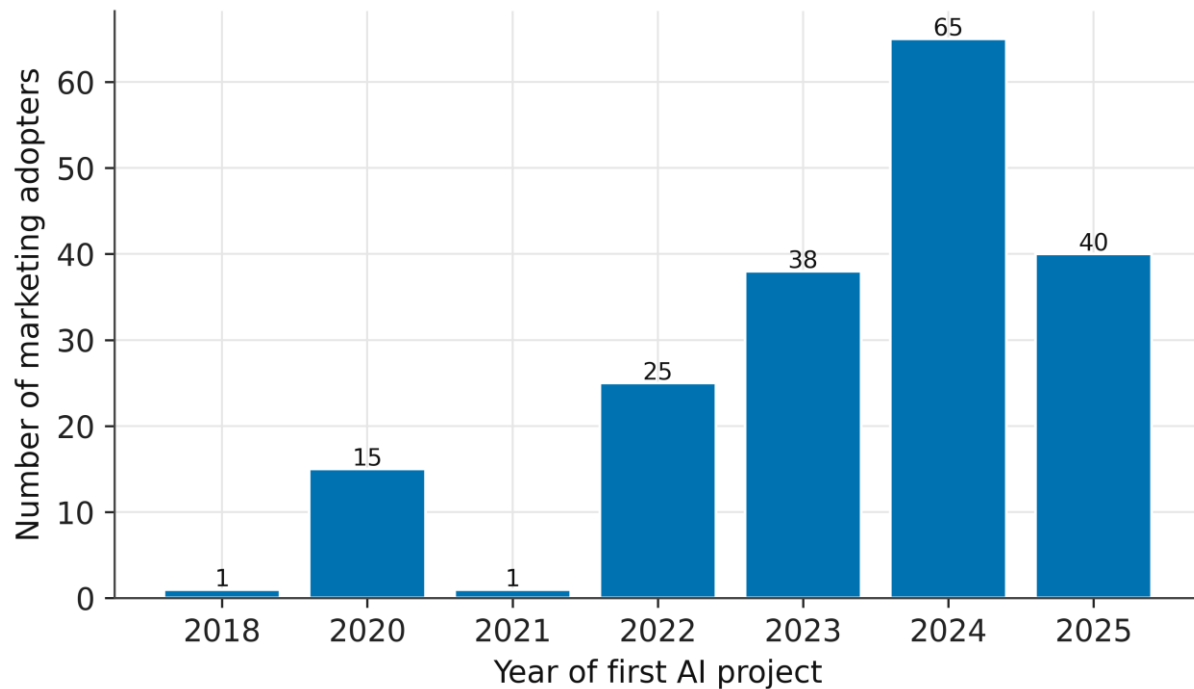


Figure 3. Year of first AI project among marketing adopters ($n = 209$). More than two-thirds began in 2023 or later.

The surveyed population skews toward established, mid-to-large firms: 42.6% employ 250 or more people, 30.1% employ 50–249, and 27.2% employ 10–49, with no micro-firms (under ten employees) in the analytical sample; 69.6% have operated for eleven years or more; and ownership is split between private Slovak companies (47.9%), foreign-owned companies registered in Slovakia (40.0%), and mixed ownership (12.1%). Manufacturing is the largest single sector (24.6%), followed by "other activities" (12.0%), information and communication (10.7%), and finance and insurance (8.9%). The sample composition by size is shown in Figure 4.

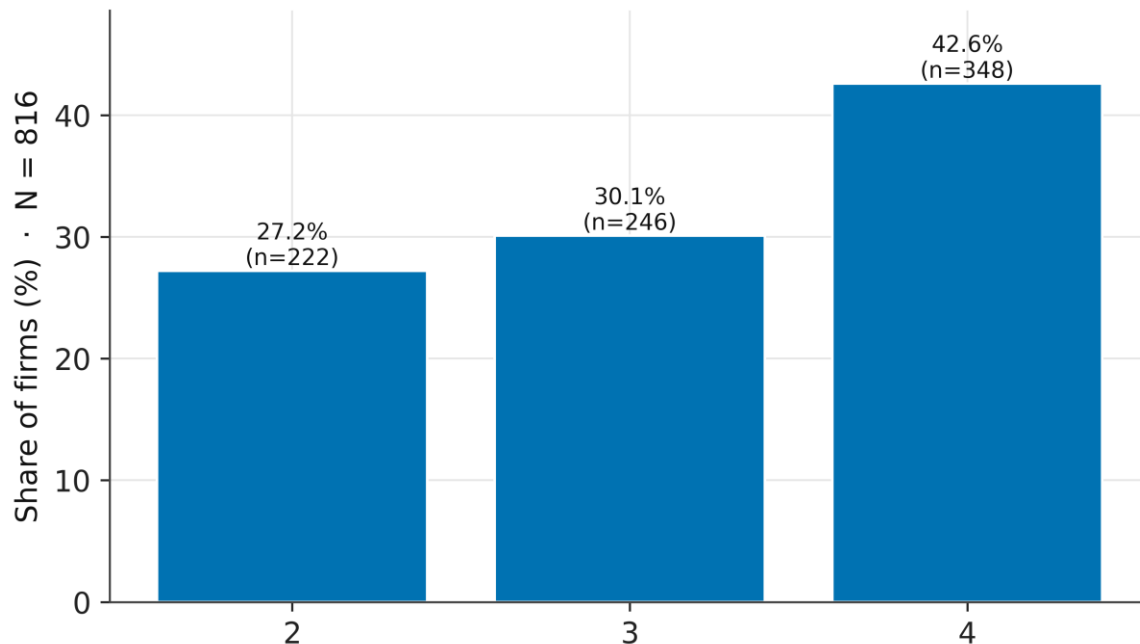


Figure 4. Sample composition by company size (N = 816).

The propensity to adopt AI in marketing does **not** rise with firm size. Among AI users, the marketing-adoption rate is 40.3% for small firms (10–49 employees) and 40.7% for medium firms (50–249), but falls to 33.2% for large firms (250+) (Figure 5). In this sample, then, marketing AI is not a large-enterprise phenomenon; if anything, smaller and mid-sized firms are marginally more likely to route their AI efforts into marketing. A plausible reason is that, for an SME, marketing is where AI's low-cost, high-visibility wins (a chatbot, an ad-automation tool, a content generator) are most immediately within reach. Adoption rates also vary by sector (Figure 6): among sectors with at least twenty AI users, the highest marketing-adoption rates appear in "other activities" (49.1%), accommodation and food service (47.8%), and administrative and support services (45.5%), with information and communication (36.0%), finance and insurance (35.1%), and manufacturing (30.3%) in the middle of the range. The pattern is consistent with a customer-facing, services-oriented tilt to marketing AI, though several sector cells are small and the differences are not individually significant.

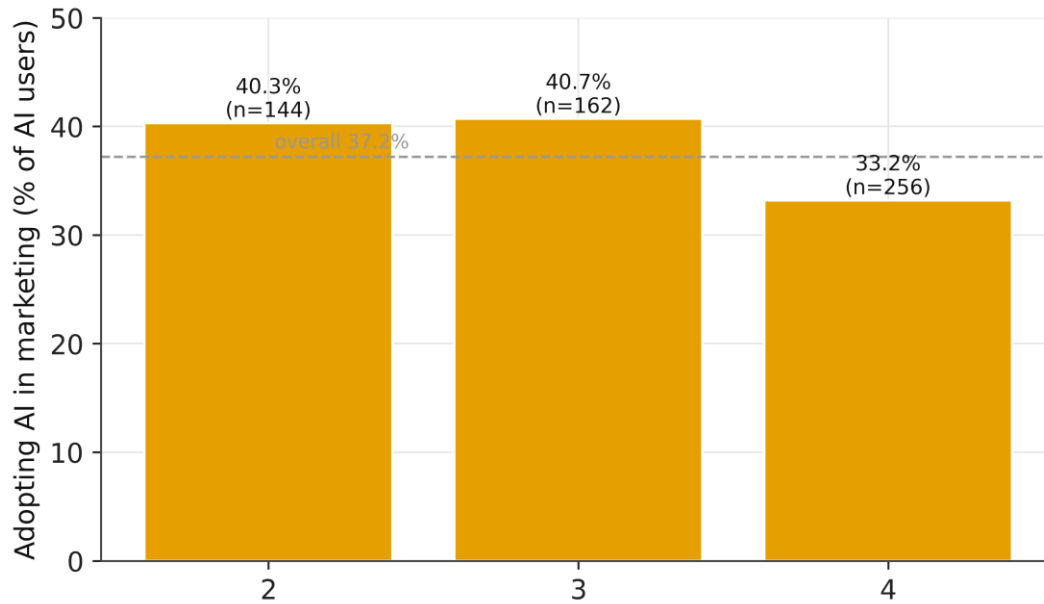


Figure 5. Marketing-AI adoption rate by company size (share of AI users in each size class). The rate is flat-to-declining in size.

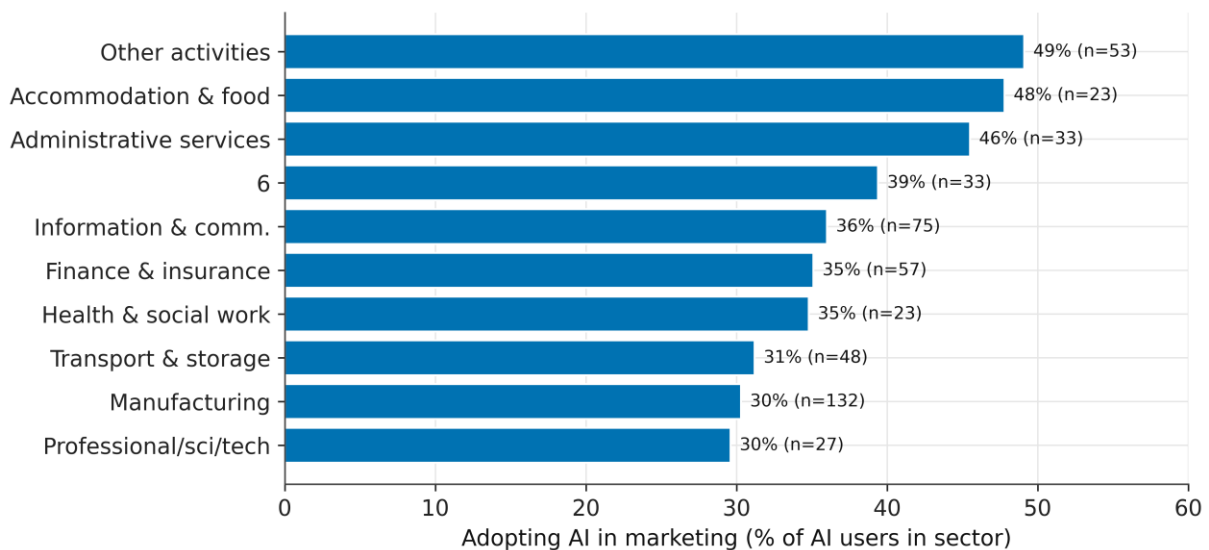


Figure 6. Marketing-AI adoption rate by industry sector (AI users; sectors with $n \geq 20$).

On RQ1, then: among the firms surveyed, marketing is the most frequently selected area for AI, the adoption is recent, and it is spread across the size range rather than concentrated in the largest firms. The size pattern is the more surprising part, and Section 5.4 returns to it.

5.2 A descriptive profile of marketing-AI adopters

Who are the 209 marketing adopters, and how do they organize, source, and equip their AI efforts? Demographically they resemble the AI-using population but lean slightly more domestic: 51.7% are private Slovak companies (versus 47.9% in the full sample), 35.4% foreign-owned, and 12.9% mixed. They span the size range (27.8% small, 31.6% medium, 40.7% large) and the sales distribution evenly. Respondents reporting on these firms are predominantly managerial—28.4% top management, 33.0% middle management—lending the self-reports reasonable organizational vantage.

The decision to adopt AI in marketing is rarely the act of a lone enthusiast. Only 17.4% of adopters report that the decision was made by an individual; 40.1% locate it in a specific department (often IT, innovation, or marketing itself), 22.2% in top management, and 20.3% in a cross-departmental collaborative process. AI in marketing is, in other words, predominantly an organizational decision embedded in functional or executive structures—consistent with the TOE emphasis on organizational rather than purely individual antecedents (Baker, 2011). Firms draw their initial AI knowledge from a fairly diffuse set of sources, none dominant: internal experts or the IT department (mean 3.09 on a 1–5 "extent of use" scale), online courses and webinars (3.04), professional articles and scientific studies (2.99), and technology providers via presentations and training (2.96) are used to broadly similar degrees. The absence of a single dominant information channel is itself informative: marketing-AI knowledge is being assembled opportunistically, which helps explain the heterogeneity in adoption depth documented below.

