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Impact of Artificial Intelligence Tools on Operating Cost Management in the Digitalisation of Marketing Processes in Small and Medium-Sized Enterprises

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Abstract: Small and medium-sized enterprises (SMEs) are rapidly adopting artificial intelligence (AI) tools in marketing, yet evidence on how these tools change marketing operating costs remains fragmented and dominated by large-firm cases. This paper develops a transparent, activity-based cost model of monthly marketing operating expenditure (OPEX) and evaluates it through a Monte Carlo experiment with 10,000 draws per scenario. Three scenarios are compared for a representative SME marketing unit: a manual baseline (S0), partial AI adoption through off-the-shelf software-as-a-service tools (S1), and integrated AI adoption built on a CRM and marketing-automation core (S2). Costs comprise labour, agency spending, media-spend wastage, tooling, amortised implementation and training, and AI oversight. For a three-person team, mean monthly OPEX falls from USD 8,879 (S0) to USD 8,362 under S1 (−5.8%) and to USD 8,523 under S2 (−3.9%). Although S2 removes far more gross cost (USD 2,150 vs. 1,135 per month), it also adds USD 1,795 of AI-related cost, so its net advantage is smaller and far less certain (probability of positive savings 79.0% vs. 99.1% for S1). Scale is decisive: integrated AI does not pay off for one- or two-person teams, and it overtakes partial AI only from roughly four to five marketing employees. Sensitivity analysis shows that the share of freed labour hours actually converted into cost savings and the recurring licence burden dominate outcomes. The findings support a staged, measurement-led adoption strategy.

Keywords: Artificial intelligence; marketing digitalisation; small and medium-sized enterprises; operating cost management; Monte Carlo simulation; total cost of ownership.

1. Introduction

1.1 Background and problem statement

Small and medium-sized enterprises form the numerical backbone of almost every national economy, and marketing is one of the first functions in which they encounter data-driven technology. Social media advertising, e-mail automation, customer relationship management (CRM) platforms, and, more recently, generative and predictive AI have become default infrastructure for customer acquisition. Scholars argue that AI is reshaping marketing strategy, customer experience, and the internal division of labour between people and machines [1], [2]. For an SME, however, the decisive managerial question is rarely whether AI is strategically interesting; it is whether a given tool will lower or raise the monthly cost of running marketing, and how confident the owner can be in that answer before signing a subscription or commissioning an integration.

The question is difficult because AI changes cost structure rather than simply cost level. Automation can compress the hours needed for content drafting, reporting, and

audience segmentation, and can reduce reliance on external agencies and wasted media spend. At the same time, it introduces recurring licence and usage fees, one-off implementation and training outlays, and new oversight duties such as prompt engineering, quality assurance, and data governance. Economists have long observed that general-purpose technologies deliver measurable productivity gains only after complementary investments in skills, processes, and organisation have been made, which explains why expectations and statistics often diverge [3]. In marketing, this logic implies that visible automation savings may be offset by less visible adaptation costs, particularly in organisations too small to spread fixed costs across many users.

Despite the practical importance of these trade-offs, most published evidence on AI in marketing is either conceptual, focused on effectiveness outcomes such as conversion and engagement, or drawn from large multinational firms with dedicated data teams [4], [5]. Studies that explicitly model the operating cost side for SMEs, with transparent assumptions that managers can adjust to their own circumstances, are scarce. This gap matters because SMEs cannot easily absorb failed technology investments, and vendor claims rarely disclose the distribution of possible outcomes. The present paper addresses this gap by treating the AI adoption decision as a problem of operating cost management under uncertainty.

1.2 Related literature and research gap

The literature relevant to this study can be organised into five streams: conceptual frameworks, machine-learning applications, innovation and strategy, firm value, and adoption theory. The first stream develops conceptual frameworks that classify AI capabilities and their implications for marketing. Davenport et al. [1] propose a multidimensional framework distinguishing levels of intelligence and forms of AI deployment, while Huang and Rust [2] structure AI applications in marketing along research, strategy, and action, using a typology of mechanical, thinking, and feeling intelligence that builds on their earlier analysis of AI in service [6]. These works clarify what AI can do, not what it costs. The second stream reviews machine-learning methods and applications in marketing, connecting computational techniques to managerial insight [4] and mapping the deployment of AI across marketing functions [5]. The third stream examines AI within innovation management and business strategy, emphasising organisational capabilities, governance, and the risks of technology-led transformation [7], [8].

