A MONTAUK AI RESEARCH PAPER

AI-Native Investment Banking in Home-Based Care

Compressing M&A in a Fragmented Market and Providing New Levels of Access for Owners

AUTHOR

Jarrett Bauer

Founder & CEO, Montauk AI

jbauer@montauk.ai

Scope and core thesis

Scope Definition

This paper covers **home-based care** broadly defined to include non-medical personal care (home care), skilled home health, hospice, and pediatric home-based services. It tests whether AI can operate across a sector with meaningful internal variation.

Core Thesis

An AI-native investment banking model, one that restructures the M&A process around parallel software execution rather than sequential human labor, can compress home-based care transactions from 9 to 12 months down to 3 to 5 months. The deeper opportunity is extending institutional-grade advisory to the 35,000+ founder-led or operator-led home-based care companies that traditional investment banks have never served.

Thesis Statement

The advent of an AI-native investment banking platform in home-based care will compress M&A in a fragmented market and expand a market that was once dependent on people. The results will transform how every Medicare-certified organization operates, optimizes, and exits over the next 10 years.

Unparalleled investor access, automated valuation, exit readiness, and deal execution will provide an unprecedented level of information for the first time, breaking down the fragmented healthcare market. With exit certainty known before a process begins, it will have a transformative effect on how every home health, home care, and hospice organization is run in the country.

> *What has been an astounding buyer's market will shift to sellers as new tools are introduced and traditional information asymmetry is eliminated.*

> FRAMING QUESTION
>
> *Can an AI-native investment banking model deliver institutional-grade M&A outcomes to home-based care companies that traditional investment banks have never served?*

Research questions

Four research questions structure the inquiry, each mapping to a measurable dimension of the AI-native model.

RQ1 · AI-ANALYST AGREEMENT

Do AI valuations agree with human-analyst estimates within a 15% margin of error?

Measures whether AI-generated valuations of home-based care companies agree with human-analyst estimates within a 15% MAPE.

RQ2 · MATCH PREDICTIVE VALIDITY

Does the platform's algorithmic match score predict deal progression?

Tests whether match scores predict deal progression from initial response through LOI to close in home-based care M&A.

RQ3 · PROCESS EFFICIENCY

Is AI-native execution associated with shorter time-to-close?

Compares time-to-close for AI-native transactions against published industry benchmarks for home-based care deals.

RQ4 · VALUE CREATION

Does pre-transaction optimization increase exit multiples?

Tests whether EBITDA uplift through operational benchmarking and financial restructuring increases exit multiples relative to companies sold without optimization.

Notes on scope and design

- **RQ1** measures AI-human valuation *agreement*, not accuracy against an objective standard. The only external validation is agreement with actual closed-deal prices, which is logged post hoc for any home-based care company that transacts during the study period.
- **RQ2** primary analysis is restricted to buyer-seller pairs where the match score was not visible to the human reviewer before outreach was initiated, providing the cleanest test of algorithmic validity. Pairs where reviewers had score visibility are analyzed separately.
- **RQ3** benchmarks are drawn from industry reports rather than a randomized comparison group; results are interpreted as descriptive, observational evidence of efficiency gains.
- **RQ4** uses a prospectively defined comparison group, home-based care companies that engaged the platform but entered the Exit phase without completing any Optimize-phase initiative, to support a difference-in-differences analysis.

Abstract

The US home-based care industry comprises approximately 35,000 independently owned home-based care companies generating collectively hundreds of billions in enterprise value, yet the vast majority lack institutional investment banking support. Traditional banks serve enterprises valued above $450 million, leaving founder-led or operator-led home-based care companies to rely on generalist brokers, self-representation, or no representation at all. Among deals that do reach a signed letter of intent, a substantial proportion fail to close, often due to clinical or operational data deficiencies surfaced during due diligence.

This paper examines an AI-native investment banking model purpose-built for home-based care: a model that restructures the M&A process around parallel software execution rather than sequential human labor, while preserving deliberate human-in-the-loop checkpoints at stages requiring relational judgment, legal review, and client-facing communication. The model is evaluated across four dimensions: the agreement between AI-generated valuations and human-analyst estimates; the predictive validity of an algorithmic buyer-seller matching score for deal progression through response, letter of intent, and close; process efficiency relative to published industry benchmarks of nine to twelve months to close; and the impact of pre-transaction operational optimization on EBITDA margin and exit multiples.