On the technology side, the AI stack of marketing adopters is led by conversational and language technologies. Chatbots and virtual assistants are the most intensively deployed AI technology type (mean intensity 3.34 on the 1–5 scale; 49.8% use them in multiple areas or as a key part of processes), followed by natural-language processing (2.97), computer vision (2.97), predictive analytics (2.88), robotic process automation (2.78), machine learning (2.74), and expert systems (2.73) (Figure 7). The primacy of chatbots and NLP—the technologies underlying customer-service automation and content generation—foreshadows the use-case structure analysed next and aligns with the broader observation that the most accessible, customer-facing AI capabilities diffuse first (Huang & Rust, 2021).

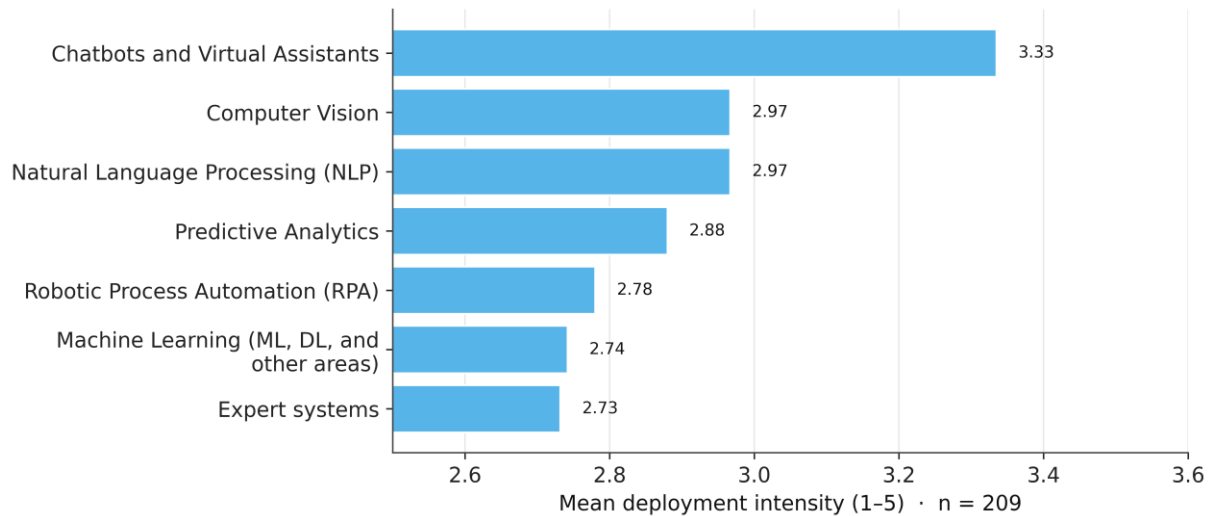


Figure 7. Deployment intensity of AI technology types among marketing adopters (n = 209; 1–5 scale).

5.3 The diffusion architecture of marketing AI use cases

The dedicated marketing module records, for each of fifteen use cases, where the firm currently stands on a five-stage scale running from "do not use and do not plan to" through planning to piloting and active regular use (Figure 8). Because the survey is a single snapshot, this is a measure of current penetration per use case, not of adoption over time; we use "diffusion" in the descriptive sense of how far each application has spread across firms, not in the temporal sense of an S-curve. Read that way, three things are visible. No use case is yet in active use by a majority of adopters: even the most widespread is at stage 4 or 5 (piloting or regular use) in only about half of firms. Customer-facing automation is furthest along. Chatbots for customer support lead, in active use by 50.2% of adopters (24.9% in regular use), followed by advertising-campaign automation (45.5%), personalized marketing offers (41.6%), price optimization (40.2%), and machine-learning-based market analysis (40.2%). The data-intensive analytical applications trail and sit mostly in the planning stages. Understanding customers through data-driven insights is in active use in only 30.6% of firms, improving CRM processes in 34.9%, and customer sentiment analysis in 34.0%; yet each carries a planning share (stages 2–3) above 54%, so a majority of adopters intend to move into them but have not. Mean stage across use cases ranges from 3.44 (chatbots) to 2.86 (data-driven insights), clustering around the planning-to-piloting boundary.

ARTIFICIAL INTELLIGENCE IN MARKETING: EVIDENCE FROM SLOVAK ENTERPRISES

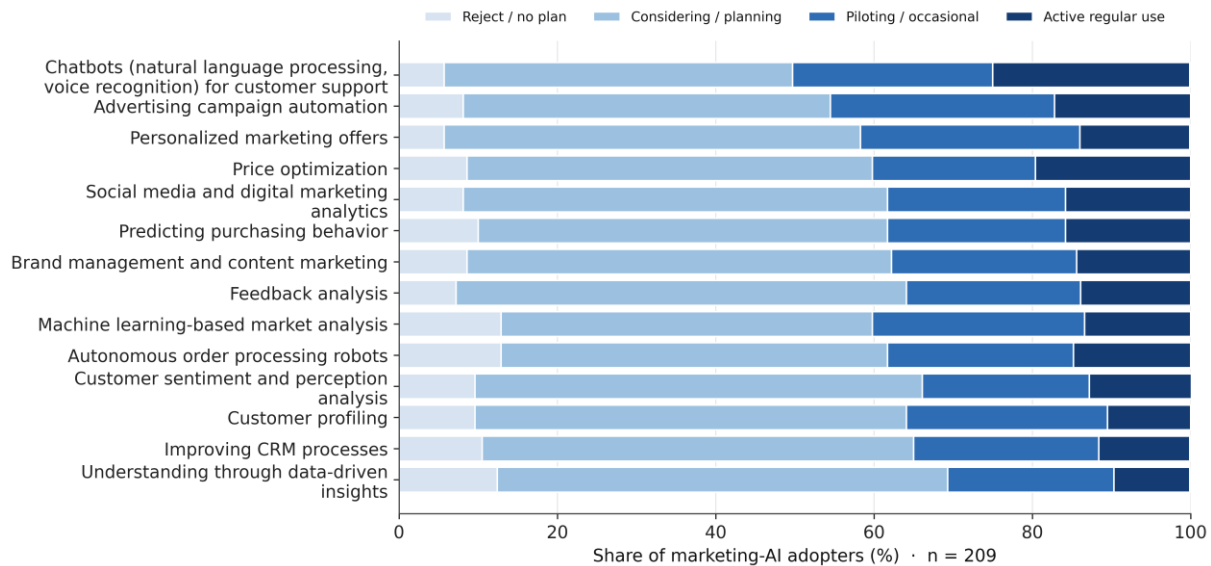


Figure 8. The five-stage diffusion ladder of fifteen marketing AI use cases ($n = 209$): reject / planning / piloting / active regular use.

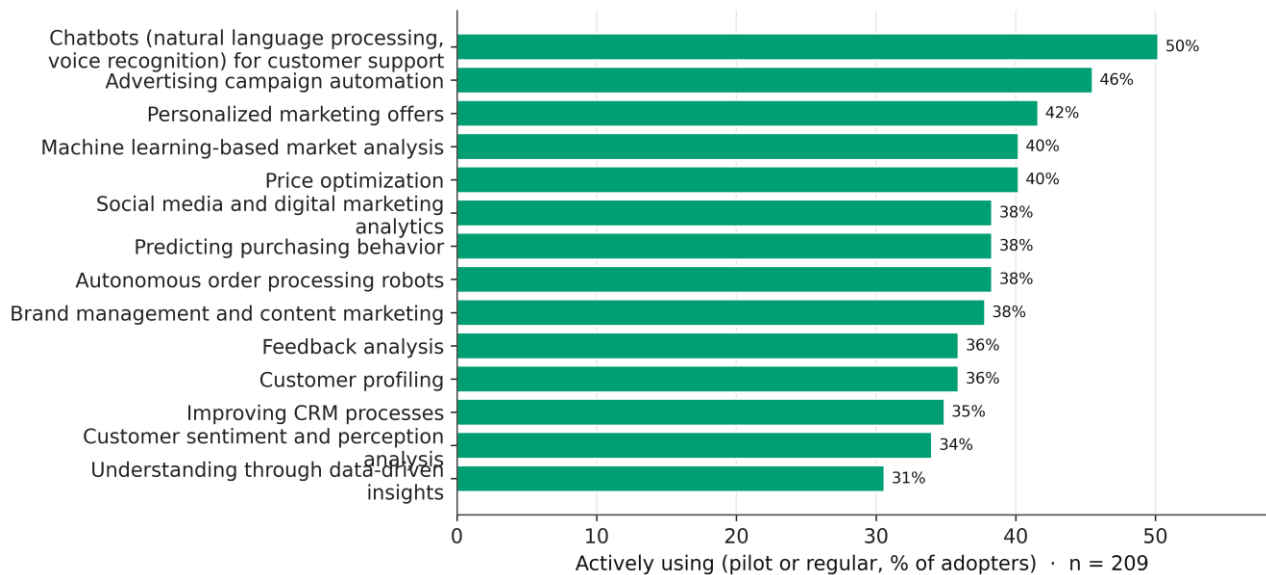


Figure 9. Share of marketing adopters actively using each use case (pilot or regular; $n = 209$).

The ordering invites an interpretation in Rogers's (2019) terms, though one offered after the fact rather than tested, since the survey did not ask firms to rate the use cases on adoption attributes. The applications that lead are the ones an SME can try cheaply and observe quickly: a chatbot or an ad-automation tool can be switched on with a vendor's help and its effect seen within weeks. The laggards (CRM intelligence, integrated customer-data analytics, sentiment analysis) need data integration, internal capability, and interpretive skill, which raise complexity and lower trialability. The gap between a roughly 50% active-use ceiling and planning shares

above 54% marks where penetration currently stops: a pool of intended adoption held back by the capability and data conditions the analytical use cases demand.

Do the fifteen applications form distinct styles of marketing AI, or one general propensity? Exploratory factor analysis of the fourteen substantive use cases gives high sampling adequacy ($KMO = .934$; Bartlett's test $p < .001$) and a single dominant factor explaining 47% of the variance, with every use case loading positively (loadings .69–.74 for the highest items). Firms thus tend not to specialize so much as to sit higher or lower on a common gradient, adopting more or fewer use cases at greater or lesser depth. Two readings of that single factor are possible and cannot be separated with single-source data: a genuine common adoption propensity, or a degree of shared response tendency across same-format items. The broader common-method check reported in Section 4.5 (a first unrotated factor across sixty-three Likert items accounting for 32.8% of variance) argues against a single method factor dominating, so we treat the gradient as substantively real while noting that about half the variance is left unexplained. With reliability high ($\alpha = .926$), active breadth and use intensity are usable firm-level summaries. Marketing adopters actively use 5.42 of the fourteen applications on average (median 5; variance 20.16), leaving plenty of between-firm variation for Section 5.5 to examine.

For RQ3, the picture is a single, broadly correlated space of marketing-AI applications, led by the low-complexity customer-facing tools, with a sizeable planning pipeline of analytical applications behind them.

5.4 Predictors of marketing-AI adoption

Why do some AI-using firms route AI into marketing while others do not? A logistic regression among the 562 AI users models marketing adoption on standardized predictors drawn from the technological and organizational contexts plus available firmographics (Figure 10). The model is significant overall (likelihood-ratio $p < .001$) but explains little (McFadden pseudo- $R^2 = .05$; AUC = .65), which already suggests that the usual firmographic variables do not separate adopters from non-adopters very well. Because ten coefficients are tested, we apply the same Benjamini–Hochberg correction used elsewhere and report adjusted q -values. Only one predictor survives it: overall AI-use intensity (OR = 1.33, 95% CI [1.10, 1.61], $p = .004$, $q = .036$). This association has to be read with care. Intensity is a recoding of the same gating item that defines the outcome, since a firm using AI "in multiple areas" has by construction selected several areas, one of which may be marketing. The positive coefficient is therefore partly mechanical, and we treat it as an engagement control rather than as evidence for a distinct organizational driver; H2 is supported only in that qualified sense. The next strongest signal is foreign ownership, where foreign-owned firms show lower odds of marketing-AI adoption than domestically owned firms (OR = 0.62, 95% CI [0.42, 0.90], $p = .011$). This coefficient does not survive the multiple-comparison correction ($q = .056$), so it is best described as suggestive

rather than robust; we return to it, with appropriate caution, in Chapter 6. H4 is thus only weakly supported.