The fourth stream concerns firm-level value and performance. Empirical work on AI-based transformation projects indicates that value creation operates through process improvements and depends on organisational context [9], and economy-level modelling suggests that benefits may be unevenly distributed between early and late adopters and between large and small organisations [10]. Multi-author perspectives further stress that AI adoption raises technological, organisational, and ethical challenges that cannot be reduced to a purchase decision [11]. The fifth stream provides the theoretical lenses for adoption itself: diffusion of innovations [12], the technology acceptance model [13], and the technology–organisation–environment (TOE) framework [14]. These lenses explain why and when SMEs adopt, but they are largely silent on the economics of running AI once adopted.

Two methodological traditions from cost management are particularly useful for closing the gap. The total cost of ownership (TCO) concept insists that the relevant cost of a technology includes acquisition, operation, and maintenance rather than the purchase price alone [15]. Time-driven activity-based costing (TDABC) estimates process costs from the time required to perform activities and the cost per unit of capacity supplied [16]. Combined, they suggest modelling marketing as a set of activities with known time shares, letting AI reduce the time each requires, and adding the full set of AI-related costs. What

is missing is an application of this logic to SME marketing that treats inputs as uncertain and reports outcome distributions rather than point estimates.

1.3 Research questions and contributions

The study is organised around four research questions. RQ1: How does the adoption of AI tools change the level and composition of monthly marketing operating cost in a representative SME? RQ2: How uncertain are these effects, and how long does it take for one-off investments to be recovered? RQ3: How does the size of the marketing team moderate the cost effect of partial versus integrated AI adoption? RQ4: Which cost and adoption parameters most strongly determine whether AI reduces operating cost?

The paper makes three contributions. First, it offers a compact and fully specified cost model that links AI-induced time reductions at the activity level to the monthly OPEX of an SME marketing unit, bridging TCO and TDABC logic with the AI-in-marketing literature. Second, it introduces the notion of a realisation factor, the share of freed working hours that is actually converted into avoided cost, and shows that it is among the most influential drivers of outcomes; this concept captures the indivisibility of labour in small firms. Third, it provides distributional evidence (probability of savings, payback, scale thresholds) that can guide staged adoption. The remainder of the paper is organised in the IMRAD structure: Section 2 describes the methods, Section 3 reports results, Section 4 discusses implications and limitations, and Section 5 concludes.

2. Methods

2.1 Research design

The study uses a scenario-based simulation design. Rather than surveying a small and possibly unrepresentative sample of firms, it builds an explicit cost model with probabilistic parameters and evaluates it through repeated random sampling. Monte Carlo methods, introduced by Metropolis and Ulam [17], are appropriate when the outcome of interest is a nonlinear function of many uncertain inputs and when the decision-maker needs the distribution of outcomes rather than a point forecast. The design therefore answers conditional questions, namely what operating cost outcomes follow if plausible parameter ranges hold, and it should not be read as an empirical estimate of average savings in any specific national or sectoral population. All assumptions are declared in Section 2.4 so that readers can substitute their own values.

The reference organisation is an SME marketing unit with three full-time-equivalent (FTE) employees, a monthly paid-media budget of USD 1,000 per FTE, and a moderate reliance on an external marketing agency. Three scenarios are compared. S0 is the manual baseline, in which marketing activities are performed with conventional tools and limited automation. S1 represents partial AI adoption: subscription-based generative-AI, analytics, and scheduling tools are added without deep integration into the firm's data systems. S2 represents integrated AI adoption: an AI-enabled CRM and marketing-automation platform is implemented, with predictive segmentation, automated campaign orchestration, and conversational agents.

2.2 Conceptual framework

Figure 1 presents the conceptual framework that guides the cost model. It draws on the TOE perspective [14], treating firm size, data readiness, skills, vendor pricing, and regulation as moderators, and on the process view of marketing in the AI literature [1], [4]. Five families of AI tools (generative AI, predictive analytics, conversational agents, programmatic advertising optimisation, and AI-enabled CRM) act on five marketing processes (content production, campaign execution, analytics and reporting, segmentation and targeting, and coordination). Each process transformation feeds five cost mechanisms: labour-hour reduction, agency substitution, media-spend wastage reduction, and two cost-increasing mechanisms, namely licence, cloud, and API fees and the combined burden

of implementation, training, and oversight. The mechanisms jointly determine three outcomes: the level of monthly OPEX, its volatility, and the payback period of one-off investments.