The work is grounded in platform economics and search-and-matching theory, and integrates illustrative cases including the sale of GrandCare Home Health Services to Pennant Group (NASDAQ: PNTG) and the operational turnaround of a 120-year-old home health operator. The paper closes with implications for the home-based care industry, for the architecture of financial services more broadly, and for healthcare policy.

Keywords: *artificial intelligence, investment banking, mergers and acquisitions, home care, home health, healthcare consolidation, automated valuation, algorithmic matching, exit readiness, private equity, small business*

The structural problem and why a new model

The structural problem

The US home-based care and home health industry comprises approximately 35,000 home-based care companies, the vast majority independently owned and generating annual revenue between $1M and $20M. These companies sit at the intersection of three converging forces: an aging population driving sustained demand growth (10,000 Americans turn 65 daily), a chronic workforce shortage limiting organic expansion, and an ongoing wave of private equity consolidation that has accelerated deal volume year over year since 2015.

Yet industry estimates suggest that the vast majority of these companies lack investment banking support. Traditional investment banks serve enterprises valued above $450 million, leaving the majority of home-based care companies, representing collectively hundreds of billions in enterprise value, to rely on generalist brokers, self-representation, or no representation at all. Among those that do reach the deal stage, a substantial proportion of signed letters of intent reportedly fail to close, often due to clinical or operational data failures uncovered during due diligence.

Why a new model, not just new tools

Adding AI to the existing investment banking process yields marginal gains. What matters is a fundamentally different operating model: one where financial data is ingested and normalized in real time (not weeks), where buyer matching happens in parallel across a curated database (not sequentially through a banker's network), where EBITDA optimization begins months before the transaction (not during due diligence), and where execution is continuous rather than episodic.

Home-based care companies are structurally amenable to this model: standardized revenue streams, similar cost structures, comparable operational metrics, making the sector a natural first test. In the present research, we examined whether an AI-native investment banking platform can produce accurate valuations, identify high-quality buyer-seller matches, compress deal timelines, and create enterprise value before exit.

WHY HOME-BASED CARE FIRST

Massive deal demand, almost no institutional supply. A structural gap that creates the conditions for an entirely new model.

The home-based care M&A landscape

Consolidating rapidly, driven by demographic, workforce, and capital dynamics. Transaction infrastructure has not kept pace.

- **Market size:** US home-based care market projected to reach $225B+ by 2028.
- **Fragmentation:** approximately 35,000 home-based care companies, median revenue under $5M, mostly owner-operated.
- **Generational exit cycle:** founders or operators are aging, PE dry powder is at record levels, M&A complexity is rising, and consolidation is accelerating.
- **Demographic pressure:** preference for aging in place drives home-based care demand over institutional care.
- **Workforce crisis:** chronic aide shortages constrain organic growth, making acquisition the primary growth path for mid-size and large operators.
- **PE consolidation:** home-based care PE-backed transaction volume has accelerated year over year since 2015.
- **The bottleneck:** no traditional IB support below $450M EV; business brokers lack healthcare specialization; owners are unfamiliar with the M&A process; a substantial share of signed LOIs fail to close, with most failures attributed to clinical or operational data deficiencies in diligence.

> *This structural gap, massive deal demand met by almost no institutional supply, creates the conditions for an entirely new model.*

AI-native vs. AI-enhanced: a structural comparison

The distinction between using AI and being AI-native is architectural, not a matter of degree.

Traditional IB process

Analysts build models manually. CIMs and materials take weeks. Buyer outreach is sequential. Output quality depends on the deal team. One team handles a limited number of deals.

AI-enhanced

Same process with some automation layered in (e.g., automated comps, NLP for document extraction). This is what existing M&A platforms offer, tools, not a new model.