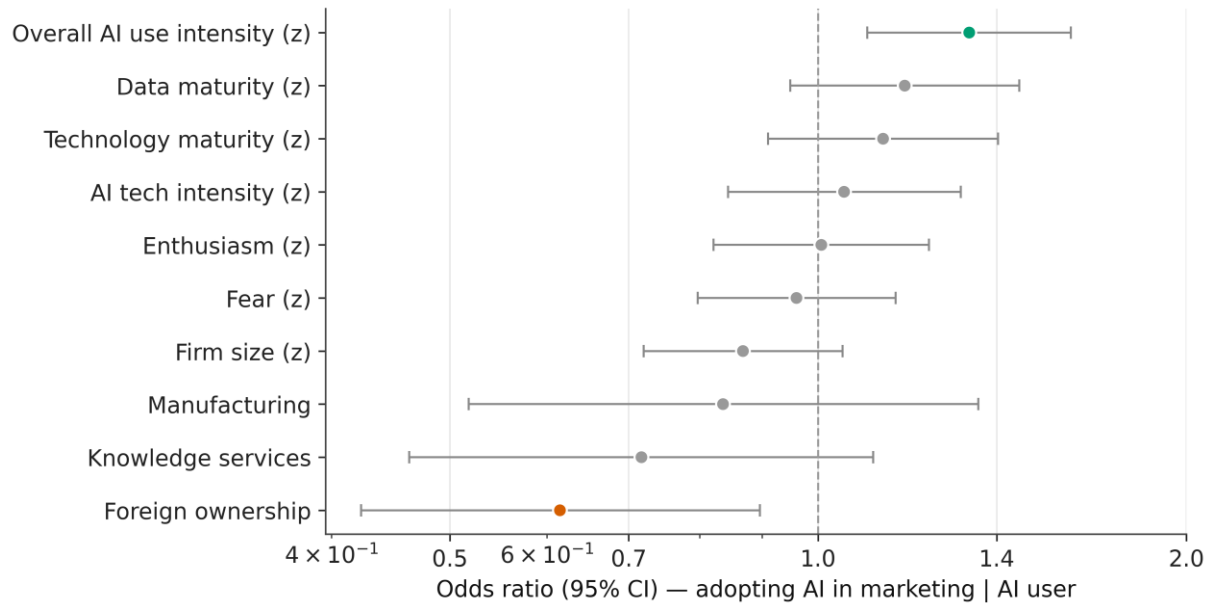


Figure 10. Logistic-regression odds ratios (95% CI) for adopting AI in marketing among AI users ($n = 562$).

None of the remaining predictors reaches significance, with or without correction: AI maturity (data OR = 1.18, $p = .14$; technology OR = 1.13, $p = .27$), technological intensity, enthusiasm, fear, sector, and firm size are all flat. H1 (maturity raises the odds of adoption) is not supported in the multivariable model, and H3 (larger firms more likely) is not supported either; the size coefficient is slightly negative (OR = 0.87, $p = .14$), in line with the flat-to-declining size gradient of Section 5.1. The short version is that, among firms already using AI, being larger or more formally mature does not make marketing a more likely site for it. What little signal there is comes from overall AI engagement, which is partly definitional, and from domestic ownership, which is suggestive at best.

The weak fit should not be over-read. A low pseudo- R^2 is consistent with several things: that adoption genuinely is not confined to large or mature firms, but also that important determinants simply were not measured, or that this sample of already-AI-using firms is too homogeneous for firmographics to discriminate within it. The last point matters for how the result speaks to the SME literature. That literature finds resource and scale constraints gating AI adoption (Schwaeke, Peters, Kanbach, Kraus, & Jones, 2024; Oldemeyer et al., 2024), but those constraints plausibly bind at the point of entering AI at all, a selection that has already happened before this subsample begins (there are no micro-firms here, and 42.6% employ 250 or more). A null association with size inside that pre-selected group refines the resource-gating account rather than contradicting it: among firms that have already crossed the threshold into AI, how far they take it in marketing is not strongly tied to their size. Section 5.5 turns from whether firms adopt to how broadly they do so.

5.5 Maturity, sentiment, and the breadth of use

It helps first to see how marketing adopters differ from the other AI adopters, since that locates where marketing AI sits organizationally. Mann–Whitney comparisons with false-discovery-rate correction (Figure 11) put marketing adopters above other AI adopters on a connected set of organizational and technological measures. They run AI across more functional areas (2.31 vs 1.39), though this gap is partly mechanical, because marketing adopters are defined by having ticked one of those areas; setting it aside, the largest difference is in the use of performance KPIs (KPI breadth 4.01 vs 2.84 indicators; $p < .001$; rank-biserial $r = -.235$). They also use AI more intensively overall (2.03 vs 1.77; $p < .001$), score higher on data maturity (3.09 vs 2.78; $p = .014$) and technology maturity (3.17 vs 2.92; $p = .011$), deploy AI technologies more intensively (2.92 vs 2.69; $p = .027$), rate adoption drivers higher (3.58 vs 3.40; $p = .004$), and, notably, perceive more barriers, not fewer (3.23 vs 3.05; $p = .020$). They are marginally more enthusiastic (3.47 vs 3.37; $p = .050$) but no less fearful, and slightly smaller by sales class ($p = .044$). The effect sizes here are modest (most rank-biserial correlations fall between .1 and .24); these are reliable group differences, not large ones. Figure 12 shows the same ordering across all seven maturity dimensions: marketing adopters above other AI adopters, both well above non- and future users, with the widest gaps on data, technology, and culture.

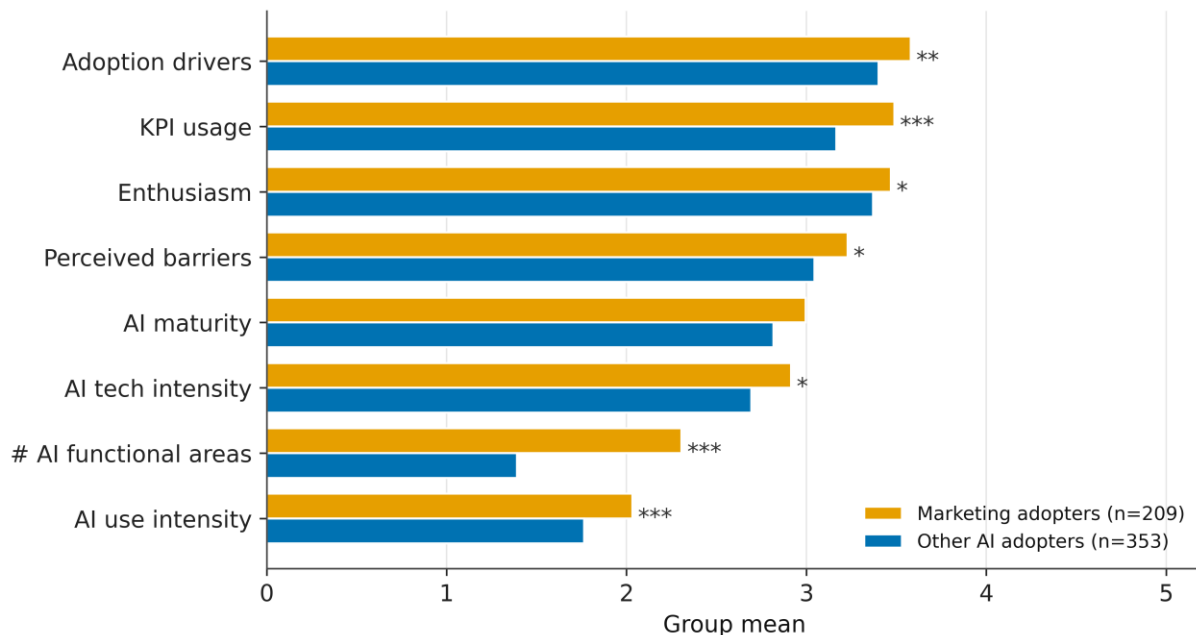


Figure 11. Marketing adopters versus other AI adopters on key dimensions (group means; * FDR-corrected $p < .05$, ** $< .01$, *** $< .001$).

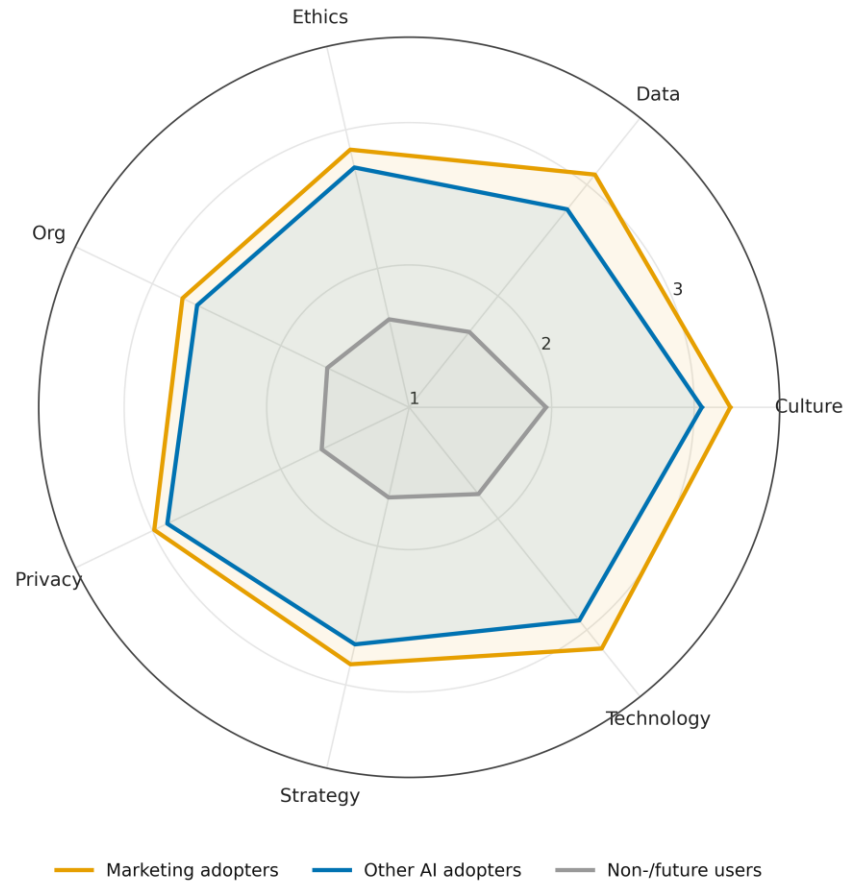


Figure 12. AI maturity profiles across the seven maturity dimensions by adopter group.

That marketing adopters perceive more barriers, not fewer, is a first sign of a pattern that recurs below: more engaged firms tend to register more of everything, benefits and obstacles alike. The question this section turns on is what is associated with the breadth of active marketing-AI use among the 209 adopters. A negative-binomial regression (chosen because breadth is over-dispersed) of active breadth on standardized maturity, sentiment, technology intensity, firm size, AI-use intensity, perceived benefit, and perceived risk gives a clear result (Figure 13): perceived benefit is the one predictor with a strong, significant association. A one-standard-deviation increase in perceived benefit corresponds to a 51% higher expected count of actively used applications (IRR = 1.51, 95% CI [1.20, 1.89], $p < .001$), supporting H7. Technology intensity is borderline (IRR = 1.22, $p = .061$); maturity (IRR = 1.06, $p = .57$), enthusiasm (IRR = 1.01, $p = .96$), firm size (IRR = 1.01, $p = .94$), AI-use intensity (IRR = 1.11, $p = .23$), fear (IRR = 0.89, $p = .14$), and perceived risk (IRR = 1.05, $p = .70$) are all non-significant with benefit in the model. One caveat governs the whole result and is easy to lose: perceived benefit and breadth were reported by the same respondent in the same questionnaire, and they correlate at $p = .55$. The data cannot tell us whether believing in the benefits leads firms to deploy more applications, or whether deploying more applications leads firms to rate the benefits higher. Both readings fit the same coefficient, and the OLS reported below points the arrow the other way.

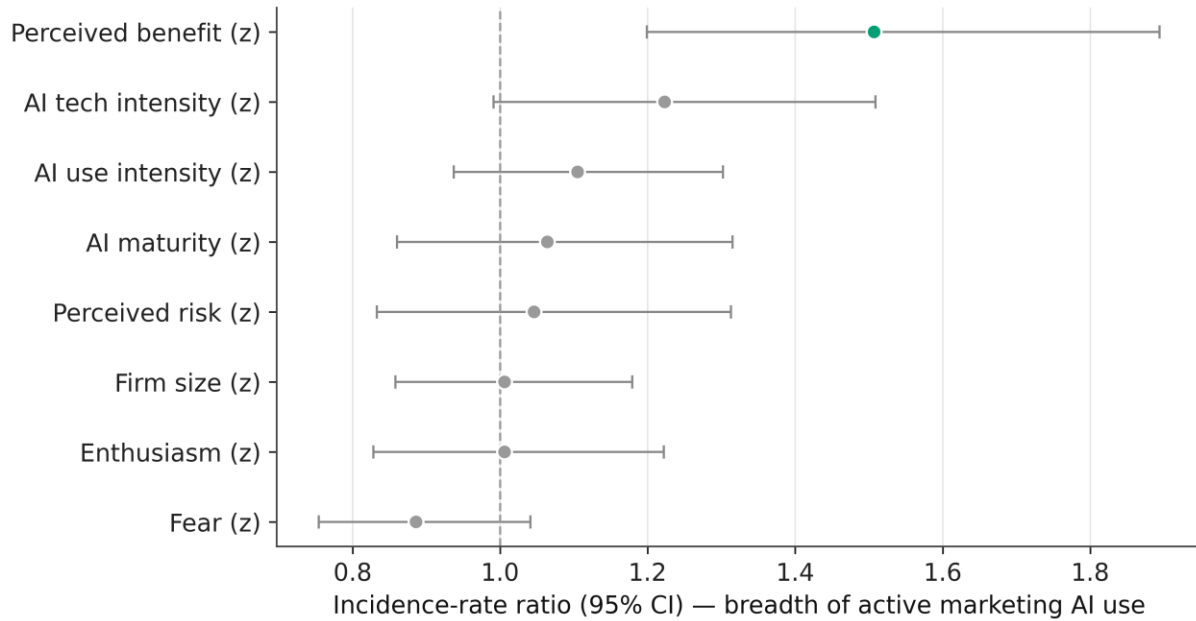


Figure 13. Negative-binomial incidence-rate ratios (95% CI) for the breadth of active marketing-AI use ($n = 209$).

