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A PERFORMANCE-BASED PATIENT ACQUISITION FRAMEWORK FOR MEDICAL SPAS: A RETROSPECTIVE COHORT AND EXPERIMENTAL ANALYSIS OF 70,079 LEADS ACROSS 50 CLINICS

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ABSTRACT

Medical spas buy advertising through agencies compensated for lead volume, while clinic revenue depends on consultations held and treatment packages sold. This study evaluates a performance-based acquisition framework in which a single operator manages the path from a paid advertisement to a deposit-backed appointment and answers for consultations that show. The analysis draws on operational data from 1 commercial platform: 70,079 leads across 50 United States clinics, 20,404 booked consultations, 143,059 outbound calls, 33,036 paid deposits, and 2 randomized landing page experiments. Deposit-backed consultations reached a show rate of 93.4% among recorded outcomes, and 39.7% of attended consultations ended in a package sale with a mean value of $2,058, of which 90.2% was collected during the first visit. Nonattendance increased with the booking interval: the adjusted odds of attendance for intervals above 30 days equaled 0.14 of the odds for bookings within 1 day. Self-serve online booking accounted for 72.2% of deposits, and panel analysis found no positive association between call speed and booking output. A randomized test of photographic content returned a 0.03 percentage point difference on the prespecified primary endpoint ($p = 0.95$). The framework ties advertising spending to appointment outcomes and offers a reproducible template for accountability in aesthetic medicine.

KEYWORDS: medical spa, patient acquisition, appointment nonattendance, online scheduling, deposit, controlled experiment, body contouring

1. INTRODUCTION

Medical spas have moved from the periphery of aesthetic medicine to a central position in its delivery. Facilities of this type outnumber physician-based cosmetic practices in 73% of major United States cities, and their staffing relies on nonphysician operators whose training differs across states and franchise systems [1]. In noninvasive body contouring, the category that accounts for 88.2% of the cohort analyzed below, medical spas had a mean ratio of 1.81 providers per physician practice across the 30 most populous American cities [2]. Demand for these services is discretionary, and the decision to purchase is driven by motives of self-image, social comparison, and media exposure, as documented in a systematic review of 21 studies and 9,005 participants [3]. A consumer who postpones a body-contouring package incurs no medical risk, which shifts the full burden of persuasion onto the acquisition process.

Acquisition in this market runs through paid social advertising, and the research literature has concentrated on the content layer of that channel. Analyses of plastic surgeons on Instagram describe which posts attract engagement and which platforms reach which age groups [4]. A systematic review of social media and digital marketing in plastic surgery identified 16 eligible studies, none of which traced advertising through to consultations held or revenue collected [5]. The economic layer of the funnel, where a click becomes a lead, a lead becomes a booked consultation, and a consultation becomes a sold package, remains unmeasured in the peer-reviewed literature on medical spas. The omission matters because standard agency contracts reward lead counts, while clinic revenue depends on attendance and purchases, events that occur days later and within the clinic. The 2 sides of this contract serve different purposes, and the resulting incentive gap has never been quantified using operational data at scale.

Performance-based contracting offers a known remedy for misaligned incentives, because payments tied to a downstream outcome force the seller to internalize the quality of every intermediate step. Advertising markets already price clicks and conversions, yet the conversion recorded by an advertising platform in aesthetic medicine is a form submission, an event separated from revenue by a call, a booking, an appointment, and a sales conversation. Each of those steps loses a share of prospects, and each loss stays invisible in a contract that settles on form submissions. The cost structure of a medical spa sharpens the problem. A body contouring package sells for close to $2,000, a consultation consumes provider time whether the patient shows up or not, and advertising in competitive metropolitan markets absorbs a material share of the package value. Under these conditions, the difference between a 60% and a 93% show rate changes the arithmetic of every marketing dollar, and an operator who answers for shown appointments has reason to build commitment mechanisms that an operator paid-per-lead lacks. Published work on aesthetic marketing has not tested such an arrangement, and operational data from a platform that runs it supplies the material for a first evaluation.

A separate body of evidence concerns what happens after a booking exists. A review of 105 studies across outpatient specialties found an average missed-appointment rate of 23% [6]. The interval between booking and the appointment date ranks among the strongest predictors of nonattendance in a model built on 1.26 million visits [7]. Machine learning frameworks predict no-shows with useful accuracy but depend on covariates that clinics record after the outcome itself [8]. A systematic review and meta-analysis of 61 studies found that behavioral commitments and financial micro-incentives reduce nonattendance across care settings [9]. Automated self-scheduling increases arrival rates and reduces labor costs [10]. Self-scheduled patients miss fewer appointments, although uptake reached 15% of kept appointments in a large academic network after 30 months [11]. Online booking was associated with a non-attendance rate of 1.8%, compared with 5.9% for offline channels, in the private practice arm of a 2-site comparison [6]. Consumer financing shapes the purchase step, and medical credit products concentrate on elective specialties [12]. These findings are isolated results from hospitals and physician networks, and no study has examined them as part of a single acquisition system in the medical spa vertical.

Operational event logs open a route to evidence that surveys and content analyses cannot reach. Every click, form submission, call, payment, and consultation outcome in a platform-mediated funnel leaves a timestamped record, and those records support 3 complementary designs at once: descriptive measurement of throughput, quasi-experimental analysis of gradients such as the booking interval, and fully randomized experiments embedded in the funnel itself. The combination matters because each design compensates for the others' weaknesses. Descriptive rates establish scale yet confound selection with treatment; gradient analyses add adjustment yet remain observational; and randomized tests deliver causal answers to narrow questions at the price of statistical power. Reading all 3 together, with prespecified endpoints and explicit handling of missing values, produces a picture that no single method yields. This layered approach, standard in large technology companies, has not previously been applied to the patient acquisition economics of aesthetic clinics.

The present study evaluates a performance-based framework that merges these mechanisms into a single accountable operation run by a technology platform for medical spas. The framework guides visitors through a diagnostic funnel page, secures the booking with a paid deposit, offers a self-serve calendar alongside a call-assisted path, and measures the operator on deposit-backed appointments that are shown. Four questions organize the analysis: where the conventional lead-chasing model loses patients and at what operational cost; what throughput and unit economics the integrated funnel produces; which conditions of the clinic visit accompany package purchase; and what randomized experiments on the funnel show when a prespecified primary endpoint disciplines the inference. The contribution is an outcome-level account of medical spa acquisition built on 70,079 leads, 20,404 booked consultations, 143,059 outbound calls, 33,036 paid deposits, and 2 controlled experiments.