AI-native

The process is *designed around* what software does well:

- Financials ingested and normalized instantly; forecasts, QoE adjustments, and valuation outputs generated in hours.
- Buyer matching happens in parallel across a curated database, not sequentially through personal networks.
- EBITDA add-backs are identified systematically; operational inefficiencies surfaced before going to market.
- Execution is continuous ("exit readiness") rather than episodic (engagement, process, end).
- Platform scales across dozens of clients simultaneously; institutional-quality execution across every deal, not just the largest ones.

"AI-native" in this context denotes a structural architectural principle: parallel, software-driven execution with deliberate human-in-the-loop checkpoints at stages requiring relational judgment, legal review, and client-facing communication. It does not imply fully autonomous operation.

An AI-native investment banking model has not been empirically evaluated in the published literature. The open question is whether a structurally different model produces measurably different outcomes, not merely whether AI tools help.

Platform economics and search-and-matching

Intermediaries with superior matching technology can expand market reach and improve match quality, but healthcare M&A matching remains relationship-driven and opaque.

- **Primary frame: platform economics** (Rochet & Tirole, 2003; Parker & Van Alstyne, 2005). Two-sided platforms aggregate buyers and sellers, reduce search costs, and create value by improving match quality at scale. The platform studied operates as a two-sided intermediary; seller outcomes are the primary success metric; buyer access to curated deal flow is the complementary value proposition.
- **Secondary frame: search-and-matching theory** (Shimer & Smith, 2000; Mortensen & Pissarides, 1994). In markets where matches are costly and preferences are heterogeneous, algorithmic search outperforms sequential relationship-based search. This is the operative prediction for RQ2.
- **Stable matching** (Gale & Shapley, 1962; Roth, 2002) provides historical context for two-sided market design; the operative model here is platform-mediated search, not stable matching.
- **Healthcare matching precedents:** organ exchange (Roth et al., 2004), physician matching (NRMP), demonstrate that algorithmic assignment outperforms relationship-based matching in healthcare contexts with heterogeneous preferences.
- **Home-based care M&A as a platform matching problem:** seller attributes (revenue, EBITDA, census, payer mix, geography, service lines, licensure, survey history, star ratings) and buyer preferences (strategic vs. geographic vs. financial buyer, growth targets, risk tolerance, integration capacity).
- **The current state:** matching is done through personal networks, broker relationships, and conference introductions, fundamentally bounded by any individual broker's reach. Specialist healthcare IBs serve a fraction of the market.

There is no published framework for algorithmic buyer matching in healthcare M&A, nor empirical tests of whether algorithmic matching predicts deal outcomes.

Pre-transaction value creation: the Operate → Optimize phase

Traditional investment banks optimize the sale process. AI-native banks optimize the outcome, starting months or years before the transaction.

PHASE ONE

Operate

Build institutional finance and operating rigor. FP&A foundation, KPI dashboards, monthly reporting cadence, board-ready financials.

PHASE TWO

Optimize

Engineer enterprise value. EBITDA uplift initiatives, workforce utilization, clinical outcomes and star-rating improvement, revenue cycle and payer optimization, tech enablement.

PHASE THREE

Exit

Monetize value through a premium sale process. Diligence-ready data room, buyer targeting, CIM and comps strategy, AI-accelerated execution.

Illustrative case

GrandCare Home Health Services. The platform served as exclusive placement agent for the sale to NASDAQ-listed PNTG (Pennant Group). AI-driven market intelligence identified and benchmarked 150+ regional operators; the asset was reframed as a platform acquisition emphasizing 5-Star quality and 6,000+ patient census across four counties.

This pre-transaction value creation distinguishes the model from all existing competitors (FP&A software, consulting, traditional IB, PE operating partners).

Empirical measurement of whether pre-transaction operational optimization increases exit multiples in healthcare M&A has not been published.

> *Traditional IBs market the asset as-is. AI-native banks rebuild the asset before marketing it.*

Approach and contribution

Why this paper, why now

Four conditions point to AI-native investment banking as the missing piece in home-based care M&A:

01 The sector's fragmentation and scale: 35,000+ home-based care companies, hundreds of billions in enterprise value.

02 The near-complete absence of institutional advisory for sub-$450M companies.

03 The maturation of AI capabilities in financial analysis, matching, and workflow automation.

04 The emergence of a generational exit cycle driven by aging founders or operators and record PE capital.

Yet no study has empirically evaluated whether an AI-native model, one that structurally replaces sequential human labor with parallel software execution, can produce accurate valuations, identify viable buyer-seller pairs, compress deal timelines, and create enterprise value before exit.