The bivariate picture is broader than the model. Breadth correlates positively with maturity (Spearman $\rho = .39$), enthusiasm (.41), KPI usage (.55), drivers (.52), and technology intensity (.39), so taken one at a time, maturity (H5) and enthusiasm (H6) look related to breadth. Those associations fall away once perceived benefit is in the model. One interpretation is that maturity and enthusiasm work through belief, helping a firm form a favourable view of AI's usefulness (in TAM terms, perceived usefulness; in Rogers's, relative advantage) that is what tracks the number of applications actually in use. That is a mediation story, and it is worth stating plainly that the study does not test it: no indirect effect was estimated, and coefficient attenuation under correlated predictors is also consistent with shared method variance or with benefit being a downstream rationalization. In the multivariable model, H5 and H6 are not supported and H8 is not supported either, fear having neither a significant coefficient nor more than a weak bivariate correlation with breadth ($\rho = -.14$). The accompanying OLS is a useful corrective to any one-directional reading: breadth of use predicts higher net perceived benefit ($b = 0.026$ per additional active application, $p = .015$), with fear weakly negative ($p = .068$). Fitting the relationship both ways does not establish reciprocity; it shows only that the sign is positive whichever variable is placed on the left, and that the cross-sectional design cannot identify direction. Figure 16 lays out the full correlation structure. Two features carry into the discussion: a cluster of positively intercorrelated measures (maturity, enthusiasm, KPI usage, drivers, breadth, intensity, benefit), and the near-independence of fear, which correlates about zero with maturity ($\rho = -.01$) and breadth ($\rho = -.14$) and only weakly with barriers ($\rho = .13$).

The separateness of enthusiasm and fear shows up in the sentiment items themselves (Figure 14). Across the full sample, the statements drawing the strongest agreement are the enthusiastic ones, excitement about AI's possibilities and top-management confidence in its

competitive value, while the skeptical statements (that AI threatens jobs, that risks outweigh benefits) draw lower but non-trivial agreement, so a single firm can, and often does, hold both. The drivers that marketing adopters rate most important fit the efficiency-and-capability reading of the benefit items (Figure 15): the desire to increase efficiency (mean 3.78), to automate business processes (3.77), to speed up innovation (3.74), to react faster to demand and trends (3.71), and to reduce costs (3.71) lead the list, with competitive imitation rated lower. Management, on this evidence, is moved more by an internal efficiency logic than by fear of falling behind.

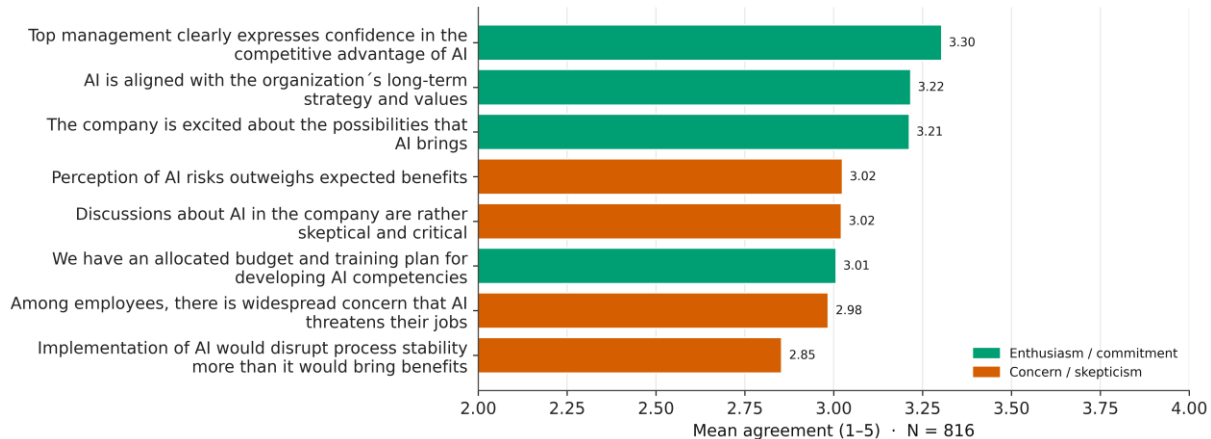


Figure 14. Corporate sentiment toward AI across the full sample (N = 816): enthusiasm versus concern items, mean agreement (1–5).

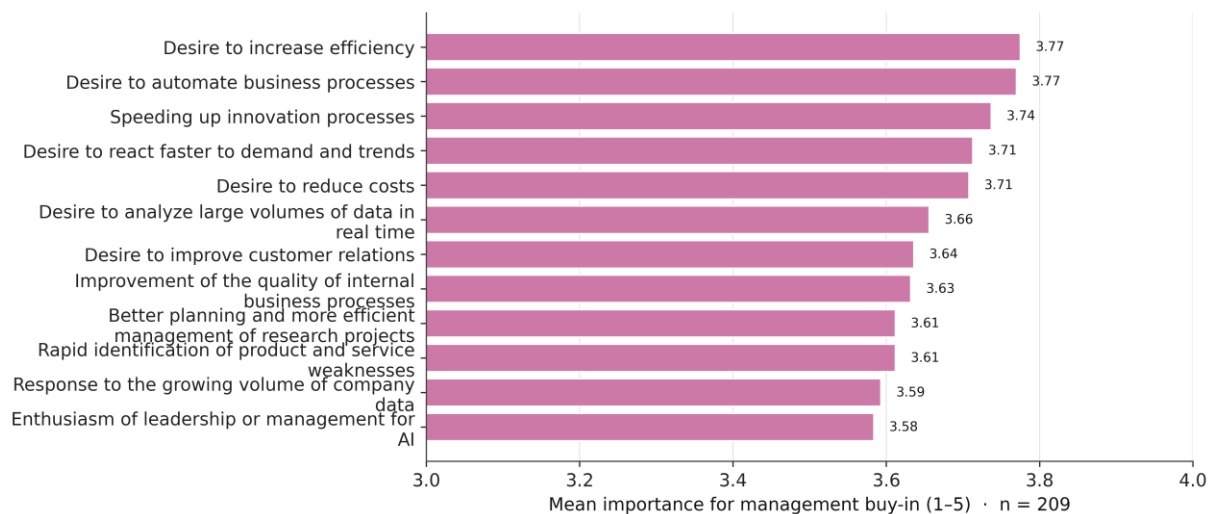


Figure 15. Factors rated most important for convincing management to adopt AI, among marketing adopters (n = 209; 1–5).

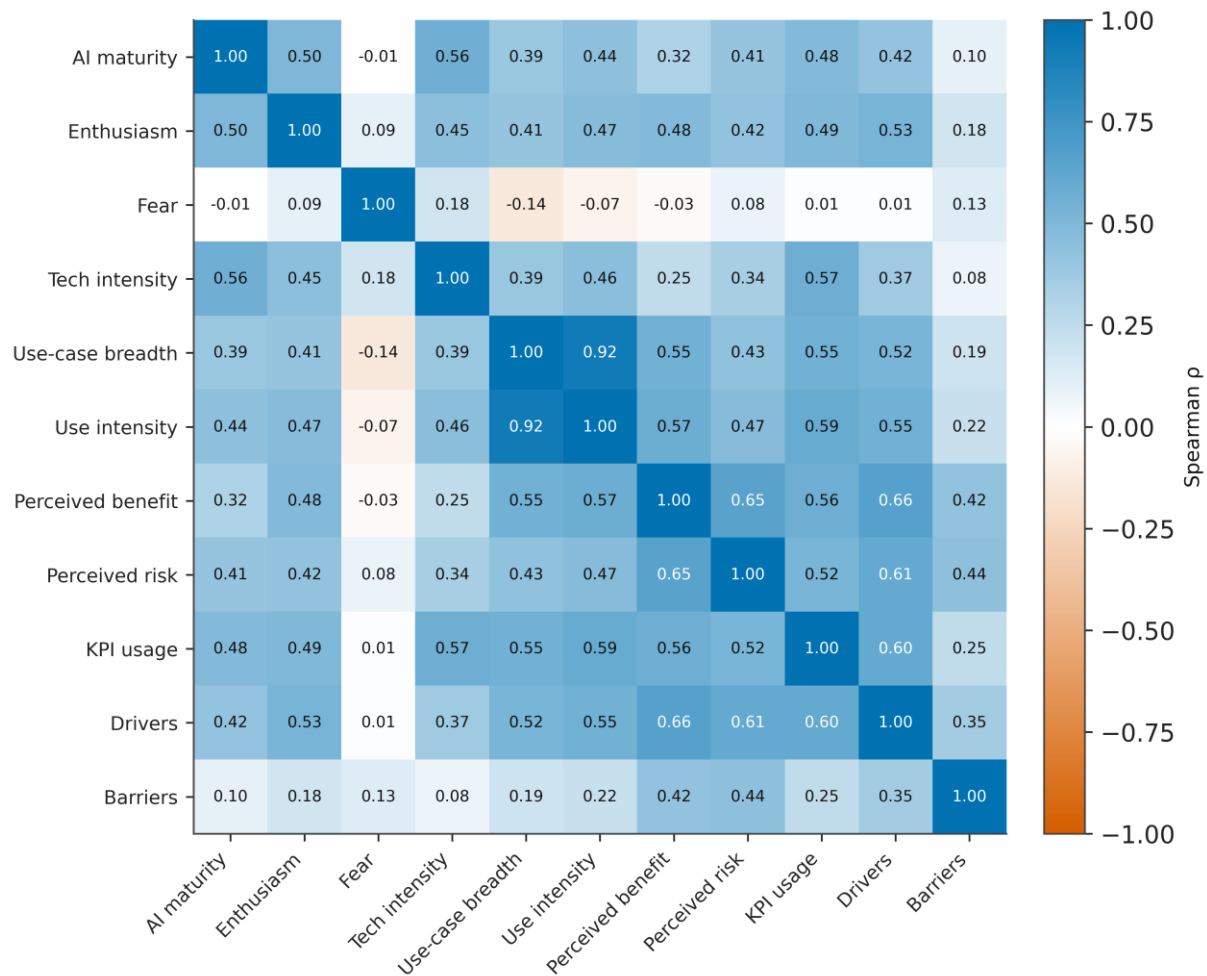


Figure 16. Spearman correlation matrix of key constructs among marketing adopters ($n = 209$).

For RQ4, then: among adopters, the breadth of marketing-AI use is most closely tied to perceived benefit, and not, once benefit is accounted for, to firm size or formal maturity. The firms using the most applications are the ones that rate the benefits highest, though, as noted, the design cannot say which way that runs. Maturity and enthusiasm relate to breadth bivariately and may work through belief, but the data place that as a hypothesis for longitudinal work rather than a tested mechanism.

5.6 The benefit–risk calculus: dual salience, not trade-off

How do marketing adopters rate AI's benefits against its risks? Each side was measured as a battery of significance ratings (1 = not significant at all, 5 = very significant), so what follows compares how significant firms judge various effects to be, not magnitudes of realized impact. On the benefit side (Figure 17), the highest-rated items are customer-facing: the possibility of precise customer targeting (mean 3.74; rated significant by 62.7%), an advanced ability to evaluate campaign success (3.73; 65.1%), increased customer satisfaction and loyalty (3.70;

57.9%), satisfaction through better product availability (3.69; 59.8%), and support for brand reputation (3.67; 59.3%). Efficiency and cost benefits rank below these. The pattern places the perceived value of marketing AI in customer understanding and targeting rather than in cost-cutting, consistent with the customer-centric emphasis of the AI-marketing literature (Kumar et al., 2019; Chandra, Verma, Lim, Kumar, & Donthu, 2022).