2. MATERIALS AND METHODS

2.1. Setting and framework design

The data originate from a commercial patient-acquisition platform that serves United States medical spas specializing in noninvasive body contouring and related treatments. The platform buys paid social advertising, routes respondents to a diagnostic funnel page with qualification questions, and collects contact details at the opt-in step. A booking becomes committed when the prospective patient pays a deposit, and there are 2 paths to that point. The first path is a self-serve calendar in which the visitor selects a slot and pays online without human contact. The second path runs through inside sales agents, called ISAs below, who telephone the lead and issue a payment invoice. The clinic then holds the consultation, performs a promotional experience treatment when the patient accepts it, and offers a multi-session package with optional third-party financing. Figure 1 presents the framework's structure and the position of its accountability metric.

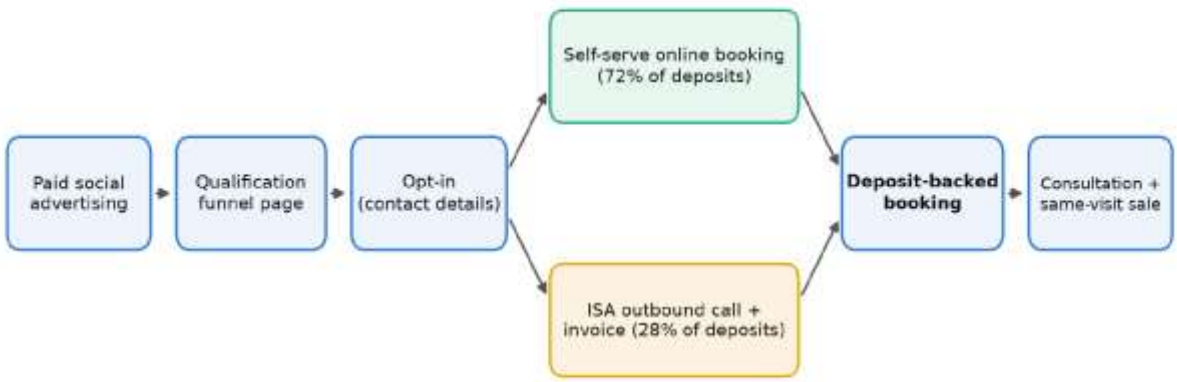

Figure 1: Structure of the performance-based patient acquisition framework

The funnel page opens with a short diagnostic quiz about treatment goals and problem areas, which filters curiosity clicks before any contact request appears. Visitors who complete the quiz reach the opt-in step and leave their name, email address, and phone number. The self-serve path then presents available consultation slots for online payment, while the ISA path queues the lead for a call in which the agent books the slot and issues an invoice. The consultation itself follows a scripted structure: an assessment conversation, a promotional experience treatment sold at a median price of $179 that lets the patient feel the procedure before committing to a package, and a closing presentation with financing options from third-party lenders. Deposits are credited toward treatment, and refunds remain available under clinic policy, which keeps the commitment device inside ordinary consumer practice. The contractual unit of performance is the deposit-backed appointment that shows. The platform earns from consultations that take place, and the clinic pays for outcomes that stand 1 step from revenue. This design contrasts with agency contracts that price leads, because a lead carries no commitment, and its later behavior stays outside the seller's responsibility.

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2.2. Data sources

Five de-identified extracts were generated from the platform event log with a snapshot date of July 21, 2026. All events are logged by the system at the moment they occur, and clinics appear under stable anonymous codes. The first extract covers 70,661 leads created since January 1, 2026, across 50 clinics, with timestamps for creation and the first call attempt. The second extract is a consultation cohort of 20,404 booked consultations across 45 clinics with scheduled dates from July 26, 2025, to December 15, 2026, of which 19,155 fall on or before the snapshot date. The third extract contains 201,489 telephone calls placed by 15 agents since October 16, 2025. The fourth extract lists 33,036 paid deposits since January 2024 with channel, refund status, and timing. The fifth extract reports arm-level results of the randomized experiments described below. Extract totals differ from window totals by construction: the common observation window from January 1 to July 21, 2026 contains 70,079 of the 70,661 extracted leads, because 582 leads created during the snapshot day fall outside its boundary, and it contains 143,059 outbound calls, because the call extract also holds records from 2025, inbound traffic, and calls placed on the snapshot day. The lead extract spans all 50 clinics active on the platform, while the consultation cohort covers the 45 clinics that hosted booked consultations, so clinic counts differ by data source. Call records carry direction, duration, ring time, agent code, and a disposition label, and 6.1% of logged calls are inbound. Lead creation spreads evenly across the week, with daily totals from 9,433 on Fridays to 10,649 on Sundays, so weekday composition plays no role in the contact timing results.

Consultation outcomes are entered by clinic staff, and 47.9% of past consultations lacked a recorded attendance value at the snapshot date. This pattern reflects entry lag concentrated in specific clinics and resembles the missingness that complicates epidemiological use of electronic health records [13]. The analysis reports outcome rates for records with recorded values and provides deterministic worst-case and best-case bounds, with all missing outcomes treated as failures or successes. A clinician-entered lead quality score was excluded from all models because it is co-populated with the outcome and averages 8.95 for buyers versus 5.16 for attendees who declined, a gap that indicates it is a post-outcome label unsuitable for prediction. The data are operational marketing records without medical interventions or protected health information, and the experiments compare marketing page versions within ordinary site analytics.

2.3. Outcomes and statistical analysis

The show rate is the share of consultations with recorded attendance in which the patient arrived. The close rate is the share of attended consultations that ended in a package sale. Cash conversion is the ratio of money collected during the first visit to the total package value among buyers. Wilson intervals provide 95% confidence limits for proportions, and 2-proportion z-tests compare arms and channels. The association between contact speed and booking output was tested on a panel of clinic-month cells restricted to cells with at least 30 leads, using Spearman correlations between the called share, the

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median time to first call, and bookings per lead. The effect of the booking interval on attendance was estimated using a logistic model with interval categories and clinic fixed effects, fitted to clinics with at least 50 recorded outcomes and attendance variation. Tests are 2-sided with a significance level of 0.05. Window-level counts of consultations held and packages sold are estimated by applying recorded outcome rates to non-canceled bookings, and the accompanying bounds treat every missing outcome first as a failure and then as a success. All computations run in Python 3.12 with pandas, SciPy, and statsmodels, and a single script reproduces every figure and table from the source extracts.