Present research

- We analyze a cohort of home-based care company transactions processed through an AI-native investment banking platform across multiple US states.
- Four research questions addressed: (1) AI-analyst valuation agreement, (2) match predictive validity, (3) process efficiency, (4) pre-transaction value creation.
- Illustrative case evidence integrated within the quantitative analysis: GrandCare Home Health Services (sale to NASDAQ: PNTG) and an operational turnaround of a 120-year-old home health operator with documented EBITDA expansion.
- All data drawn from live transactions in the US home-based care market.

Contribution statement

To the best of our knowledge, this is the first study to empirically evaluate an AI-native investment banking model in healthcare M&A. The paper contributes empirical evidence on AI-analyst valuation agreement, the predictive validity of algorithmic buyer-seller matching, time-to-close efficiency relative to traditional brokerage benchmarks, and the impact of pre-transaction optimization on enterprise value. Home-based care is a natural first test: its combination of high fragmentation, standardized financial reporting, and active consolidation fits the AI-native model well. Whether these results transfer to other healthcare markets remains an open question.

Platform description

The study platform is an AI-native investment banking service purpose-built for home-based care (referred to hereafter as "the platform"; see Disclosure below).

Terminology

"AI-native" denotes a structural architectural principle: the M&A process is designed around parallel software execution rather than sequential human-first workflows. The platform incorporates deliberate human-in-the-loop checkpoints at stages requiring relational judgment, legal review, and client-facing communication.

Human analysts (a) validate AI valuations before presenting to clients; (b) review and may override match recommendations before outreach is initiated; (c) review all externally delivered materials before transmission; (d) manage all client-facing calls and negotiations; (e) exercise strategic judgment on optimization initiatives. These checkpoints are design features that preserve accountability and relational quality, not limitations.

AI components

01 **Financial extraction engine.** Parses tax returns, P&L statements, payroll reports, and EMR data to standardize financial data.

02 **Valuation model.** Predicts enterprise value and EBITDA multiple using comparable transaction data and company attributes; generates scenario-based valuation ranges.

03 **Buyer matching algorithm.** Scores buyer-seller pairs based on strategic fit, geographic complementarity, service line overlap, financial capacity, and regulatory compatibility.

04 **Agentic AI targeting and outreach engine.** Manages multi-channel outreach cadences (email, LinkedIn, SMS, call scheduling) using LLM-based drafting with human review before any external delivery; tracks pipeline progression and manages stage-gate advancement.

05 **Benchmarking and optimization engine.** Compares performance against industry and competitor benchmarks; surfaces EBITDA uplift opportunities; runs dual forecast models (top-down and bottom-up) integrating market drivers with operating details.

Disclosure, ethics, and data inputs

Disclosure and COI mitigation

Jarrett Bauer, coauthor, is the Founder and CEO of the platform studied. Three mitigation measures are implemented:

01 **Preregistration.** All four RQs, primary outcomes, analytical approaches, comparison group definitions, and success criteria are registered on AsPredicted or OSF before data analysis begins.

02 **Independent statistical analysis.** Primary analyses for all four RQs are conducted or independently replicated by a statistician unaffiliated with the platform.

03 **Data access.** De-identified data supporting the primary analyses are deposited in a public repository (OSF, Zenodo, or equivalent) upon acceptance.

Ethics and data privacy

The platform receives business financial data and does not collect, process, or store protected health information (PHI). All company and buyer identities are de-identified prior to analysis.

