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DATA-DRIVEN PROJECT MANAGEMENT AND RESOURCE OPTIMIZATION FOR IMPROVING CHILDCARE AFFORDABILITY AND OPERATIONAL EFFICIENCY IN EARLY CHILDHOOD EDUCATION INSTITUTIONS

Deborah Achiaa Ansah*[1], and Collins Mawulorm Kwesi Ofori-Kumeni[2]

[1]West Falmouth Childcare LLC, Falmouth, ME, USA.

[2]Bank of America, USA.

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***Corresponding Author: Deborah Achiaa Ansah**

West Falmouth Childcare LLC, Falmouth, ME, USA.

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ABSTRACT

Early childhood education (ECE) institutions face a structural tension: the labor intensity of staff-to-child ratios drives costs that many families cannot afford, while thin margins leave little capacity to absorb shocks or invest in quality. This paper asks whether data-driven project management, combined with operations research, can ease that tension for a representative center-based provider. Drawing on literature in childcare economics, operations research, and project management, it formulates five propositions and tests them with four linked models: integer programming for staff scheduling, mixed-integer programming for classroom allocation, Monte Carlo simulation of annual operating surplus, and a Program Evaluation and Review Technique model of the implementation project. Parameters are synthetic and calibrated to ranges reported in the cost-of-care literature, so the results are normative rather than empirical. For a six-classroom center serving 84 children, the interventions raise capacity to 89 children, reduce annual teaching labor cost by $66,990, and lower cost per paying child by 15.3%. Operating margin rises from -8.2% to 11.1%, and the simulated probability of an annual loss falls from 93.2% to 0.03%. Enrollment and fee management accounts for 64% of the surplus gain. Infant cost-based tuition nonetheless remains at 26.3% of median family income, against a 7% benchmark. Operational efficiency recovers a meaningful share of avoidable cost, but it complements rather than substitutes for public investment in affordability.

KEYWORDS: Early Childhood Education; Childcare Affordability; Staff Scheduling; Mixed-Integer Programming; Monte Carlo Simulation; Pert; Data-Driven Project Management; Iron Triangle.

1. INTRODUCTION

1.1 Background and Problem Statement

Childcare occupies an unusual position among essential services. It is simultaneously a labor market support for parents, a developmental intervention for children, and a small business that must balance its books. Research on parental employment consistently finds that the price and availability of care shape labor force participation, particularly for mothers (Morrissey, 2017). At the same time, the cost structure of center-based care is dominated by personnel, because licensing rules fix minimum staff-to-child ratios and maximum group sizes that cannot be relaxed without risk to safety and quality (Helburn, 1995; Blau, 2001). The result is what the National Academies of Sciences, Engineering, and Medicine (2018) described as a financing system that is simultaneously too expensive for families, too poorly paid for the workforce, and too thin for providers.

Affordability problems of this kind are not unique to childcare. Studies of essential services in other sectors show that price barriers persist when supply is costly to deliver and financing instruments reach low-income households unevenly, whether the service is medication (Asiedu & Asiedu, 2023b), distributed electricity (Komi & Adeniji, 2020; Komi & Adeniji, 2024a), or community-level economic development (Anene & Clement, 2024). Work on equity in data-driven planning adds that accurate forecasts are not automatically fair ones, and that analytics must be designed to reveal unmet need in underserved groups rather than to optimize only for average performance (Atakpa & Abolaji, 2020; Komi, 2023; Orise & Niniola, 2024b). Evidence from enterprise finance likewise shows that access to capital shapes whether small providers can grow at all (Michael & Ogunsola, 2019a), a constraint that applies directly to small, owner-operated childcare businesses.

Policy debates usually treat affordability as a matter of demand-side subsidy or supply-side grants. Those levers matter, and this paper does not argue otherwise. However, a complementary question receives less attention: how much of the cost of care is structural, fixed by ratios and wages, and how much is operational, created by how classrooms are allocated, how shifts are designed, how enrollment gaps are managed, and how fees are collected? Practitioners have long recognized the operational dimension. Stoney's (2010) "Iron Triangle" holds that provider solvency depends on full enrollment, full fee collection,

and revenue that covers per-child cost. Yet most centers manage these levers with spreadsheets, rules of thumb, and fixed staffing templates rather than with explicit optimization.