2.4. Randomized experiments

Visitors were assigned to page versions in a 50/50 split by a deterministic hash of an anonymous visitor identifier, a standard mechanism for online controlled experiments [14]. The first experiment tested a before-and-after treatment photograph above the fold across 13 clinics from July 11 to July 17, 2026, and completed with 10,102 visitors. The second experiment tested a personalized voucher flow that renders the visitor's name and splits the contact form into 2 steps. Two single-day pilot iterations of this test, each below 150 visitors, served instrumentation checks and were excluded from inference. The powered run remained in progress at the snapshot, with 7,344 visitors, and its interim figures remain outside confirmatory analysis, in line with guidance against reporting unfinished experiments [15]. The primary endpoint for both experiments, specified before launch, is the opt-in rate defined as opt-ins divided by visitors. This choice reflects 2 considerations. The opt-in occurs on the tested page itself, keeping the measured effect free of downstream influences such as clinic scheduling capacity or agent behavior. The opt-in count exceeds deposit counts by an order of magnitude, giving the test its highest available power. Deposit-based measures are secondary, and the studies lacked power to detect them. The minimal detectable effect for the completed experiment equals 1.70 percentage points at 80% power and a 2-sided 0.05 level. A Bayesian posterior probability that the variant exceeds control, computed from uniform priors, complements the frequentist test.

3. RESULTS

3.1. Cohort, funnel throughput, and unit economics

Table 1 summarizes the consultation cohort. Body contouring accounts for 88.2% of the case mix, followed by submental treatments at 9.7%. Among past consultations with a recorded status, 18.6% were canceled before the visit. The median interval between booking and the scheduled date equals 9 days.

Table 1: Characteristics of the consultation cohort

Characteristic	Value
Booked consultations	20,404
Clinics	45
Scheduled consultation dates	July 26, 2025 – December 15, 2026
Consultations on or before the snapshot date	19,155
Body contouring share	88.2%
Submental treatment share	9.7%
Cancellation rate among past consultations	18.6%
Attendance outcome recorded among past consultations	52.1%
Median booking-to-consultation interval, days	9

The common observation window from January 1 to July 21, 2026, allows all extracts to describe 1 period. During this window, the platform generated 70,079 leads, of which 98.7% carried a paid advertising campaign identifier, and clinics received 14,410 booked consultations, for an average of 0.206 bookings per lead. Paid deposits in the same window numbered 14,698. Figure 2 traces the window funnel from leads to estimated package sales and shows the deterministic bounds imposed by missing outcome entries.

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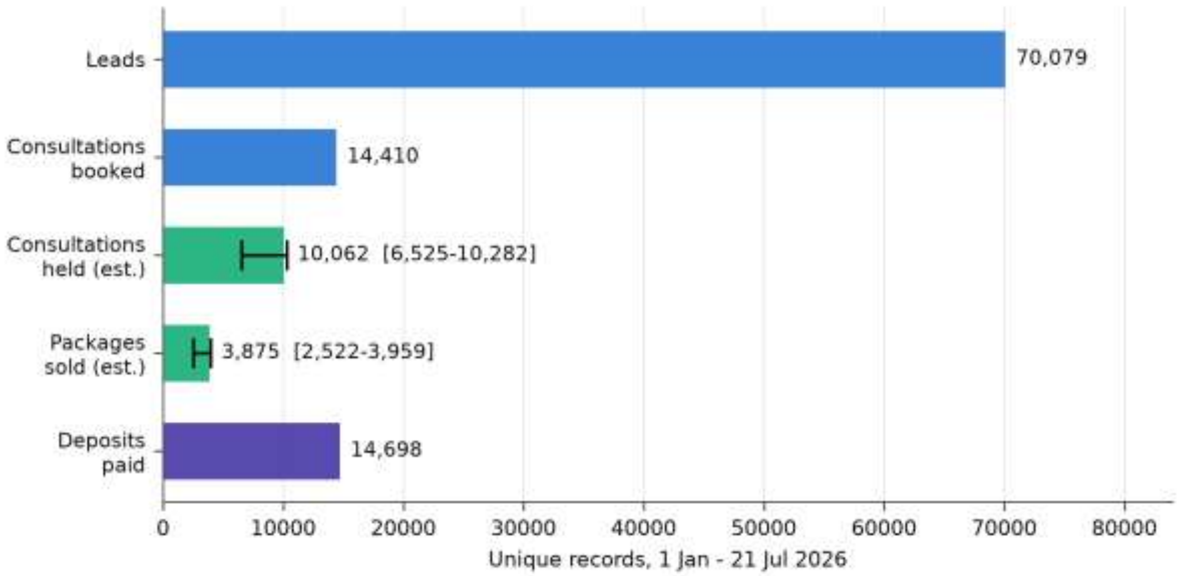

Figure 2: Patient acquisition funnel for the common observation window, January 1 to July 21, 2026

Applying recorded outcome rates to non-canceled bookings yields an estimate of 10,062 consultations held, with bounds from 6,525 to 10,282, and 3,875 packages sold, with bounds from 2,522 to 3,959. Table 2 assembles the throughput and unit economics of the window.

Table 2: Funnel performance and unit economics for the common observation window

Metric	Value
Leads	70,079
Consultations booked	14,410
Bookings per lead	0.206
Show rate among recorded outcomes, % and 95% CI	93.4, CI 92.9–93.8
Show rate bounds under worst and best case	48.6% – 96.5%
Close rate among attended, % and 95% CI	39.7, CI 38.7–40.7
Mean package value, USD	2,058
Median package value, USD	1,800
Cash collected at first visit as share of package value	90.2%

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Buyers paying in full at first visit	86.2%
Second appointment scheduled among buyers	92.3%
Paid deposits	14,698
Self-serve channel share of deposits	72.2%
Refund rate, self-serve against agent-assisted	10.8% against 12.0%, z = 2.94

Within the window, deposits at 14,698 exceed booked consultations at 14,410 by 2%, a gap produced by bookings that migrate across window edges and by deposits awaiting scheduling at the snapshot. The cancellation rate within the window, at 19.1%, matches the cohort-wide 18.6%, and the recorded show rate of 93.8% sits within 0.4 percentage points of the cohort estimate, indicating a stable regime across the observation period. Nearly the entire demand stream originates from paid traffic, since 98.7% of leads carry a campaign identifier. The funnel operates without meaningful organic inflow, and its economics reflect purchased demand.