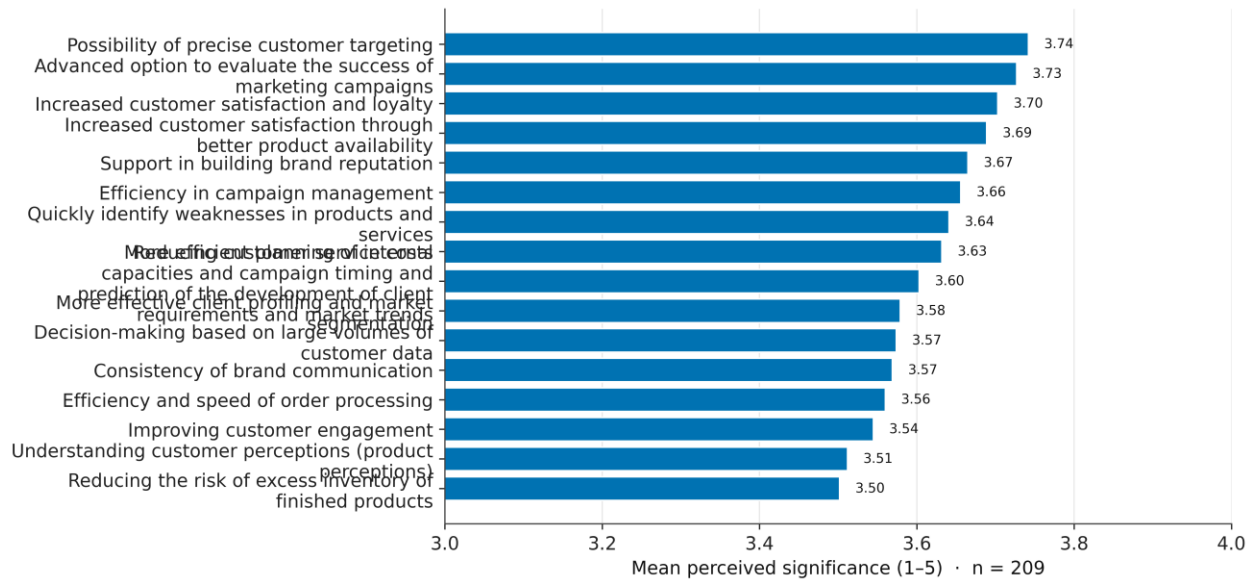


Figure 17. Perceived positive impacts of AI in marketing, ranked by mean significance ($n = 209$; 1–5).

On the risk side (Figure 18), the most significant perceived negatives are not the ethical or reputational hazards that dominate the AI-ethics literature (Hagendorff, 2020; Kunz & Wirtz, 2023) but rather *capability and integration* requirements: the need for knowledge to interpret extensive marketing analytics (mean 3.56), the need for appropriate campaign settings (3.56), the need to integrate AI into existing corporate information systems such as CRM and customer databases (3.54), the risk of using incorrect models in ad personalization or segmentation (3.51), and the risk of misinterpreting analytics outputs (3.49). The ethical-content risk of AI-generated material sits lower in the ranking. In short, Slovak marketing adopters experience the downside of AI primarily as an *operational and competence* challenge—data, integration, interpretation, model correctness—rather than as a moral one. This is consistent with the analytical-use-case bottleneck identified in Section 5.3: the very capabilities firms most lack are those the analytical use cases most demand.

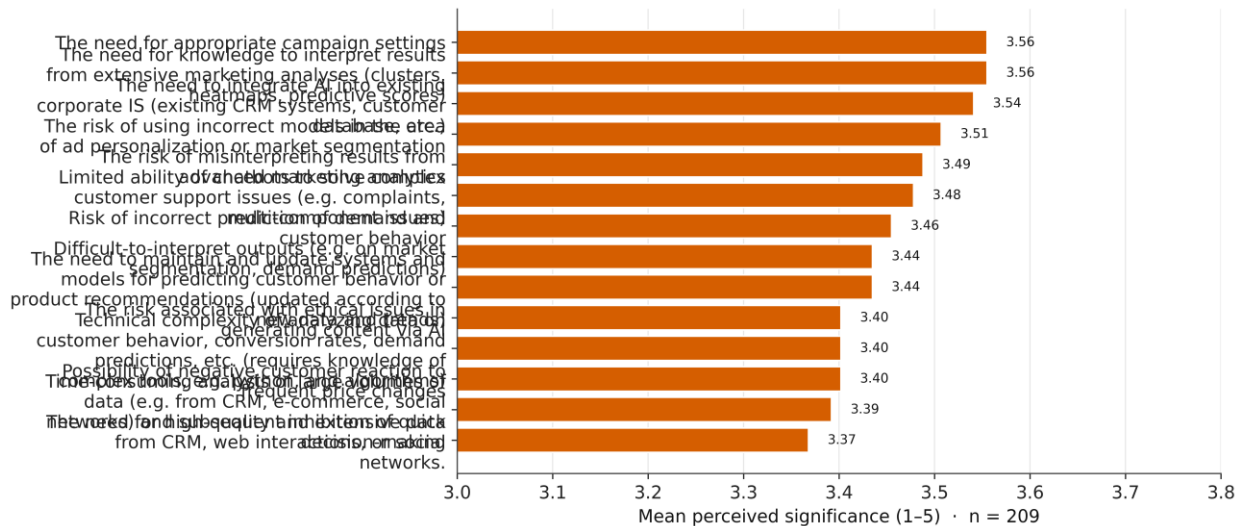


Figure 18. Perceived risks and challenges of AI in marketing, ranked by mean significance (n = 209; 1–5).

The same capability-and-cost emphasis appears in the separate barriers battery (Figure 19), a list of twenty generic obstacles to AI implementation. The highest-rated are the cost of maintaining and developing AI systems (mean 3.37), legal and regulatory uncertainty (3.30), insufficient quality or availability of the data AI needs (3.26), the lack of high-quality training data (3.25), and the high initial investment in AI technologies (3.25). The barrier means sit in a narrow band (about 3.1–3.4), which here means no single obstacle stands out as decisive; adopters report a diffuse bundle of moderate cost, data, and regulatory frictions rather than one binding constraint. Two cautions apply to this scale. Its third response option is labelled "no impact" and sits between "rather not a barrier" and "rather a barrier," so it functions as a not-applicable category rather than a clean midpoint, and the means should be read as relative rankings, not as distance from a neutral point. As with the sentiment battery, the item help text documents a six-point scale while the data are five-point; we use the five-point coding present in the data.

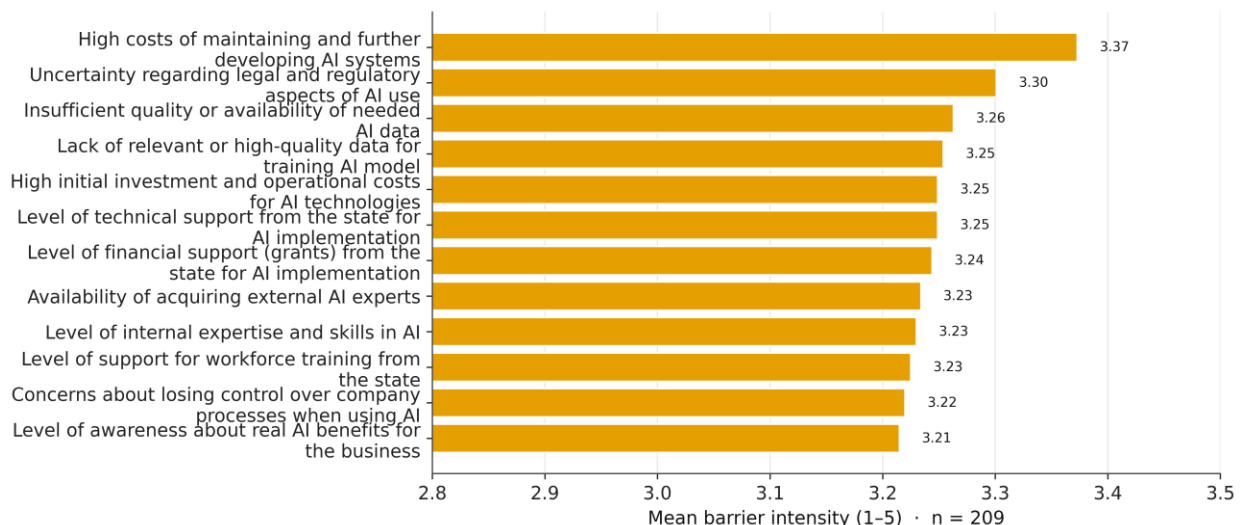


Figure 19. Highest-rated barriers to AI implementation among marketing adopters ($n = 209$; 1–5).

Do benefits outweigh risks? On average yes, but only modestly. Mean perceived benefit (3.62) exceeds mean perceived risk (3.46) on a paired Wilcoxon test ($p < .001$), with a small effect (Cohen's $d_z = 0.28$). About 54.5% of adopters rate benefits above risks, 37.8% rate risks at or above benefits, and 7.7% are level (Figure 20). H9 is supported but weakly: among these adopters, marketing AI is judged a promising technology whose advantages edge out its drawbacks, not a clear-cut win.

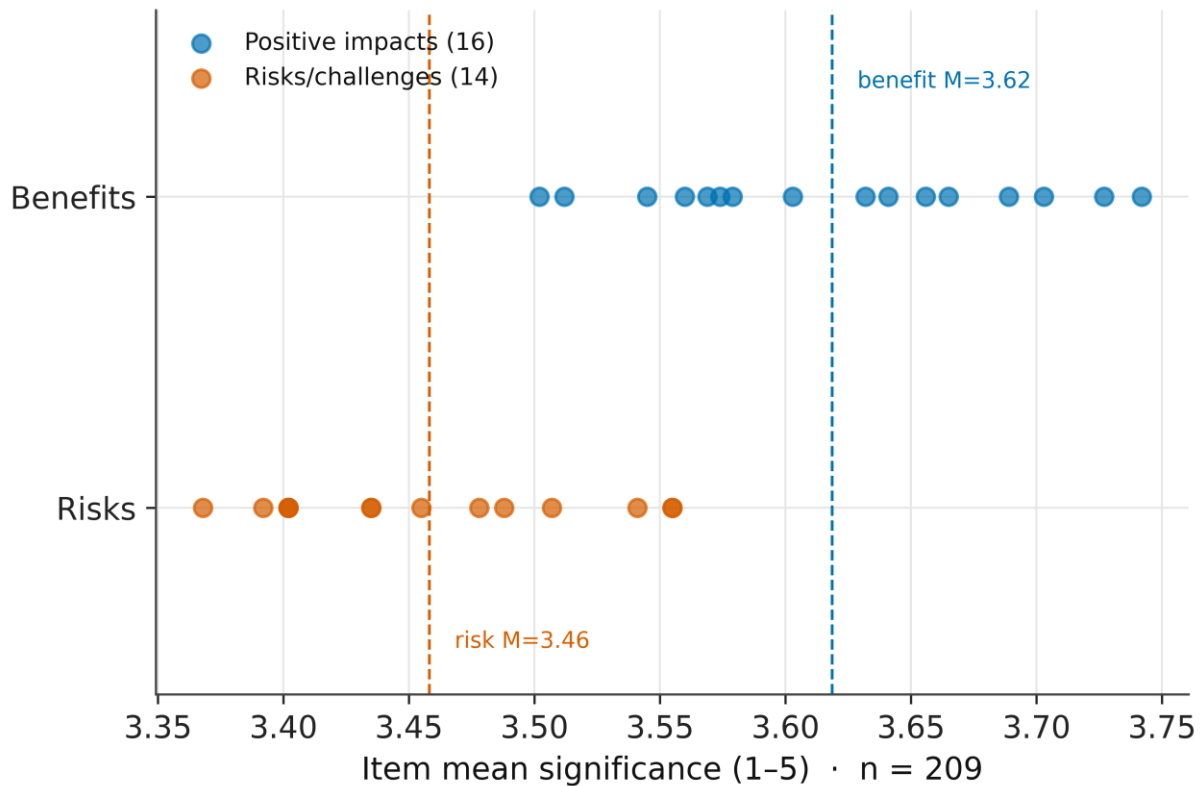


Figure 20. Item-level distribution of perceived benefits (16 items) and risks (14 items), with group means ($n = 209$).

The relationship between benefit and risk is more interesting than the comparison of their averages. A trade-off, the expectation behind H10, would have firms that see more benefit seeing less risk. The data show the reverse: perceived benefit and perceived risk are positively correlated (Spearman $\rho = .65$). H10 is not supported. Two things have to be checked before reading anything into this. First, whether benefit and risk are even distinct: a joint exploratory factor analysis of the thirty items separates them cleanly onto two factors, with benefit items loading on one (mean loading .69) and risk items on the other (.63) and almost no cross-loading, so firms do answer the two batteries as different things rather than as one undifferentiated attitude. Second, how much of the positive correlation is a response style. Some of it is: when an independent "rate-high" tendency (each firm's average across the maturity, technology, and driver batteries) is partialled out, the benefit–risk correlation falls from

.65 to about .47. It remains clearly positive. The substantive reading, which we label dual salience for short, is that firms more alert to AI's benefits tend also to be more alert to its risks, both rising with engagement and depth of use; barriers behave the same way, correlating .42 with benefit and .44 with risk. The methodological reading is that engaged respondents rate everything higher. The design cannot fully separate the two, and the truth is likely some of each. Either way, marketing AI is not appraised along a single optimism-to-pessimism line; benefit and risk move together, which shifts the practical question in Chapter 6 from striking a balance toward raising informed awareness.