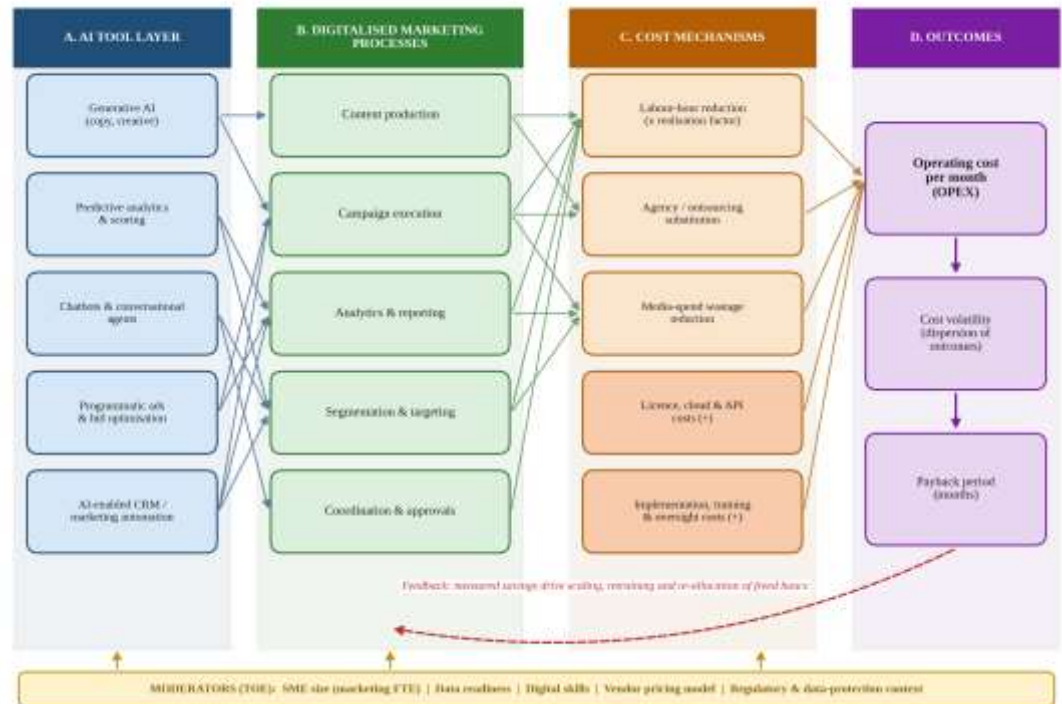


Figure 1. Conceptual framework linking AI tool families, digitalised marketing processes, cost mechanisms, and operating-cost outcomes, moderated by technological, organisational, and environmental factors.

2.3 Cost model

Monthly operating cost under scenario s is defined as the sum of six components, following the TCO principle that all recurring and amortised costs attributable to the technology must be counted [15]:

$$C_s = L_s + G_s + W_s + T_s + K_s + O_s \quad (1)$$

where L is marketing labour, G external agency spending, W media-spend wastage, T tooling (licences, cloud, and API usage), K amortised implementation and training, and O the cost of AI oversight and rework. Following the logic of time-driven costing [16], labour cost is derived from the time share of each marketing activity and the proportional time reduction that AI achieves in that activity:

$$L_s = N \cdot c \cdot (1 - q \cdot \sum_a w_a r_{a,s}) \quad (2)$$

where N is the number of FTE, c the fully loaded monthly cost per FTE, w_a the share of working time devoted to activity a , $r_{a,s}$ the proportional time reduction achieved in that activity under scenario s , and q the realisation factor. The realisation factor is central: because labour is lumpy, an SME that frees 20% of a marketer's time cannot usually reduce payroll by 20%, so only a fraction q of the freed hours becomes avoided cost, while the remainder is absorbed as slack or redeployed to non-cost-saving work. The time shares are fixed at 35% for content production, 20% for campaign execution, 15% for analytics and reporting, 10% for segmentation and targeting, and 20% for coordination and approvals. Agency spending and media wastage are modelled as:

$$G_s = G_0 \cdot (1 - \sigma_s); \quad W_s = B \cdot \omega \cdot (1 - \delta_s) \quad (3)$$

where G_0 is baseline agency spending, σ the share of agency work substituted by AI, B the paid-media budget, ω the baseline share of media spend that is wasted (for example, poorly targeted impressions), and δ the proportional reduction in that wastage owing to