The deposit series dates back to April 2024 and documents the model's growth. Figure 3 plots monthly paid deposits by channel across 27 complete months.

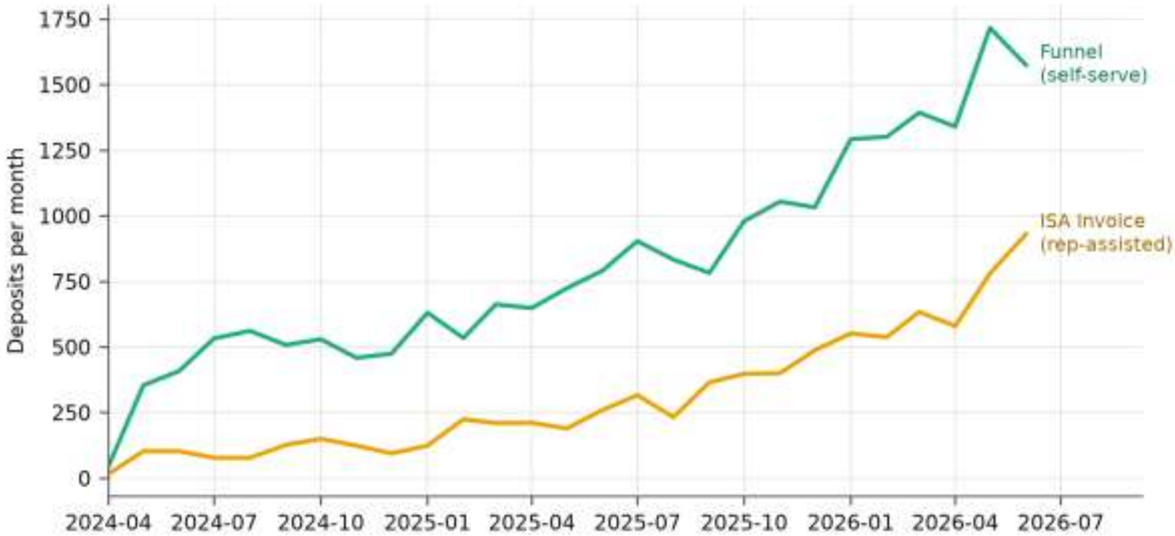

Figure 3: Monthly paid deposits by booking channel, April 2024 to June 2026

Monthly self-serve deposits grew from under 100 in spring 2024 to a peak of 1,716 in May 2026, and agent-assisted deposits reached 930 in June 2026. Across the full series of 32,449 deposits with a known channel, the self-serve share equals 72.2%. Refunds occurred in 10.8% of self-serve deposits, compared with 12.0% of agent-assisted deposits, a difference with z = 2.94 and p = 0.003. Among the 3,073 refunds carrying a timing label, 1,937 occurred before the appointment and 1,136 after it.

3.2. Contact timing and the cost of manual follow-up

Among the 66,774 leads with at least 7 days of follow-up, a first-call attempt ever reached 48.3%. Figure 4 shows the cumulative share of leads receiving a first call as a function of time since lead creation, separated by whether the lead was created during business hours or outside them, among 66,988 leads with at least 7 days of follow-up.

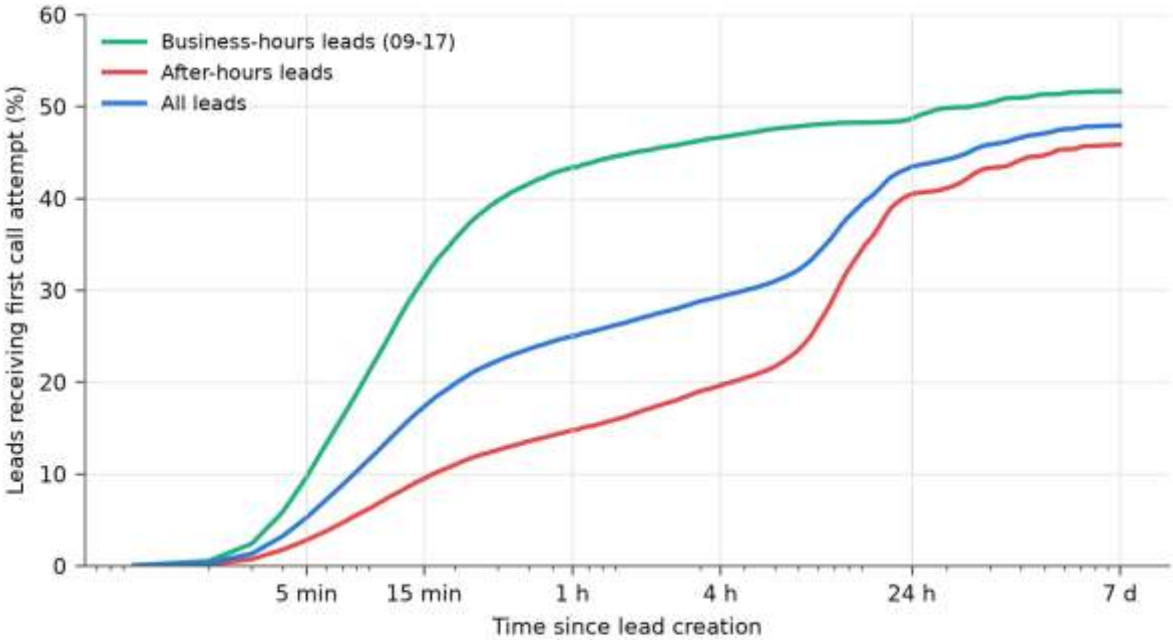

Figure 4: Cumulative share of leads receiving a first call attempt by time since lead creation

Within 5 minutes of creation, 5.2% of leads received a call, within 1 hour 25.0%, within 24 hours 43.4%, and within 7 days 47.9%. The split by time of day locates the constraint. Leads created between 09:00 and 17:00 account for 35.7% of volume, and their median time to first call is 12 minutes, with 43.3% calling within 1 hour. Leads created outside business hours constitute 64.3% of volume, their median time to first call equals 483 minutes, and 14.7% received a call within 1 hour. The gap between 12- and 483-minutes measures the mismatch between a 24-hour advertising channel and a business-hours calling operation. The cumulative curves in Figure 4 flatten after the first day, and the 7-day mark adds less than 5 percentage points to the 24-hour value, indicating that a lead missed on day 1 stays missed. More than half of all leads, 52.1%, never received a call attempt within a week of creation, and this share sets the ceiling of any strategy that routes conversion through the telephone.