5.7 Perceived value and employment effects

Marketing adopters report mostly favourable effects of AI on their financial and operational indicators (Figure 21). The item is worded so that firms using AI for at least twelve months report the realized change and others give an expectation; since 68.4% of these adopters started in 2023 or later, the figures are mainly expectational, and Figure 21 should be read accordingly. On the five-point change scale (3 = no change), the largest reported gains are in operating cash flow (mean 3.68; 59.3% report an increase), labour productivity (3.66; 62.7%), revenue from sales (3.60; 57.4%), the financial result (3.60; 55.5%), decision-making speed (3.57; 53.6%), and customer-service quality (3.55; 56.5%). Cost lines move less and in a way that is harder to read as good or bad: material and energy costs (3.32) and personnel costs (3.28) are reported as rising by about four firms in ten, which is consistent with AI as an investment that raises some costs while firms expect revenue and productivity to climb. Business risk is closest to "no change" (3.13). The reported pattern leans toward top-line and productivity effects rather than cost reduction.

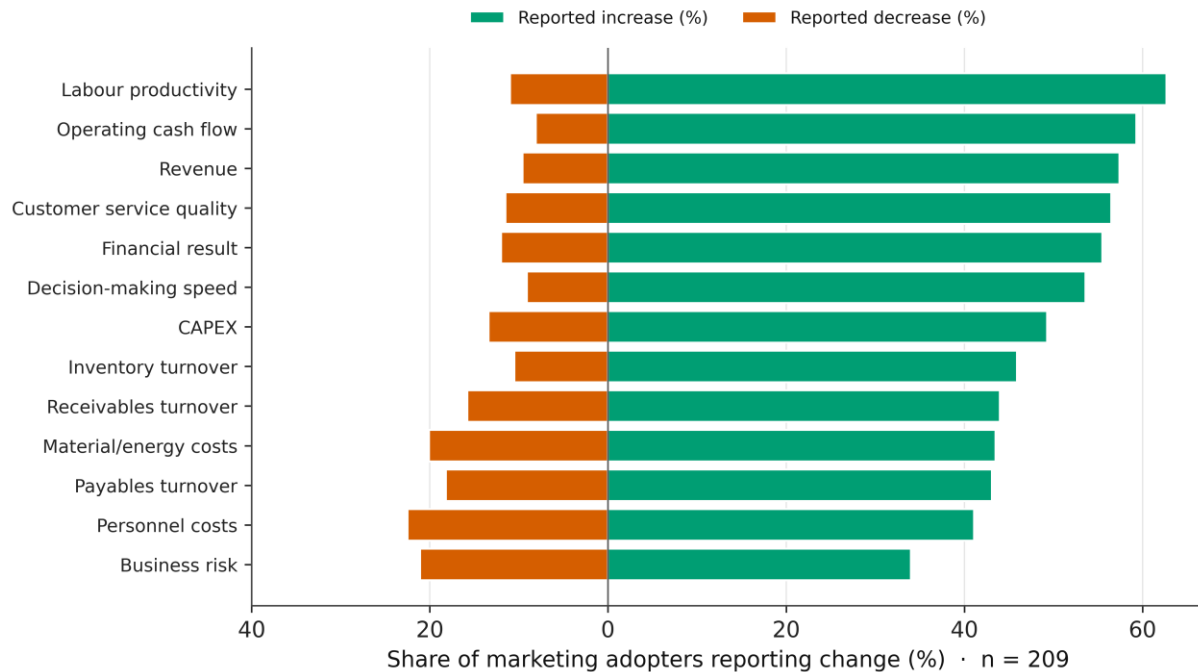


Figure 21. Perceived impact of AI on financial and operational indicators (n = 209): share reporting increase versus decrease.

These reported outcomes vary with engagement. Breadth of active use, use intensity, and perceived benefit each correlate positively with every outcome examined: revenue ($\rho = .35, .37, .39$ for breadth, intensity, benefit), labour productivity (.34, .33, .34), customer-service quality (.34, .37, .42), financial result (.31, .27, .31), and decision-making speed (.31, .34, .31). All fifteen survive a Benjamini–Hochberg correction across the family ($q < .001$; $n = 209$), so H11 is supported. The interpretation has to stay modest. These are perceptions, correlated with other perceptions reported by the same person, and the relationship could reflect real value, optimistic self-assessment, common-method variance, or the selection of better-performing firms into deeper use. It is also worth holding against a counter-current in the literature: a meta-analysis of forty-five studies documents a "dark side" of AI in marketing, with adverse customer reactions to personalization and automation that firm self-reports of this kind would not capture (Barari, Ferm, Quach, Thaichon, & Ngo, 2024). The association between depth of use and perceived benefit is real in the data; whether it reflects realized value is beyond what a single self-report cross-section can show.

Employment is the most charged question about AI, and the items here are blunt: two yes/no questions asking whether AI has led, or is expected to lead, to layoffs, and whether the firm has introduced or plans to introduce new roles because of AI. Counting firms, 8.6% answer yes to layoffs (realized or planned) and 22.5% to new roles (Figure 22). This says that more adopters anticipate adding marketing roles than cutting them; it does not establish a net employment effect, because a firm adding one role and a firm cutting fifty each count once, the items mix realized with planned action, and social desirability likely inflates "creating" over "cutting." Read

narrowly, the result shows no sign of marketing-led displacement at this early stage and is consistent with an augmentation pattern, in which AI adds analytical, content, and orchestration tasks alongside existing work, as in the "new tasks" mechanism (Acemoglu & Restrepo, 2019) and in field evidence that generative AI augments customer-facing roles (Brynjolfsson et al., 2023). It is not evidence that marketing AI creates jobs on net. H12 is supported only as a statement about the balance of firm-level perceptions, not about headcount.

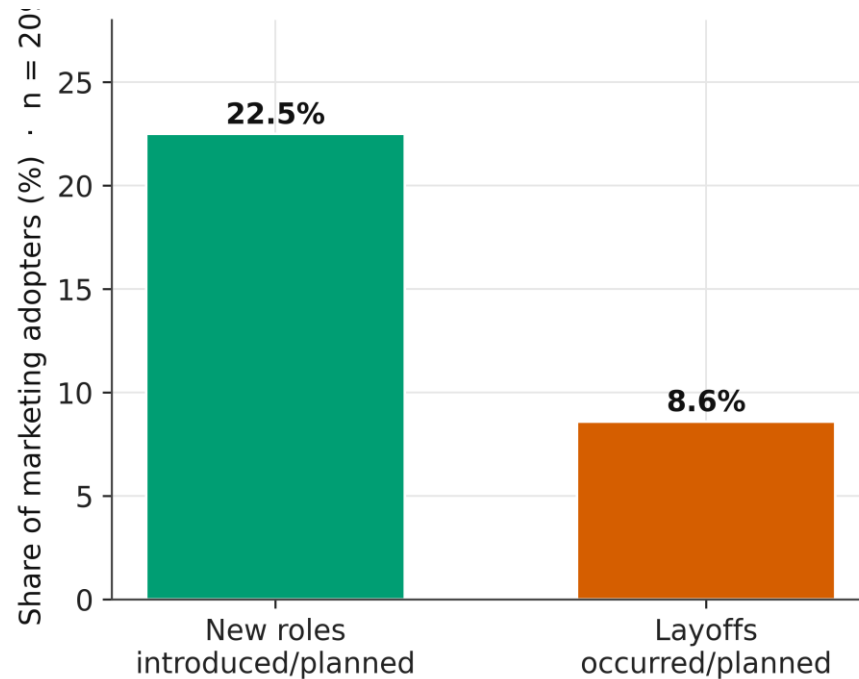


Figure 22. Employment effects of AI among marketing adopters: new roles created/planned versus layoffs ($n = 209$).

On RQ5 and RQ6, the short answers are: benefits are rated slightly above risks but the two move together rather than trading off; the reported value sits in customer, revenue, and productivity outcomes and rises with depth of use; and the employment signal, such as it is, leans toward role creation rather than loss, within the strict limits of what two binary items can show.

5.8 A typology of marketing-AI adopters

The earlier sections describe adopters one dimension at a time; the last analysis asks whether those dimensions group firms into recognizable segments. K-means and Ward clustering on standardized engagement and perception features (use intensity, benefit, risk, maturity, enthusiasm, fear, technology intensity) point to a two-group solution, but the separation is weak. The silhouette at $k = 2$ is 0.255, only just above the 0.25 mark conventionally read as little real structure; three-, four-, and five-cluster solutions are weaker still (around 0.16–0.18). Kruskal–Wallis tests confirm the two groups differ on every feature (all $p < .001$), but they differ in

degree, not in kind: one group scores higher than the other on all features in the same direction, including fear, and a single engagement composite reproduces the split almost perfectly (AUC $\approx$ 0.94). What the clustering recovers is therefore the upper and lower halves of one engagement gradient rather than qualitatively distinct types. With that understood, the two halves (Figure 23) are worth describing, and we give them working labels:

- **Advanced Integrators (n = 118; 56% of adopters).** Broader and deeper use (mean use intensity 3.45; 6.9 of 14 applications in active use), higher ratings of both benefit (3.90) and risk (3.78), higher AI maturity (3.43), enthusiasm (3.84), technology intensity (3.49), KPI usage (3.85), and drivers (3.79), and the higher rate of planned or realized new roles (26%).
- **Cautious Experimenters (n = 91; 44% of adopters).** Narrower use (intensity 2.71; 3.5 applications active), lower ratings of benefit (3.25) and risk (3.04), and lower maturity (2.43), enthusiasm (2.99), technology intensity (2.17), and KPI usage (3.02). They have started but stayed shallow.

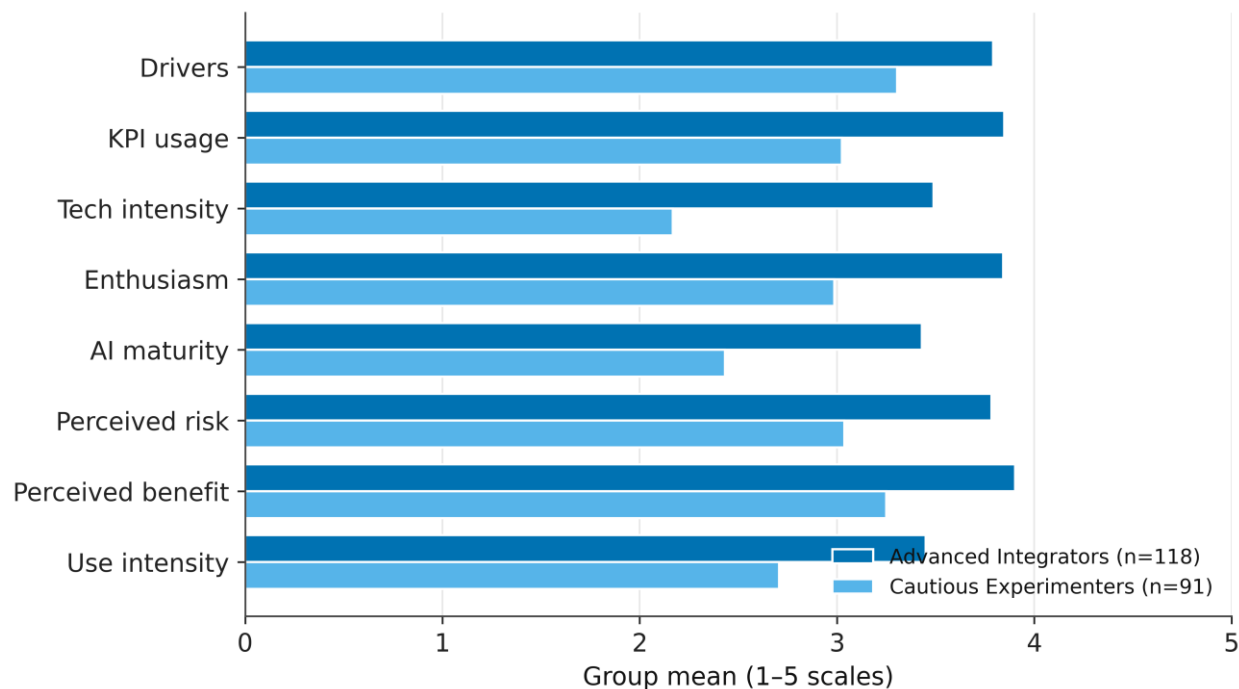


Figure 23. Profiles of the two adopter segments across key dimensions (group means; n = 118 and 91).