AI-enabled targeting and bid optimisation. One-off implementation cost I and training cost E are amortised over 36 months, and oversight is proportional to post-automation labour:

$$K_s = (I_s + E_s) / 36; \quad O_s = \theta_s \cdot L_s \quad (4)$$

The saving relative to the baseline is $\Delta_s = C_0 - C_s$, and the simple payback period in months is $PB_s = 36 \cdot K_s / (\Delta_s + K_s)$, that is, one-off outlays divided by the operating saving before amortisation. Tooling, implementation, and training costs are scaled with team size through sub-proportional factors ($0.6 + 0.4 N/3$ for tooling and $0.7 + 0.3 N/3$ for one-off costs), reflecting the fixed-cost element of SaaS subscriptions and integration work, whereas agency spending and media budget scale proportionally with N .

2.4 Parameters and distributions

Every uncertain input is represented by a triangular distribution defined by a minimum, a most likely value, and a maximum. The triangular form suits situations in which only expert-style bounds are available and is easy for practitioners to modify. The ranges in Table 1 were set to be plausible for a small marketing unit in a mid-income market, with tool-related costs reflecting the price bands of commercially available SaaS and CRM products and time reductions set conservatively, in line with the view that AI gains are heterogeneous across tasks and are typically larger for routine analytical and content tasks than for coordination [6], [1]. The parameters are assumptions, not estimates from primary data, and their purpose is to make the model's logic explicit; the sensitivity analysis in Section 3.4 examines how much the conclusions depend on them.

Table 1. Model parameters (triangular distributions: minimum / mode / maximum). Monetary values are in USD per month unless stated; tooling and one-off costs are given for a three-FTE team.

Parameter	S0 (manual)	S1 (partial AI)	S2 (integrated AI)
Loaded cost per FTE, c	1,800 / 2,200 / 3,000	same	same
Realisation factor, q	0.40 / 0.60 / 0.85	same	same
Baseline agency spend, G_0	600 / 900 / 1,400	same	same
Baseline media wastage, ω	0.15 / 0.25 / 0.35	same	same
Time reduction: content	0	.15 / .30 / .45	.25 / .40 / .55
Time reduction: campaigns	0	.05 / .15 / .25	.20 / .35 / .50
Time reduction: analytics	0	.20 / .35 / .50	.35 / .55 / .70
Time reduction: segmentation	0	0 / .10 / .20	.25 / .45 / .60
Time reduction: coordination	0	0 / 0 / .05	0 / .10 / .20
Agency substitution, σ	0	.05 / .20 / .35	.25 / .45 / .65
Wastage reduction, δ	0	0 / .10 / .20	.10 / .25 / .40
Tooling, T	100 / 150 / 250	250 / 450 / 700	600 / 1,100 / 1,800
Implementation (one-off), I	0	1,500 / 2,500 / 4,500	7,000 / 12,000 / 22,000
Training (one-off), E	0	600 / 1,000 / 2,000	2,500 / 4,000 / 7,000
Oversight rate, θ	0	.01 / .03 / .06	.02 / .05 / .09

2.5 Simulation procedure and sensitivity analysis

For each scenario, 10,000 independent parameter vectors were drawn using a fixed random seed (42) and the model was evaluated for each draw, yielding empirical distributions of monthly OPEX and of the saving relative to S0. Reported statistics comprise means, standard deviations, the 5th, 50th, and 95th percentiles, the probability that the saving is positive, and the median payback period. To answer RQ3, the procedure was repeated for team sizes from one to eight FTE, with agency spending and media budget scaled proportionally and tooling and one-off costs scaled sub-proportionally as described above. To answer RQ4, global sensitivity was assessed by computing Spearman

rank correlations between each uncertain input and the resulting saving, a simple and robust screening approach for monotonic relationships in models of this type [18]. Internal validity is supported by common random numbers across scenarios and a fixed seed, and external validity is bounded to readers whose own cost environment falls inside the stated ranges. No personal or proprietary data were used, and all parameters are listed in Table 1.