Manual follow-up consumed 143,059 outbound calls during the window, for an average of 2.04 calls per lead. Of these calls, 33.1% connected for at least 30 seconds. Among the 9 agents with at least

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1,000 calls, booked dispositions per 100 calls ranged from 0 to 3.41 with a median of 1.62, a 2-fold spread around the median that adds agent variance to the cost of the calling path. A panel of 150 clinic-month cells, each with at least 30 leads, tested whether calling performance predicts booking output. The call share showed no association with bookings per lead (Spearman's $r = -0.072$, $p = 0.38$), whereas the median time to first call correlated with bookings per lead in the direction opposite to the call-speed hypothesis ($r = 0.251$, $p = 0.002$). Under a framework in which 72.2% of deposits arrive through self-serve booking, these results suggest that the deposit mechanism reduced the dependence of booking output on manual call speed. Inbound traffic remains marginal at 6.1% of the call log, confirming that the calling model relies on outbound pursuit.

3.3. Booking interval, cancellation, and attendance

The interval between booking and the scheduled date orders every loss channel in the cohort. Table 3 reports cancellation, attendance, and close rates by interval category, and Figure 5 displays the same gradients with 95% confidence intervals.

Table 3: Consultation outcomes by booking-to-consultation interval

Interval, days	Cancellation rate	Show rate among recorded	Close rate among attended
0–1	3.8%	95.3%	37.8%
2–3	9.6%	95.8%	40.1%
4–7	13.4%	94.8%	42.3%
8–14	20.9%	93.8%	40.4%
15–30	26.6%	92.8%	38.7%
Above 30	35.5%	81.3%	32.8%

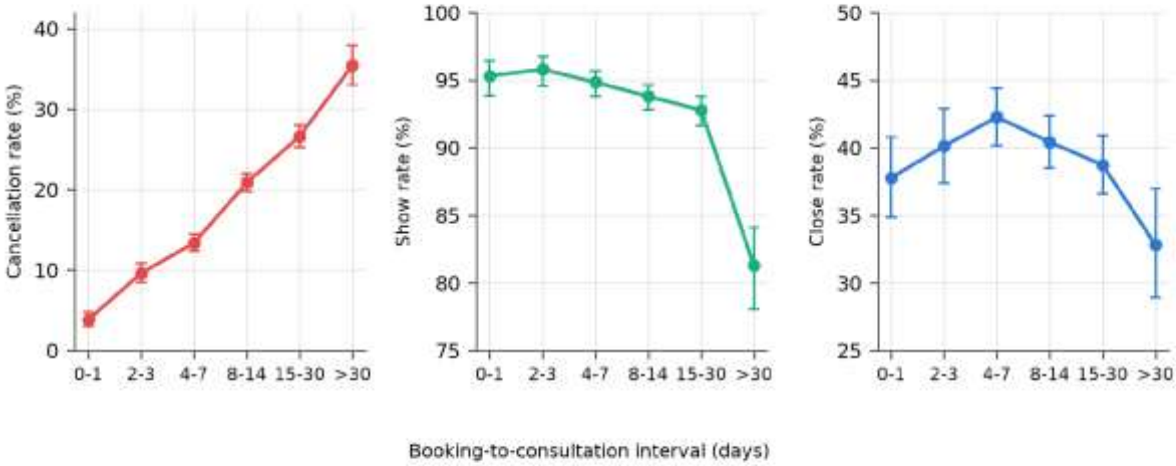

Figure 5: Cancellation, show, and close rates by booking-to-consultation interval

Cancellation rises from 3.8% for bookings within 1 day to 35.5% above 30 days. Attendance among recorded outcomes falls from 95.3% to 81.3% across the same categories, and the close rate peaks at 42.3% in the 4-to-7-day band before declining to 32.8% above 30 days. In the logistic model with clinic fixed effects, the odds of attendance for intervals greater than 30 days are 0.14 times the odds for the 0-to-1-day category, with a 95% confidence interval of 0.10 to 0.21, which excludes clinic composition as the source of the gradient. Combining cancellation and attendance, a booking made for a date within 1 day reaches the consultation room with a probability near 92%, while a booking placed more than 30 days ahead arrives with a probability near 52%. The shape of the close rate curve adds a nuance to the general rule of short horizons. Same-day and next-day bookings show at 95.3% yet close at 37.8%, below the 42.3% of the 4-to-7-day band, a pattern consistent with impulsive booking that survives to the visit while carrying weaker purchase intent. The commercial optimum therefore lies in a window of 2 to 14 days, where cancellation stays below 21%, attendance stays above 93%, and the close rate holds its plateau.

3.4. Heterogeneity across clinics

Standardized acquisition did not equalize downstream performance. Figure 6 presents clinic-level show and close rates with 95% confidence intervals for clinics with at least 100 recorded observations.

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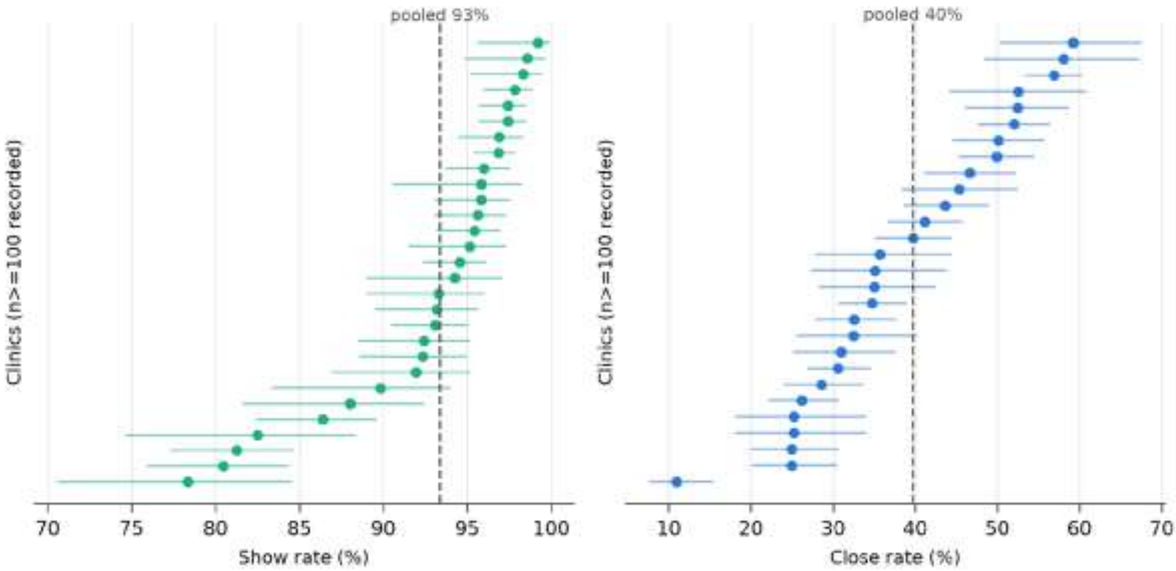