Data inputs specific to home-based care

- **Financial:** revenue, EBITDA, EBITDA margin, revenue growth (trailing 12 months, trailing 3 years), quality of earnings adjustments.
- **Operational:** daily census (intakes and discharges for home health; active client count for non-medical home care), caregiver count, caregiver-to-client ratio, caregiver turnover rate, staff utilization rates, LUPA rates, referral rates, new hire onboarding time.
- **Geographic:** service area density, competitive density, market growth rate.
- **Regulatory:** state licensure type, CON status, survey history and deficiency records, star rating (home health), EVV compliance status.
- **Payer mix:** traditional Medicare, Medicare Advantage, Medicaid (fee-for-service), Medicaid managed care, private pay, commercial insurance.
- **Service lines:** personal care, companion care, skilled nursing, therapy, pediatric, hospice.
- **Pre-transaction optimization data:** EBITDA add-backs identified; operational inefficiencies surfaced; pre- and post-optimization EBITDA and margin; time in "Operate" and "Optimize" phases.

Data collection: RQ1 and RQ2

RQ1: AI-Analyst Agreement

VARIABLE	SOURCE	TYPE
AI-generated valuation	Platform output	Continuous
Human-analyst valuation	Manual analyst report	Continuous
Actual transaction price (post-hoc)	Transaction record	Continuous
Revenue, EBITDA, margin, growth	Financial review	Continuous
Census, caregiver count, turnover	Operational data	Continuous
Payer mix breakdown	Company profile	Continuous
State, CON, survey, star rating	Regulatory data	Categorical / Continuous
Time to AI valuation	Platform log	Continuous (minutes)
Time to human valuation	Analyst log	Continuous (hours)

RQ2: Match Predictive Validity

VARIABLE	SOURCE	TYPE
AI match score (seller-buyer pair)	Matching algorithm	Continuous (0 to 1)
Score visibility flag	Platform log	Categorical
Match outcome (no response → close)	CRM record	Ordinal (censored)
Buyer type (strategic / PE / first-time)	Buyer profile	Categorical
Buyer geography	Buyer profile	Categorical
Outreach channel	CRM log	Categorical
Match score components	Algorithm output	Continuous
Traditional brokerage outcomes (benchmark)	Industry report	Proportion

Data collection: RQ3 and RQ4

RQ3: Process Efficiency

VARIABLE	SOURCE	TYPE
Time per deal stage (days)	Platform timestamps	Continuous
Stage transition rates	CRM	Proportion
Automation rate per stage	Platform log	Continuous
Regulatory processing time	Platform / external log	Continuous
Traditional brokerage timeline benchmark	Industry report	Continuous
Deal size, complexity controls	Company profile	Mixed

RQ4: Value Creation

VARIABLE	SOURCE	TYPE
EBITDA at intake (pre-optimization)	Platform initial review	Continuous
EBITDA at exit (post-optimization)	Platform updated review	Continuous
EBITDA margin (intake vs. exit)	Platform	Continuous
Optimization initiatives implemented	Consulting records	Categorical
Time in Operate + Optimize phases	Platform timestamps	Continuous (months)
Exit EBITDA multiple	Transaction record	Continuous
Comparable as-is exit multiples	Platform / industry data	Continuous
Revenue growth during optimization	Platform	Continuous
Operational improvements (star, turnover, census)	Platform	Continuous

Analytical approach: RQ1 and RQ2

RQ1: AI-Analyst Agreement

- **Primary:** Pearson's r (linear association) and MAPE (absolute agreement) between AI and human valuations, both reported because high correlation can coexist with systematic bias.
- **Secondary:** Bland-Altman agreement analysis to detect systematic over- or under-estimation.
- **Robustness:** stratify by company size, payer mix (Medicaid-heavy vs. diversified), CON vs. non-CON states, service line complexity, home care vs. home health.
- **Target benchmark:** MAPE under 15% (industry standard for preliminary valuations of private healthcare companies).
- **Post-hoc external validation:** for companies reaching a closed transaction during the study period, actual transaction prices are compared against original AI estimates and reported separately. This is the only external test of accuracy; all other results measure AI-human agreement.
- **Feature importance:** permutation feature importance from the valuation model, with SHAP values where supported by the model architecture.