3. Results

3.1 Level and composition of operating cost

For the reference three-FTE unit, the manual baseline S0 has a mean monthly OPEX of USD 8,879 (standard deviation 775), of which labour accounts for USD 6,993 (78.8%), and agency spending, media wastage, and basic tooling for the remainder. Under partial AI adoption (S1), mean OPEX falls to USD 8,362, a mean saving of USD 517 or 5.8%. Under integrated AI adoption (S2), mean OPEX is USD 8,523, a mean saving of USD 355 or 3.9%. Figure 2 decomposes these totals and shows how the composition shifts: labour, agency, and wastage components shrink, whereas tooling, amortised implementation and training, and oversight components appear or grow.

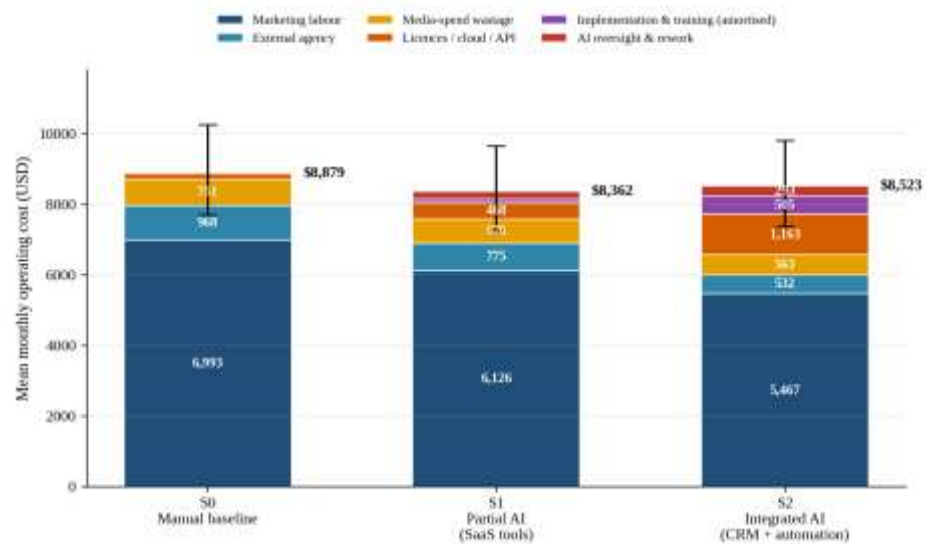


Figure 2. Mean monthly marketing operating cost by component and scenario (three-FTE team). Error bars show the 5th–95th percentile range of total OPEX.

The decomposition reveals an important asymmetry. Integrated AI (S2) removes more gross cost than partial AI: labour falls by USD 1,526 (21.8%) compared with USD 867 (12.4%) under S1, and agency spending and wastage fall proportionally even more (Table 2 reports the gross totals). However, the cost of the AI itself is much higher under S2: tooling rises by about USD 997 relative to the baseline, amortised implementation and training add USD 505, and oversight adds USD 293, for a total of roughly USD 1,795 of added cost, compared with about USD 618 under S1. Net of these costs, S1 saves USD 517 and S2 USD 355. In other words, at this scale, the additional automation ambition of S2 is largely consumed by the additional cost of delivering it.

Table 2. Summary of Monte Carlo results for the three-FTE reference unit (10,000 draws per scenario; monetary values in USD per month).

Metric	S0 (manual)	S1 (partial AI)	S2 (integrated AI)
Mean monthly OPEX	8,879	8,362	8,523
Standard deviation	775	724	739
5th–95th percentile of OPEX	7,698–10,260	7,248–9,651	7,371–9,814

Metric	S0 (manual)	S1 (partial AI)	S2 (integrated AI)
Gross savings (labour + agency + wastage)	—	1,135	2,150
Added AI-related cost	—	618	1,795
Mean net saving vs. S0	—	517	355
Mean net saving vs. S0 (%)	—	5.8	3.9
90% interval of saving (%)	—	1.7 to 10.0	-4.2 to 11.7
Probability of positive saving (%)	—	99.1	79.0
Median payback of one-off costs (months)	—	6.5	20.9