Figure 6: Clinic-level show and close rates with 95% confidence intervals

Among 29 clinics, show rates range from 78% to 99%, with the 10th percentile at 83.8% and the 90th percentile at 97.9%, around a pooled value of 93%. Close rates across 28 clinics range from 11% to 59% around a pooled value of 40%, and the interdecile range of 25.2% to 53.8% remains wide after excluding the extremes. The 5-fold spread in close rate under identical acquisition conditions indicates that in-clinic consultation practice, staffing, and sales capability govern the final conversion step. These comparisons rest on recorded outcomes within each clinic, and clinics differ in the speed of outcome entry, so individual positions in the distribution carry more uncertainty than the pooled estimates. The width of the spread itself, however, exceeds anything that differential recording could produce, since a clinic would need to withhold most of its successful outcomes to move from the bottom decile to the top.

3.5. Conditions of the first visit and package purchase

Two recorded conditions of the visit separate buyers from non-buyers with large margins. Figure 7 shows close rates by the delivery of the promotional experience treatment and by the financing outcome.

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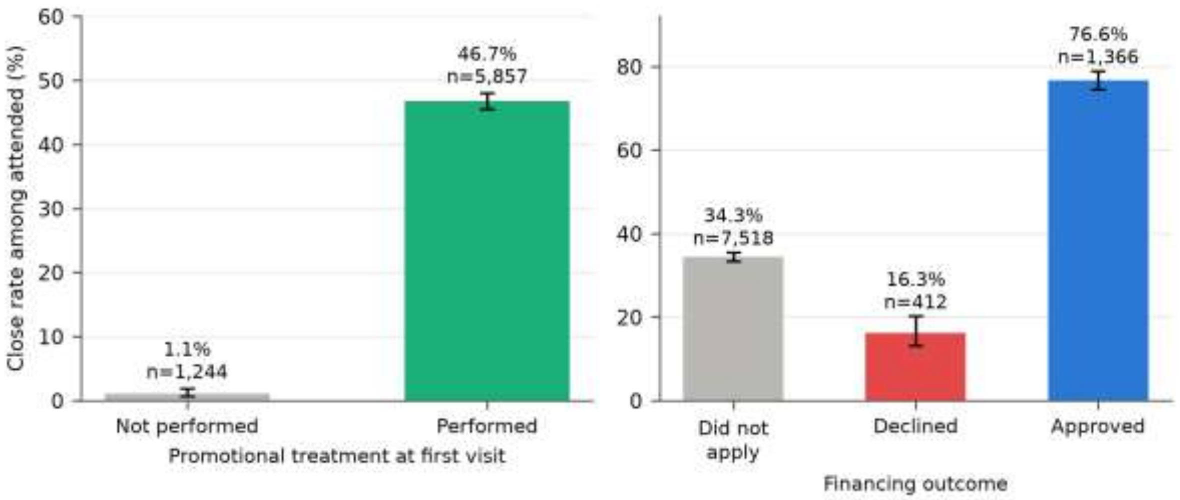

Figure 7: Close rate among attended consultations by promotional treatment status and financing outcome

Attendees who received the promotional treatment purchased a package in 46.7% of 5,857 cases, and attendees without it purchased a package in 1.1% of 1,244 cases. Patients with approved financing closed at 76.6% across 1,366 cases, patients with declined applications at 16.3% across 412 cases, and patients who never applied at 34.3% across 7,518 cases. Both gradients are observational, and self-selection contributes to them because a patient who accepts a trial treatment or applies for credit has revealed intent. Their size nonetheless identifies the visit protocol and the financing step as the levers with the widest dynamic range in the data. The purchase itself concentrates cash at the point of decision: buyers paid 90.2% of the total package value during the first visit, 86.2% paid in full, and 92.3% scheduled a second appointment before leaving. Close rates in the 2 largest categories run close together, 39.0% in body contouring and 42.7% in submental treatments, which argues against category mix as an explanation of the aggregate figures.

Post-visit surveys, completed by 662 patients, describe the visit from the patient's side. Among respondents, 92.4% reported feeling comfortable and cared for, 92.1% assessed the provider as knowledgeable, and 61.9% expressed full confidence that the package would help achieve their goals, with an additional 30.7% agreeing while holding some doubts. Respondents constitute 3.5% of past consultations and skew toward completed, positive visits, so these figures provide descriptive context and are not included in the model.

3.6. Randomized experiments on the funnel

The completed experiment assigned 10,102 visitors across 13 clinics to a page with a before-and-after photograph above the fold or to the same page without it. Table 4 reports all endpoints, and Figure 8 plots the arm differences with confidence intervals against the minimal detectable effect of the primary endpoint.

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Table 4: Outcomes of the randomized landing page experiment

Endpoint	Arm A, x/n	Arm A, %	Arm B, x/n	Arm B, %	Diff., pp	95% CI, pp	p
Opt-in rate, primary	523/5,148	10.16	505/4,954	10.19	+0.03	-1.14 to +1.21	0.954
Scheduled among opt-ins	336/523	64.24	321/505	63.56	-0.68	-6.55 to +5.19	0.820
Deposit among scheduled	50/336	14.88	58/321	18.07	+3.19	-2.49 to +8.86	0.271
Deposit per visitor	50/5,148	0.97	58/4,954	1.17	+0.20	-0.20 to +0.60	0.331