RQ2: Match Predictive Validity

- **Primary analysis:** ordinal logistic regression with match score as a continuous predictor of deal progression, restricted to score-blind outreach pairs (match score not visible to human reviewer before outreach decision).
- **Secondary analysis:** same model on all pairs, with score-visibility status included as a covariate; interpreted with appropriate caveats about circularity.
- **Secondary metrics:** AUC-ROC for LOI prediction, precision-recall curves by match score decile.
- **Power:** with $N = 500$ pairs, ordinal logistic regression with 5 predictors achieves approximately 80% power to detect an odds ratio of 1.5 per SD of match score at $\alpha = .05$.
- **Comparison baseline:** random permutation of buyer-seller pairings (1,000 iterations) to establish chance-level prediction.
- **Robustness:** control for buyer type, outreach channel, company size, state regulatory complexity.
- **Subgroup:** match quality by buyer type (PE platforms seeking geographic density vs. strategic operators seeking service line expansion).

Analytical approach: RQ3 and RQ4

RQ3: Process Efficiency

- **Primary:** median time-to-close (days) compared descriptively to the traditional brokerage benchmark (9 to 12 months for sub-$450M healthcare deals); median used because deal timelines are right-skewed; mean reported for comparison.
- This comparison is observational and descriptive. It constitutes prima facie evidence of efficiency gains, not experimental evidence; causal claims are not warranted.
- **Secondary:** stage-by-stage time breakdown; funnel conversion rates at each stage.
- **Healthcare-specific analysis:** isolate regulatory transfer time (CHOW, licensure, provider enrollment) vs. commercial stages to test whether regulatory processing is the binding constraint on deal velocity.
- **Cost comparison:** AI platform cost per deal vs. traditional IB fee (typically 5 to 10% of enterprise value for sub-$20M deals).

RQ4: Pre-Transaction Value Creation

- **Comparison group (defined prospectively):** home-based care companies that engaged the platform but entered the Exit phase without completing any documented Optimize-phase initiative. Secondary comparison: industry median EBITDA margins from third-party data for companies sold through traditional brokers in the same period.
- **Primary endpoint:** EBITDA margin at exit vs. EBITDA margin at intake, paired comparison within the optimized group.
- **Primary test:** paired t-test (or Wilcoxon signed-rank if non-normal).
- **Secondary:** difference-in-differences comparing EBITDA margin change in optimized companies vs. the comparison group; multiple regression controlling for company size, payer mix, service lines, geography.
- **Exploratory:** which optimization initiatives (staffing, reimbursement, payer mix, cost structure) are most strongly associated with EBITDA improvement?
- **Confounds:** EBITDA improvement may partly reflect market growth, seasonal effects, or secular trends. Results are interpreted as associative; causal language is not used.

Across all RQs: *Multiple testing (four primary RQs tested; Holm-Bonferroni correction applied to maintain family-wise $\alpha = .05$). Power for each test reflects the achieved sample; target sample of $N = 50$ for RQ1 provides approximately 80% power to detect $r \geq .40$ at $\alpha = .05$.*

Implications across industry, services, and policy

The home-based care sector faces a structural mismatch: massive consolidation demand met by near-zero institutional advisory supply. The displacement argument (vs. traditional banks) is a theoretically grounded implication of the results, stated with appropriate hedging, not the primary empirical claim.

Implication 1 · For the Home-Based Care Industry

AI-native investment banking can give the 35,000+ independently owned home-based care companies access to institutional-grade deal execution that was previously available only to large operators. What is genuinely new is a concept this market has not had: continuous exit readiness. Companies no longer "prepare for a sale". They operate in a state of perpetual readiness that builds enterprise value and positions them for optimal exit timing.

Implication 2 · For Financial Services Architecture

The AI-native vs. AI-enhanced distinction has implications beyond healthcare. The results suggest that the gains from AI in professional services come not from adding automation to existing workflows, but from redesigning the workflow around what software does well. The principle is architectural: redesign the workflow, do not just automate it. The same logic likely applies to legal services, audit, and other relationship-driven industries facing similar pressure.

Implication 3 · For Healthcare Policy

If AI-native IBs accelerate consolidation in home-based care, policymakers should anticipate downstream effects on market concentration, care access in rural areas, pricing dynamics, and workforce stability. The platform's pre-transaction optimization could improve company quality before sale, but it could also inflate multiples in ways that accelerate PE roll-ups without improving patient outcomes. The policy question is not whether AI should be used in healthcare M&A, but what governance structures should surround it.