3.2 Uncertainty, risk, and payback

The distributions show that the expected saving is only part of the story. Under S1, the 90% interval of the percentage saving runs from 1.7% to 10.0%, and the probability that partial AI lowers OPEX is 99.1%. Under S2, the interval runs from -4.2% to 11.7%, and the probability of positive savings falls to 79.0%; in about one case in five, integrated AI raises operating cost relative to the manual baseline. The median payback period of one-off outlays is 6.5 months for S1 but 20.9 months for S2, and 79.0% of S2 draws recover their investment within the 36-month amortisation horizon. The dispersion of OPEX is similar across scenarios, so the added risk of S2 lies in its thinner margin: adverse parameter combinations are more likely to reverse the sign of the saving.

3.3 Effect of team size

Team size moderates the results strongly, as Figure 3(a) shows. For a one-person marketing function, partial AI is roughly cost-neutral (mean change -0.1%, probability of positive saving 49.3%), and integrated AI is clearly value-destroying (mean change -17.3%, probability of saving 1.0%). At two FTE, S1 already delivers a 4.3% mean saving, while S2 remains slightly negative (-1.5%). From three FTE, both options are positive on average, but S2 overtakes S1 in mean saving only at about four FTE (6.6% vs. 6.5%), and it does so decisively from five FTE (8.2% vs. 7.0%). At eight FTE, S2 saves 10.7% (about USD 2,533 per month) against 7.7% for S1. The pattern reflects the fixed-cost character of integration and licensing, which is diluted only when more users share the platform.

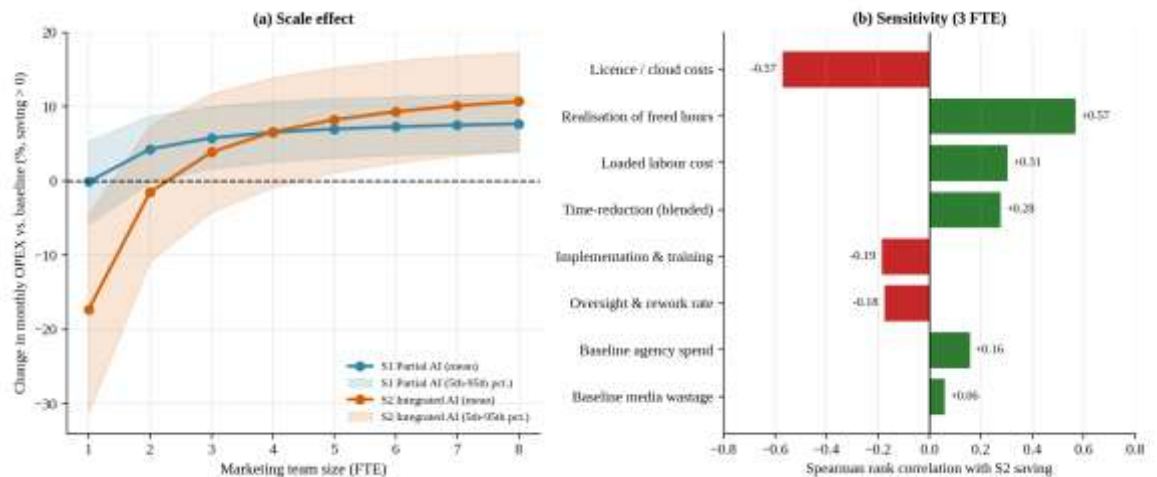


Figure 3. (a) Percentage change in monthly OPEX versus the manual baseline as a function of marketing team size, with 5th–95th percentile bands; (b) Spearman rank correlations between uncertain inputs and the S2 saving for the three-FTE unit.

3.4 Sensitivity of outcomes

Figure 3(b) reports the rank correlations between each uncertain input and the S2 saving. Two drivers dominate. The realisation factor has a strong positive association ($\rho_s = 0.57$), and tooling cost has a strong negative association ($\rho_s = -0.57$). Loaded labour cost (0.31) and the blended time reduction (0.28) are next, followed by implementation and

training cost (-0.19), the oversight rate (-0.18), and baseline agency spend (0.16). Baseline media wastage has almost no association (0.06). Overall, the results show that whether AI reduces OPEX depends less on how much time the tools save than on how much of that time saving the firm can actually monetise and on how much it pays for the tools each month.