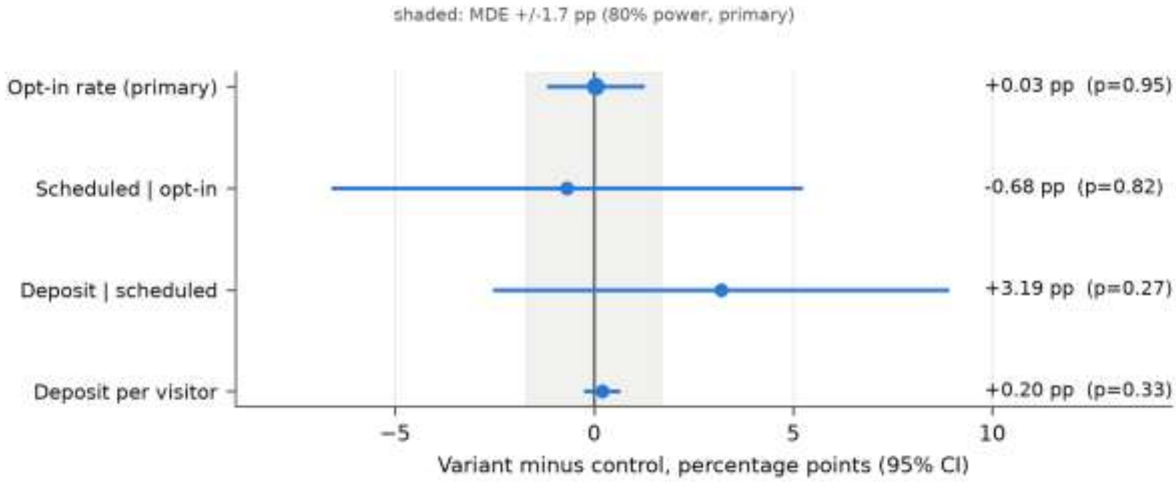

Figure 8: Differences between experimental arms with 95% confidence intervals, experiment 1

The primary endpoint showed a difference of 0.03 percentage points (p = 0.95), and the Bayesian posterior probability that the variant exceeds the control is 52.3%, a value indistinguishable from a coin flip. The design could detect a difference of 1.70 percentage points, which equals 17% of the 10.16% baseline, so the null excludes any creative effect of that size or larger. Secondary endpoints remain within their confidence intervals, including a positive difference of 3.19 percentage points in deposits among scheduled visitors, which the study lacked the power to confirm. The voucher experiment assigned 3,656 visitors to the standard single-step contact form and 3,688 to a variant that renders the visitor's name on a personalized voucher and splits the form into 2 steps, across 16 clinics. This run continued past the snapshot, and per protocol, its interim arm-level figures remain outside confirmatory claims until completion.

4. DISCUSSION

Four results form the core of the study. Deposit-backed consultations showed at a rate of 93.4% among recorded outcomes, and the framework collected 90.2% of the package value during the first visit. The booking interval ordered cancellation, attendance, and purchase, with adjusted attendance odds of 0.14 for bookings more than 30 days apart. Self-serve booking supplied 72.2% of deposits, while calling operations reached under half of matured leads, and panel analysis suggests that this channel mix reduced dependence on manual call speed. A randomized experiment with a prespecified endpoint yielded an informative null result for creative content. Together, these findings describe an acquisition system in which financial commitment, short scheduling windows, and self-service replace telephone pursuit as the engine of conversion.

Beyond attendance, the study contributes the first published benchmarks for the commercial stages of the medical spa funnel. A close rate of 39.7% among attended consultations, a mean package of $2,058, a cash conversion of 90.2% at the first visit, and 0.206 bookings per paid lead provide operators with reference points that the literature has lacked, and the clinic-level distributions around these means define realistic target ranges for individual locations. Benchmarks of this kind circulate in the industry as vendor claims, without denominators or confidence intervals, and their replacement with measured values, bounded to account for missing data, changes the quality of operational planning that the sector can perform.

The attendance result gains meaning against external baselines. Outpatient nonattendance averages 23% across 105 studies [6], and the strongest lever identified in intervention research is patient behavioral commitment [9]. The deposit implements this commitment in its most direct form, a payment that converts an intention into a sunk stake before the visit. The observed nonattendance rate of 6.6% among recorded outcomes is less than a third of the literature average and approaches the 1.8% observed for online bookings in a private practice setting [6]. The channel structure adds a second mechanism. Self-scheduling correlates with fewer missed appointments in academic networks, where its uptake reached 15% of kept appointments [11]. The framework studied here reverses those proportions, with 72.2% of deposits arriving through self-service, and barriers to adoption identified in the implementation literature, such as workflow integration and staff resistance, dissolve when the operator controls the entire path from advertisement to calendar [10].

The booking interval gradient replicates a robust finding of the no-show literature within a commercial vertical where it had not been measured. Lead time predicts nonattendance in models built on millions of hospital visits [7], and the present data extend the pattern to cancellations and to the purchase decision itself, with a close rate that peaks at 4 to 7 days. A booking placed within a week of the consultation preserves the motivational state that produced the click, while a booking placed a month ahead exposes the intention to decay and competing claims. The practical rule that follows is direct: calendars should fill available slots within a 14-day horizon, and demand beyond that horizon should be placed on a waitlist with re-engagement contact points. Since the gradient survives clinic fixed

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effects, slot scarcity at individual locations does not explain it. Reminder messaging, the most studied nonattendance intervention, addresses forgetting, while the interval gradient documented here reflects decay of intent, a process that reminders reach with difficulty and that scheduling architecture prevents at the source. A calendar that refuses distant bookings and offers a first-available waitlist converts a 35.5% cancellation risk into a routing decision made before any capacity is committed.

The contact timing results quantify the operational ceiling of manual follow-up. A calling operation that runs during business hours faces an advertising channel that generates 64.3% of its leads outside those hours, and the median first-call delay for those leads is 8 hours. Each lead absorbed 2.04 calls on average, 2 of every 3 calls failed to connect for 30 seconds, and booking productivity varied 2-fold across agents. Prediction models can rank leads by callback priority [8], yet the panel analysis found no association between calling speed and booking output after the self-serve channel accounted for the majority of deposits. The framework narrows the after-hours gap by letting booking proceed without waiting for a human response, and automated intake systems that answer around the clock represent the natural extension of the same logic. A service-level target formulated as a response within minutes at any hour is unreachable for a business-hours team facing a demand stream that peaks in the evenings and on weekends, and it becomes a default configuration once booking and payment run through software. The residual role of the human agent then shifts toward leads that stall within the self-serve flow, a queue smaller than the full lead stream and, correspondingly, cheaper to serve.