Two points are worth drawing out. The split is not a firmographic one: the two groups have almost identical foreign-ownership shares (36% vs 35%), similar size distributions, and similarly low layoff rates, so the difference between deep and shallow engagement is organizational and attitudinal rather than structural, echoing Section 5.4. And the axis separating them is the same one Section 5.6 described, with the higher group rating both benefit and risk above the lower group; the segmentation is, in effect, a restatement of that engagement-and-salience pattern, not an independent finding. Because the clustering only sorts firms high or low, it is more useful to separate level of adoption from stance directly (Figure 24). Crossing adoption intensity

(median split) with the sign of net benefit gives four roughly even quadrants: high adoption and benefit-leaning (31.6%), high adoption but risk-or-parity-leaning (21.5%), low adoption but benefit-leaning (23.0%), and low adoption and risk-or-parity-leaning (23.9%). The even spread is the point: adopters vary both in how far they have gone and in how they weigh the technology, and the two do not line up neatly, which gives Chapter 7 a simple way to target different firms.

For RQ7, the honest answer is that adopters sort along a single engagement gradient that can be cut into a more- and a less-engaged half, useful as a description and for targeting, but not a typology of distinct kinds.

5.9 Summary of results

Pulling the eight analyses together, with the caveats each carries. Among the firms surveyed, marketing is the most frequently chosen area for AI, recently and across the size range (5.1). Adopters decide organizationally rather than individually, draw on a spread of information sources, and equip themselves first with conversational and language technologies (5.2). Their use cases form one broad gradient led by low-complexity customer-facing automation, with the analytical applications mostly in planning (5.3). Adoption is associated with overall AI engagement, a partly definitional measure, and weakly and not robustly with domestic ownership, but not with size or formal maturity (5.4). Breadth of use is associated above all with perceived benefit, with maturity and enthusiasm dropping out once benefit is included, though the design cannot fix the direction of that link (5.5). Benefits are rated slightly above risks and the two move together rather than trading off, partly substantively and partly as response style, and the risks firms weigh most are about capability and integration rather than ethics (5.6). Reported value sits in customer, revenue, and productivity outcomes, rises with depth of use, and comes with firms reporting more role creation than loss, none of it a measured effect (5.7). And the adopters sort along a single engagement gradient rather than into distinct types (5.8). The next chapter reads these against theory and prior work.

6. Discussion

This chapter reads the results against theory and prior work. It takes them in the order they were presented (marketing as a common entry point, what relates to breadth, how benefit and risk are perceived, ownership, value and jobs) and closes with what the study does and does not contribute to the TOE and diffusion literatures. Throughout, the design imposes a discipline that the discussion tries to keep: the data are one cross-section of self-reports from a non-probability sample, so they speak to associations and perceptions among these firms, not to causes or to the Slovak economy as a whole.

6.1 Marketing as a common entry point for enterprise AI

The first result is simply that, among the AI-using firms surveyed, Marketing and Sales is the area most often chosen for AI, a little ahead of production and logistics. That is worth registering because regional research on enterprise digitalization has concentrated elsewhere, on Industry 4.0 in manufacturing and logistics (Richnák, 2022; Valášková et al., 2022) and on HR and e-commerce digitalization (Čirčová et al., 2025; Wiktor et al., 2021). In this sample at least, marketing is where firms are about as likely as anywhere, and somewhat more likely, to be applying AI. The fit with theory is loose but reasonable: the capabilities that diffuse first, language handling, prediction, and the automation of routine judgement, line up with marketing tasks (Huang & Rust, 2021; Davenport et al., 2020). Two qualifications keep this from being more than it is. The survey option bundles marketing with sales, so part of its lead over narrower functions is category width, and the sample is not representative of Slovak firms, so the share is a feature of these respondents rather than a national rate. A cautious way to put the practical point is that, for a good number of firms, marketing is an early and visible place where the organization meets the unglamorous parts of AI, data quality, vendor choice, model oversight, and change management, which makes it a useful vantage point for studying enterprise adoption even if it is not literally the "front line" everywhere.

6.2 What relates to breadth, and what does not

Among adopters, the breadth of marketing-AI use is associated with perceived benefit and, once benefit is in the model, with little else: not firm size, not sales, not formal AI maturity (IRR for benefit = 1.51, $p < .001$). This is consistent with the perceived-usefulness idea at the centre of the Technology Acceptance Model (Davis, 1989) and with Rogers's relative-advantage attribute (Rogers, 2019), that depth of use follows the belief that a technology pays off. It is consistent with, not a demonstration of, that idea, and two cautions matter. The first is direction. Benefit and breadth were reported by the same respondent at the same time; the regression

cannot say whether belief leads firms to deploy more or whether deploying more leads firms to believe, and the companion OLS, in which breadth predicts net benefit, points the other way. The second is level of analysis. TAM is a theory of individual beliefs, and the study measures benefit at the level of a single firm informant, so the parallel is an analogy rather than a test of TAM proper. The role of maturity and enthusiasm is best stated carefully: both correlate with breadth on their own ($p = .39$ and $.41$) and lose that association once benefit enters, which is consistent with their working through belief, but coefficient attenuation under correlated, same-source measures is also consistent with shared method variance, and no mediation was estimated.

This bears on the SME literature without overturning it. That literature finds resource and scale constraints gating AI adoption (Schwaeke et al., 2024; Oldemeyer et al., 2024; Bhalerao et al., 2022). The present sample contains only firms that have already adopted AI and already use it in marketing, with no micro-firms and a large-firm skew, so the constraints that gate entry have largely operated before this group is observed. Finding that size does not predict how far these firms then go refines the resource account rather than contradicting it: among firms past the entry threshold, depth tracks perceived benefit more than scale. The intervention implication in Chapter 7 follows from that more modest statement, and from the diffusion reading that credible evidence of benefit, rather than size, is what moves firms further along.

6.3 Dual salience: benefit and risk rise together

The benefit–risk pattern runs against the simple intuition that the two trade off. They do not; they co-occur ($p = .65$), and the engagement split in Section 5.8 falls along the same line, with the more engaged half rating both benefit and risk higher. Before making anything of this, two checks are needed, and both were run. Benefit and risk are not one undifferentiated attitude: a joint factor analysis separates the two batteries cleanly, so firms answer them as distinct things. And the positive correlation is partly, not wholly, a response style: adjusting for a general tendency to rate things highly lowers it from $.65$ to about $.47$, where it stays clearly positive. With those in hand, the cautious reading is that firms more alert to AI's benefits tend also to be more alert to its risks, a pattern we label dual salience for brevity, with engagement rather than optimism as the underlying difference. The competing reading, that engaged respondents simply rate everything higher, cannot be ruled out with single-source data. The substantive version resonates with the "sharply divided" organizational discourse described by Bankins et al. (2023), recast as a matter of depth of involvement rather than fixed optimist and pessimist camps; the methodological version is a standard caution about common-method variance, taken up again in the limitations.

Two smaller points hold up regardless of which reading dominates. Organizational fear is close to unrelated to adoption (about zero with maturity, $-.14$ with breadth), so the common story that fear of AI is a primary brake gets no support in this sample. And the risks firms rate highest are

about capability and integration, interpreting analytics, fitting AI to existing CRM systems, avoiding model error, rather than ethics or privacy, which sit lower. That ordering differs from the emphasis of the AI-ethics literature (Hagendorff, 2020; Kunz & Wirtz, 2023) and from consumer-side privacy concerns (Palos-Sánchez et al., 2018); at the firm level here, the felt downside is operational competence more than moral hazard. Both point to capability-building and credible demonstration of benefit, rather than reassurance about ethics or jobs, as the more relevant levers for deeper adoption.

6.4 The ownership association

One firmographic signal points in an unexpected direction: foreign-owned firms show lower odds of marketing-AI adoption than domestically owned firms (OR = 0.62, $p = .011$). It should be treated lightly. The coefficient does not survive the multiple-comparison correction applied to the model ($q = .056$), the model itself fits weakly, and a single odds ratio carries little on its own. With that said, the sign is worth a tentative explanation because it inverts the usual expectation that foreign ownership proxies for resources and sophistication. Several readings are consistent with the data and cannot be separated here. Marketing strategy, brand management, and the associated customer data and MarTech are often centralized at a multinational's headquarters, so a capable Slovak subsidiary may apply AI in the operations it controls rather than in a marketing function run abroad. Foreign-owned plants may also over-index on production AI for reasons specific to their role in a value chain, or local respondents may not report group-level marketing AI as their own. Each is a conjecture for subsidiary-level data, not a conclusion. To the extent the centralization reading holds, it fits the TOE point that a firm's environment, here its place in a corporate hierarchy and where decision rights over customer data sit, shapes where AI is applied and not only whether. We resist turning one fragile coefficient into a firm policy prescription; the conditional version appears in Chapter 7.

6.5 Value with jobs

The value items describe marketing AI, in the eyes of its adopters, as more of a growth-and-productivity technology than a cost-cutting one. The largest reported gains are in cash flow, labour productivity, revenue, customer-service quality, and decision speed, with cost lines moving less and less clearly, and depth of use correlates with these reported outcomes across the board ($\rho \approx .27-.42$, surviving correction). The concentration in customer-facing and top-line outcomes fits the customer-centric emphasis of AI-marketing work (Kumar et al., 2019; Luo et al., 2021) and the broader AI-capability and firm-performance literature (Mikalef & Gupta, 2021; Wamba-Taguimdje et al., 2020). The standing against that, which the chapter should hold rather than bury, is that these are perceptions correlated with other perceptions from the same respondent, and that a meta-analysis of forty-five studies finds a "dark side" of AI in marketing, adverse customer reactions that firm self-reports of this sort will not register (Barari et al., 2024).

The association is real in the data; that it reflects realized value is not something a single self-report cross-section can establish.

The employment result is easy to over-read and is reported here narrowly. More adopters say they have added or plan AI-related marketing roles (22.5%) than say AI has cut or will cut roles (8.6%). That is a count of firms, not of jobs: it cannot net one firm's new hire against another's fifty redundancies, it mixes realized with planned action, and it is open to a social-desirability tilt toward reporting creation. What it does show is no sign of marketing-led displacement at this early stage, which is consistent with an augmentation pattern in which AI adds analytical, content, and orchestration tasks alongside existing work, the "new tasks" channel of Acemoglu and Restrepo (2019) and the augmentation found for customer-facing work by Brynjolfsson et al. (2023). It is not evidence of net job creation, and it would be a mistake to read it as a rebuttal of the displacement literature (Frey & Osborne, 2017; Acemoglu & Restrepo, 2020) rather than as a small, early, perception-level signal that points the other way.

6.6 What the study contributes, and how far

The contributions are best stated modestly. The most novel of them is the benefit–risk pattern. Where the SME-AI literature tends to weigh benefits against barriers as opposing forces (Čubrić, 2020), the firm-level evidence here shows benefit and risk perceptions rising together rather than trading off, distinct as constructs but moving in step with engagement. That suggests adoption models would do well to treat the two as jointly increasing with involvement, while taking seriously, as this study does, that part of the co-movement is response style. Second, separating whether a firm adopts AI in marketing from how broadly it does so is analytically useful: the two relate to different things in these data, adoption to overall AI engagement (a partly definitional measure) and breadth to perceived benefit. This is less an extension of TOE or diffusion theory than an application of them to depth and portfolio of use, a question with its own older tradition in information systems on the extent and infusion of use that future work in this vein should engage directly. Third, locating the study in a CEE economy is a reminder that determinant weights are context-bound (Baker, 2011; Neumann et al., 2022): size and maturity do less work here than the Western and Asian literature might lead one to expect, at least within a sample of firms that have already adopted. None of this displaces the resource-based reading, which sits in tension with the belief result rather than being settled by it; perceived benefit may itself be a capability, data, skills, and absorptive capacity, expressed as belief (Mikalef & Gupta, 2021), and a study that measured those capabilities directly could test whether belief is a mediator or a proxy. The honest summary is that the work supplies use-case-level description and a set of associations, foregrounds a benefit–risk pattern worth following up, and does so for a setting and a function the literature has largely passed over, while leaving the causal and mechanism questions to the longitudinal designs the data here cannot support.