4. Discussion

4.1 Interpretation of the main findings

The central finding is that AI can lower the operating cost of SME marketing, but that the magnitude is modest, sensitive to scale, and highly dependent on managerial conversion of efficiency into savings. A mean saving of 5.8% for partial adoption and 3.9% for integrated adoption at three FTE is meaningful but far below the dramatic reductions sometimes suggested in vendor communication, and the result is consistent with the productivity-paradox argument that visible technological potential is partly offset by adaptation and complementary costs [3]. Most of the additional gross savings under S2 are consumed by higher licence fees, amortised integration, and oversight.

The finding that partial adoption is the safer option for very small teams, while integrated adoption becomes attractive only at around four to five FTE, adds nuance to the diffusion and adoption literature. Rogers' diffusion framework [12] and the technology acceptance model [13] predict adoption on the basis of perceived advantage and ease of use, and the TOE framework [14] adds organisational and environmental determinants. The present results suggest that an additional economic condition should be considered: the scale threshold at which fixed integration and licensing costs can be spread over enough users. Below this threshold, an SME may find AI useful and easy to use and still be worse off if it selects an over-engineered solution. This qualifies the assumption that deeper integration is always better [9], [10].

4.2 Theoretical implications

The study contributes to theory in three ways. First, it connects the conceptual AI-in-marketing frameworks [1], [2], [4] with cost-management theory by translating capability typologies into activity-level time reductions and full-cost accounting [15], [16]. Second, the realisation factor provides a parsimonious construct for a phenomenon that is well known to practitioners but rarely formalised: efficiency gains and cost savings are different quantities, and the gap between them is larger in small firms because of labour indivisibility. Third, evaluation of AI investments should be distributional: because the probability that S2 reduces cost is only 79.0% at three FTE despite a positive mean, point estimates give a misleading impression of certainty.

4.3 Managerial implications

Several practical recommendations follow. First, SMEs with one or two marketing employees should begin with low-cost, subscription-based tools targeted at the highest-yield activities (content production and analytics) and defer deep integration until scale justifies it. Second, managers should plan how freed hours will be converted into value (reduced agency contracts, avoided hires, or redeployment to revenue work); without such a plan the realisation factor stays low. Third, vendors with transparent, scalable pricing should be preferred. Fourth, oversight and training should be budgeted as explicit recurring line items rather than hidden overhead. Finally, adoption should be staged with measured checkpoints, in line with the feedback logic of Figure 1: a pilot with a defined baseline OPEX, scaled up only if realised savings meet pre-agreed thresholds.

4.4 Limitations and directions for future research

The study has several limitations. The most important is that the results derive from a simulation with assumed parameter distributions and not from primary firm-level data; they show what follows from plausible assumptions but do not establish empirical

averages. Future research should calibrate the distributions with observed cost and time-use data from SMEs and test whether the scale thresholds hold in practice. Second, the model is static: it ignores learning effects and tool price changes, which are salient in the fast-moving generative AI market. Third, the model omits revenue effects, customer-experience gains, and risk-related costs such as data-protection compliance; a fuller evaluation would embed it in a profit or net-present-value framework. Finally, inputs are drawn independently although some are correlated in reality, and the reference firm is stylised; extensions could therefore incorporate correlated inputs, dynamic adoption paths, and sector-specific calibrations informed by adoption theory [13], [14].

5. Conclusion

This paper examined how AI tools affect the operating cost of marketing in small and medium-sized enterprises using an activity-based, full-cost model evaluated through Monte Carlo simulation. For a reference three-person marketing unit, partial AI adoption reduced mean monthly OPEX by 5.8% with a 99.1% probability of positive savings and a median payback of about 6.5 months, whereas integrated adoption reduced it by 3.9% with a 79.0% probability of positive savings and a median payback of about 20.9 months. Integrated AI removes more gross cost but adds substantially more AI-related cost, and it becomes clearly superior only when the marketing team reaches about five FTE. The realisation of freed hours as actual savings and the recurring licence burden are the dominant determinants of results. For SME managers, AI-enabled marketing digitalisation is a cost-management decision that should be staged, measured, and matched to organisational scale; for researchers, the cost side of AI in SMEs deserves distributional, empirically calibrated analysis, for which the model reported here offers a transparent starting point.

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