The visit-level correlates locate the remaining leverage inside the clinic. The experience treatment separates close rates of 46.7% and 1.1%, and financing approval separates 76.6% and 16.3%. Self-selection inflates both contrasts, because acceptance of a trial procedure and a credit application reveal existing intent, and the study makes no causal claim for them. Their magnitude still matters for practice design, since a protocol that offers the trial treatment to every attendee and prequalifies financing before the visit exercises the 2 widest levers the data contain. The financing gradient aligns with national evidence that medical credit products cluster in elective specialties [12], and the 5-fold spread in clinic-level close rates across identical acquisition conditions shows how much of the outcome the consultation room still controls. Variation of this size under standardized inputs echoes the training and oversight concerns raised for the medical spa workforce [1].

The unit economics assemble into a managerial picture. The window produced 0.206 booked consultations per lead and an estimated 3,875 package sales worth close to $8.0 million at the mean package value, which corresponds to revenue between $74 and $116 per lead under the outcome bounds. A 90.2% cash conversion at the first visit compresses the collection cycle to the day of service, and a 92.3% second-appointment rate carries the relationship into treatment delivery without additional acquisition cost. On the cost side, the calling path required 62 calls per booked disposition at the median agent, a workload that scales linearly with lead volume, whereas the self-serve path scales with software capacity. The refund differential between channels, 10.8% against 12.0% with $p = 0.003$, adds a quality argument to the cost argument, since self-booked patients withdraw their

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commitment less often than agent-booked ones. An operator weighing investment in calling capacity against investment in self-serve booking finds all 4 quantities pointing in the same direction.

The experimental results carry 2 lessons. The null on photographic content, bounded at 17% relative effect, protects the operator from reallocating attention toward creative iteration that the data cannot support. Industry experience documents how often plausible interface changes fail to move outcomes and how interim or underpowered readings mislead [15]. The discipline of a prespecified primary endpoint, deterministic assignment, and withholding interim results follows the methodological standards of the experimental literature [14] and distinguishes the analysis from promotional case reporting. A positive secondary reading on deposits among scheduled visitors, at $p = 0.27$, illustrates the temptation the standard exists to resist. The null also carries a resource lesson: creative iteration consumes design and engineering capacity, and a bounded null licenses the operator to redirect that capacity toward the structural levers, scheduling architecture, visit protocol, and financing, where the observed dynamic ranges are 10-fold and wider.

The refund pattern clarifies the economics of the commitment device itself. Refunds accounted for 11.0% of all deposits, and the labeled cases split into 1,937 before the appointment and 1,136 after it, indicating that deposits serve as commitments with an exit door open in both directions. This openness matters for interpreting the attendance result, because a patient who can recover the payment still shows at 93.4% among recorded outcomes, suggesting the mechanism lies more in psychology and planning than in financial coercion. A refundable deposit filters intent at the moment of booking, concentrates scheduling among patients who expect to attend, and imposes no loss on those whose circumstances change, a combination that consumer protection frameworks accommodate without friction.

The transfer conditions of the framework deserves a statement. Its mechanisms presuppose discretionary demand, a ticket size that justifies a deposit, a consultation that mediates the sale, and an audience reachable through paid social channels. Elective verticals such as dental implantology, vision correction, hair restoration, and fertility services share this profile, and the deposit, the short scheduling horizon, and the experienced treatment have direct analogs in each. Sectors with insurance-mediated demand or emergency presentation lack the voluntary booking decision on which the commitment mechanism operates, and the framework offers them little. Within aesthetics, the dominance of body contouring in the present cohort leaves the transfer to injectables and skin care, categories with lower ticket and higher visit frequency, as an open empirical question.

A methodological byproduct of the study deserves mention alongside its substantive results. Every figure and table is derived from event-log extracts via a single reproducible script, and the accountability contract between the platform and the clinic rests on the same records. Performance-based arrangements require measurement that both parties trust, and automatic event logging removes the disputes that manual reporting invites. The same infrastructure that settles the contract also enables research of the present kind, and the 2 uses reinforce each other, since a metric that carries money attracts scrutiny that a vanity metric never receives. Operators evaluating acquisition partners can apply the reporting standard used here as a due diligence checklist: a prespecified accountability event, outcome rates with recorded-value denominators, and explicit bounds for missing entries, a practice aligned with methodological guidance on incomplete operational records [13].

Limitations bound the conclusions. All data comes from 1 platform operating in 1 treatment vertical, and replication across operators and categories remains open. The funnel links stages at the aggregate level because no person-level identifier connects leads, calls, deposits, and consultations across extracts, so stage ratios describe cohorts within a shared window. Attendance outcomes were missing for 47.9% of past consultations at the snapshot, and while the worst-case bound of 48.6% is reported alongside the point estimate, entry lag concentrated in specific clinics makes the recorded-outcome estimate the more plausible one [13]. The visit-level correlates are observational; the voucher experiment is awaiting completion; and the panel analysis of calling speed is ecological. The observation window covers 7 months of 1 calendar year, leaving seasonal patterns unexamined, and deposits and bookings arise from separate extracts whose totals reconcile within 2% despite small timing mismatches at the window edges. Future work should randomize deposit size, scheduling horizon caps, and financing prequalification, extend the linkage to the person level, and test the framework in categories beyond body contouring.

5. CONCLUSION

This study provides the first outcome-level account of patient acquisition in the medical spa vertical, built on operational records of 70,079 leads, 20,404 booked consultations, 143,059 calls, and 33,036 paid deposits. A framework that secures every booking with a deposit, routes 72.2% of conversions through self-service, and measures its operator on the number of shown appointments achieved 93.4% attendance among recorded outcomes and converted 39.7% of consultations into package sales averaging $2,058, with 90.2% of that value collected during the first visit.

The booking interval emerged as the dominant controllable risk factor, raising combined attrition from 8% for next-day bookings to 48% for bookings placed more than 30 days ahead. Manual calling reached under half of matured leads across a 24-hour demand stream, and the data suggest that deposit-backed self-service booking reduced dependence on manual call speed, which supports architectures that lighten the load on human response time. A randomized experiment with a prespecified endpoint showed that photographic creative changes produce no detectable effect, while the levers with the widest observed range, the experience treatment and financing, operate inside the consultation room. For clinic operators, the results argue for deposit-backed scheduling within a 14-day horizon, universal trial-treatment protocols, and prequalification for financing.

For the industry, the study demonstrates that accountability can shift from lead counts to appointment outcomes, and that ordinary operational data suffice to hold an acquisition system to that standard.

Replication across operators, categories, and geographies, together with randomized tests of the deposit amount and the scheduling horizon, would turn this template into an evidence base for the sector.

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