7. Implications

7.1 For managers and marketing leaders

With the caveats of the previous chapters in mind, the patterns suggest a few practical orientations for marketing leaders rather than firm prescriptions. The applications that most peers are already running, chatbots, advertising-campaign automation, personalized offers, and price optimization, are the low-complexity, quick-to-observe entry points, and a firm starting out has good company in beginning there. The analytical applications that sit in the planning stages, CRM intelligence, integrated customer-data analytics, sentiment analysis, are held back less by reluctance than by the capability and integration demands that adopters themselves rate as their main difficulties, so investment in data integration with CRM, in the skills to interpret analytic output, and in basic model governance is where a firm wanting to deepen its use is likely to get the most traction. Because breadth travels with perceived benefit (in whichever causal direction), credible internal evidence of benefit, pilots with explicit KPIs of the kind the more engaged firms already use, documented before-and-after results, and shared internal cases, is more useful than enthusiasm alone. And since the data show role creation outweighing role loss in firms' own accounts, leaders can reasonably plan for new analytical and content roles and for the reskilling that turns existing marketers into people who can direct and check AI, while not assuming that adoption is costless in headcount terms.

7.2 For policymakers

For policy in a small, open, FDI-intensive economy, the results are more suggestive than directive. The clearest is that marketing-AI adoption in this sample does not rise with firm size, so support aimed only at large firms would miss much of where the activity is; small and mid-sized firms are adopting at comparable rates and are a reasonable focus for national programmes. The ownership signal points, tentatively, in the same direction, since domestically owned firms were the more likely marketing adopters, but that coefficient is weak and does not survive correction, so any "target domestic firms" reading should be treated as conditional on confirmation rather than as an established basis for allocating funds. What firms describe as their main difficulties, data quality and integration, analytic skills, and the cost of building and maintaining systems, argues for public effort on data skills, on help integrating AI with existing business systems, and on shared analytical infrastructure, in preference to generic awareness campaigns, since awareness is not the binding constraint here. Finally, the timing, with most adoption beginning since 2023 and a large planning pipeline behind it, means the process is at an early and probably malleable stage, which is an argument for engaging now rather than after the patterns have set.

7.3 For technology providers and educators

For vendors, the sample divides loosely into more-engaged firms that need depth (integration, governance, advanced analytics) and less-engaged firms that need guided, low-risk starting points and evidence that the benefits are real. Because the more engaged buyers register benefits and capability risks together, pressing only on benefits is unlikely to move them; credible enablement, training, integration services, and reference cases, is the more plausible differentiator. For educators and business schools, the applications that firms most want next are the data-intensive analytical ones, and the difficulties they report are about interpreting analytic output and integrating systems, which points to a gap that tool familiarity alone does not fill: the marketing workforce needs the analytic-interpretation and data-integration skills the next wave of use cases will require.

8. Limitations and future research

The conclusions are bounded by several limitations, some of which have been flagged in place and are drawn together here because they shape how much weight the results can carry.

The design is cross-sectional and the measures are self-reported by a single informant per firm. This raises two distinct problems. One is direction: the headline association, between perceived benefit and breadth of use, is between two things reported at the same time, and the data cannot say which way it runs; the companion regression points the opposite way, and the most that can be claimed is association. The other is common-method variance. Because benefit, risk, breadth, maturity, and the rest come from one questionnaire, a general tendency to rate things high or low can inflate correlations among them, and the strong benefit–risk correlation is a candidate symptom. We examined this directly rather than only noting it. A first unrotated factor across sixty-three Likert items accounts for 32.8% of the variance, below the rough 50% threshold at which a single method factor is judged to dominate, so method variance is present but not overwhelming; about 15.3% of adopters nonetheless gave the same answer to at least four-fifths of the thirty benefit-and-risk items, and adjusting the benefit–risk correlation for a response-style proxy lowers it from .65 to about .47. The substantive patterns survive these checks, but they are not free of method effects, and a future design with a marker variable or, better, multiple respondents per firm would settle how much of the co-movement is real.

The sample is not a probability sample of Slovak enterprises. There is no stated sampling frame, the analytical file contains no micro-firms (under ten employees) and skews toward larger firms, and the resulting AI-use rate is far above representative EU benchmarks, precisely because the least-adopting firms are absent. Prevalence figures such as the 37.2% marketing share or the 68.9% AI-use rate should therefore be read as properties of these respondents, not as economy-wide rates, and the determinant results speak to variation within an already-adopting population, not to what gates entry into AI in the first place. Relatedly, the dependent variable is self-labelled: at a moment when most adoption is recent and the most common application is chatbots, some of what firms record as "AI in marketing" may be relabelled rule-based automation, which would overstate genuine AI adoption. The study cannot adjudicate this and flags it as a validity threat specific to this early period.

Two further measurement points temper specific results. The "overall AI-use intensity" predictor in the adoption model is a recoding of the same gating item that defines the outcome, so its positive coefficient is partly mechanical and is treated as a control rather than a finding. The financial and operational "impact" items blend realized change for longer-standing users with expectations for the rest, and given how recent this cohort is, they are mainly expectational; they are not audited outcomes. The ownership association, finally, does not survive multiple-

comparison correction and rests on a single coefficient in a weakly fitting model, which is why the chapter treats it as a lead for subsidiary-level research rather than a result.

With 209 adopters the subsample is adequate for the analyses reported but thin for fine sector-by-size breakdowns, several of which have small cells. And the data describe one country at one early moment. Cross-country replication within the V4 and the wider EU, re-measurement over time, and designs that link survey responses to later, objective performance would all help separate what is general here, plausibly the benefit-and-breadth association and the benefit–risk co-movement, from what is specific to Slovakia, to 2025, or to this sample. The dataset's parallel modules for production, finance, HR, logistics, and ICT offer a natural extension: testing whether the patterns found for marketing hold across functions, and whether the benefit–risk co-movement is a property of marketing AI or of enterprise AI more generally.

9. Conclusion

The question behind this study was how enterprises, and especially the SMEs that make up most of the European economy, actually take up AI in their marketing function, a question the consumer-centric literature on AI in marketing has largely left open and one with almost no evidence from Central and Eastern Europe. Working from the AI-IMPACT survey of 816 Slovak enterprises and its 209 marketing-AI adopters, and reading the data through the Technology–Organization–Environment and diffusion frameworks, the study offers a description of an early stage of that take-up rather than a settled account of its causes.

Among the firms surveyed, marketing is the area most often chosen for AI, spread across the size range rather than concentrated in the largest firms, and recent. The fifteen use cases form one broad gradient led by the low-complexity, customer-facing tools, with the data-intensive analytical applications still mostly in planning, held there by the capability and integration conditions they need. Within this already-adopting population, how far firms take marketing AI is associated above all with how beneficial they judge it to be, and not, once that is accounted for, with size or formal maturity, though the cross-sectional, single-respondent design cannot establish the direction of that link. Benefits are rated a little above risks, and the two move together rather than trading off, a co-movement that is partly substantive and partly a feature of how people answer surveys. Organizational fear plays little role. The reported value sits in customer, revenue, and productivity outcomes and rises with depth of use, and firms report adding marketing roles more often than cutting them, though neither result can be read as a measured effect. The adopter population sorts along a single engagement gradient that can be split into a more- and a less-engaged half, useful for description and targeting but short of a typology of distinct kinds.

What the study adds is use-case-level evidence on AI in marketing for a setting and a function the literature has mostly passed over, a clearer separation of whether firms adopt from how far they take it, and a benefit–risk pattern, co-occurrence rather than trade-off, that is worth following up with designs better suited to it. Its practical value is in pointing managers toward the applications their peers already run and the capabilities the next ones demand, in pointing policy toward small and mid-sized domestic firms and toward data and integration skills rather than awareness, and in marking, for vendors and educators, where the bottleneck lies. These are early findings from one country at one moment, offered with their limits stated, as a starting point for the longitudinal, cross-country, and outcome-linked work that the questions ultimately require.

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Appendix A. Codebook of derived variables

The analyses use the following firm-level derived variables, constructed from native survey items. Composite indices are means of their constituent items unless stated otherwise; reliabilities (Cronbach's α) are reported in Chapter 4.

Derived variable	Definition	Scale / range
ai_user	Firm uses or pilots AI (gating item <i>AIuse</i> $\in$ {multiple areas, several processes, testing})	Binary
ai_intensity	Depth of overall AI use: 1 = testing/piloting, 2 = several processes, 3 = multiple areas	1–3
mkt	Marketing-AI adopter: selected "Marketing and Sales" as an area of AI implementation/testing	Binary (n = 209)
maturity_mean	Mean of seven AI-maturity items (culture, data, ethics, organization, privacy, strategy, technology)	1–5
sentiment_enthus	Enthusiasm subscale: mean of four positively worded sentiment items (1, 3, 5, 8)	1–5
sentiment_fear	Fear/skepticism subscale: mean of four negatively worded sentiment items (2, 4, 6, 7)	1–5
mk_active_breadth	Count of the 14 marketing use cases at diffusion stage ≥ 4 (piloting or active regular use)	0–14
mk_regular_breadth	Count of use cases at stage 5 (active regular use)	0–14
mk_pipeline_breadth	Count of use cases at stage ≥ 3 (planning, piloting, or active)	0–14
mk_intensity_mean	Mean diffusion stage across the 14 use cases	1–5
benefit_mean	Mean of 16 perceived positive-impact items	1–5
risk_mean	Mean of 14 perceived negative-impact (risk) items	1–5
net_benefit	$\text{benefit_mean} - \text{risk_mean}$	–4 to +4
driver_mean	Mean of 19 adoption-driver importance items	1–5
kpi_mean / kpi_breadth	Mean of 8 KPI-usage items / count at level ≥ 4	1–5 / 0–8
barrier_mean	Mean of 19 barrier-intensity items	1–5

Derived variable	Definition	Scale / range
tech_intensity_mean	Mean of 7 AI-technology-type deployment-intensity items	1–5
n_areas	Count of functional areas in which the firm applies AI (excluding "Other")	0–8
layoffs_yes / newjob_yes	AI led/will lead to layoffs / new roles introduced or planned	Binary
foreign	Foreign-owned company registered in Slovakia	Binary
size_large	50 or more employees	Binary

Appendix B. Research questions, hypotheses, and verdicts

Verdicts reflect multiple-comparison correction (Benjamini–Hochberg q-values) and the common-method caveats discussed in the text; associations from a cross-sectional single-respondent design are not evidence of causation.

#	Statement	Lens	Key result	Verdict
RQ1	Prevalence/recency of AI in marketing	—	Most-selected area (37.2% of AI users; 25.6% of surveyed firms); chosen more than production (McNemar $p = .003$); 68.4% began ≥ 2023 , similar to non-marketing adopters (74.2%)	Descriptive
H1	Higher AI maturity $\rightarrow$ adoption	Technology	Data OR = 1.18 ($p = .14$); Tech OR = 1.13 ($p = .27$)	Not supported
H2	Higher overall AI-use intensity $\rightarrow$ adoption	Organization (engagement)	OR = 1.33 [1.10, 1.61], $p = .004$, $q = .036$, but partly mechanical (derived from the gating item)	Supported only as a qualified engagement control
H3	Larger firms $\rightarrow$ adoption	Organization (size)	OR = 0.87 ($p = .14$); rate flat-to-declining in size	Not supported
H4	Ownership associated with adoption	Environment proxy	Foreign OR = 0.62 [0.42, 0.90], $p = .011$, $q = .056$ (fails correction)	Not supported after correction; suggestive only
RQ3	Use-case architecture	Diffusion (descriptive)	Customer-facing automation leads (40–50% active); single dominant factor (47% var, KMO = .93), partly a method factor	Descriptive/EFA
H5	Maturity $\rightarrow$ breadth	Organization	NB IRR = 1.06 ($p = .57$); bivariate $p = .39$	Not supported in model
H6	Enthusiasm $\rightarrow$ breadth	Sentiment	NB IRR = 1.01 ($p = .96$); bivariate $p = .41$	Not supported in model
H7	Perceived benefit $\rightarrow$ breadth	TAM/Diffusion (analogue)	NB IRR = 1.51 [1.20, 1.89], $p < .001$; direction not identified (same-respondent)	Supported as association; causal direction open

#	Statement	Lens	Key result	Verdict
H8	Fear inhibits breadth	Sentiment	NB IRR = 0.89 ($p = .14$); $\rho = -.14$	Not supported
H9	Benefits exceed risks	—	3.62 vs 3.46; Wilcoxon $p < .001$; $d_z = 0.28$; 54.5% rate benefit higher	Supported (modest)
H10	Benefit–risk trade-off (negative corr.)	—	Positively correlated $\rho = .65$ ($\rightarrow .47$ adjusted for response style); benefit/risk distinct in joint EFA	Not supported (co-occurrence, "dual salience")
H11	More use $\rightarrow$ better perceived outcomes	Business value	$\rho = .27-.42$ across revenue/productivity/customer quality, all $q < .001$; perceptual, same-respondent	Supported as association
H12	Net job creation	Employment	22.5% report new roles (realized/planned) vs 8.6% layoffs (realized/planned); firm counts, not headcount	Supported only as a role-creation perception; net effect not estimable
RQ7	Adopter typology	—	Two groups differ in degree not kind (silhouette = 0.255; one composite reproduces split at AUC ≈ 0.94) + 2×2 map	Engagement gradient, not a typology of distinct types