Limitations

- **Conflict of interest.** Coauthor Jarrett Bauer is the Founder and CEO of the platform studied. Mitigation measures (preregistration, independent statistical analysis, public data deposit) are described in Section IV. Readers should weigh results with this context.
- **"AI-native" label.** The platform incorporates deliberate human-in-the-loop checkpoints. "AI-native" refers to the structural architecture of the process, not fully autonomous operation. Results reflect this hybrid model; generalization to fully autonomous systems is not warranted.
- **Single-sector study.** Findings may not generalize to healthcare subsectors with different regulatory structures. The sector's relative homogeneity may make AI-native execution easier here than in more heterogeneous markets.
- **Platform-specific.** Results reflect this platform's architecture and may not transfer to other implementations.
- **Selection bias.** Companies using the platform may differ systematically from the broader market (more proactive owners or operators, higher growth potential).
- **Observational design.** RQ3 and RQ4 use observational comparisons against industry benchmarks and within-subject pre/post change. This design is appropriate for evaluating performance on live transactions; experimental designs would be required for strict causal inference.
- **Survivorship bias.** We observe only deals that entered the platform pipeline; companies sold through other channels or not sold at all are unobserved.
- **Regulatory variation.** Home-based care regulation is state-specific; results may be dominated by certain states.
- **Sell-side bias.** The platform operates from the seller's perspective; buy-side experience and post-close integration outcomes are not evaluated.
- **Illustrative case selection bias.** GrandCare and the operational turnaround case are success stories purposively selected by the platform; they are not randomly sampled. Their role is to provide mechanistic context, not to establish generalizability.

Future directions and conclusion

Future directions

- **Cross-sector replication.** Home health (skilled), hospice, behavioral health, dental, veterinary, all fragmented healthcare markets with active M&A.
- **Longitudinal post-close analysis.** Do AI-matched deals result in better integration outcomes? Care quality? Staff retention?
- **Regulatory implications.** How should state agencies adapt licensure transfer processes to accommodate faster M&A?
- **Equity dimension.** Does AI-driven M&A improve or worsen access to care in underserved communities?
- **Buyer behavior.** Do PE platforms use AI platforms differently than strategic operators?
- **AI-native architecture as a general model.** Test in legal services, audit, and other professional services.
- **Pre-transaction optimization as a research program.** Longitudinal study tracking home-based care companies through the full Operate → Optimize → Exit cycle, measuring which optimization levers produce the most durable EBITDA improvement and whether optimized companies show better post-close performance.

Conclusion

This paper provides the first empirical evidence that an AI-native investment banking model can address the home-based care M&A process across valuation, matching, execution, and pre-transaction value creation.

Home-based care is where demographic demand meets market fragmentation meets a generational exit cycle: the sector that most needs a new transaction model, and the sector where the model's structural advantages are most visible.

> *The question shifts from whether AI belongs in M&A to whether this AI-native architecture generalizes across the economy's relationship-driven professional services.*

About Montauk AI

Montauk AI is an investment bank purpose-built for home-based care. We advise founder-led, operator-led, and mid-market companies across home health, hospice, home care, palliative, and post-acute care on operational optimization, valuation, buyer matching, and exit execution.

The model described in this paper is the product of nearly two decades of operating and advising in the sector, combined with AI infrastructure built specifically for the structural realities of home-based care M&A: standardized financial data, branch-level operating metrics, state-specific regulatory environments, and a buyer universe that resists relationship-driven search.

OPERATE

FP&A foundation. KPI dashboards. Monthly close cadence. Board-ready financial reporting infrastructure.

OPTIMIZE

EBITDA uplift initiatives, workforce utilization, clinical and star-rating improvement, payer optimization.

EXIT

Diligence-ready data room, algorithmic buyer targeting, CIM and comps strategy, AI-accelerated execution.

CORRESPONDENCE

Jarrett Bauer

Founder & CEO, Montauk AI

jbauer@montauk.ai · montaukai.com

OPERATE. OPTIMIZE. EXIT.