A growing body of applied work argues that organizations of this size can close the gap between intuition and evidence through structured performance data. Frameworks for data-driven operations management in educational institutions (Efobi et al., 2021), real-time performance and governance dashboards (Ashore-Onisemo et al., 2026; Orise & Niniola, 2022; Tonoyan et al., 2024b), and performance intelligence models for public services (Adelanwa et al., 2024) all describe how routinely collected data can be turned into management decisions. Comparable frameworks exist for multi-site operational efficiency and benchmarking (Akin-Oluyomi & Akhigbe, 2023a; Anene et al., 2023), continuous visual performance monitoring (Ogbole et al., 2021), and dashboard-based operations decision making (Ezeako et al., 2024). For micro and small enterprises, which most childcare providers are, the literature emphasizes lightweight process optimization (Eyetsemitan et al., 2024b), lean-digital scaling (Eyetsemitan et al., 2025), change management for digital adoption (Eyetsemitan et al., 2023a), AI readiness assessment (Alieme et al., 2023), and basic financial governance and accountability systems (Eboh et al., 2025).

1.2 Research Questions and Contributions

This paper addresses that gap by building and solving an integrated set of quantitative models for a representative center, framed within a project management lifecycle so that the analysis is actionable rather than purely descriptive. The study is organized around four research questions:

- **RQ1.** How much teaching labor cost can be avoided by demand-driven scheduling that matches staffing to hourly attendance while preserving every licensing ratio?
- **RQ2.** How should a center assign classrooms to age groups and set enrollment to maximize financial sustainability without reducing the number of children served?
- **RQ3.** How do these operational improvements change cost per child, operating margin, financial risk, and the tuition a family must pay, relative to an affordability benchmark of 7% of household income?
- **RQ4.** What implementation schedule, critical path, and completion risk should an ECE institution expect when adopting a data-driven management system?

The paper makes three contributions. First, it formulates a coherent two-stage optimization structure in which a strategic allocation MILP and an operational scheduling integer program are linked through a labor cost proxy and then re-evaluated exactly. Second, it decomposes the total financial improvement into the contributions of space allocation, shift design, and enrollment and fee management, which identifies where managerial attention yields the greatest return. Third, it translates operational gains into family-facing affordability metrics, including an "affordability dividend" and the residual public funding gap, which clarifies what efficiency can and cannot achieve.

1.3 Literature Review and Synthesis

1.3.1 The Economics of Childcare Cost and Affordability

The Cost, Quality, and Child Outcomes study (Helburn, 1995) established that labor accounts for the large majority of center expenses and that higher quality is associated with modestly higher cost. Blau (2001) framed the "child care problem" as a combination of low quality, high price relative to family income, and low compensation, and argued that these features arise from the economics of a labor-intensive service with limited productivity growth. More recent reviews of United States markets reach similar conclusions and emphasize that market prices often fall below the true cost of high-quality care, especially for infants and toddlers (Herbst, 2023; Workman & Jessen-Howard, 2018).

Affordability is commonly benchmarked against household income. The 2016 Child Care and Development Fund final rule identified 7% of family income as an affordable copayment benchmark (U.S. Department of Health and Human Services [HHS], 2016), and a 2024 rule capped family copayments for subsidized families at that level (HHS, 2024). For unsubsidized families, published prices for infant care in many states far exceed this threshold. The workforce side of the market is equally strained: low wages and limited benefits contribute to turnover that undermines continuity of care (Whitebook et al., 2018).

Parallel literatures on health care financing illuminate the same structural tension between mandated service standards and family ability to pay. Reviews of insurance financing and provider payment reform (Ilodigwe & Adesemoye, 2019a), the financial sustainability of safety-net hospitals (Odeyemi & Idowu, 2025), value-based delivery measurement (Osinem et al., 2025a), payer and provider incentive alignment (Ilodigwe & Adesemoye, 2026a), and integrated population health models (Ilodigwe & Adesemoye, 2026b) each show how public and private funding flows determine whether high-cost, labor-intensive services remain accessible. Studies of community health nonprofits (Odihi et al., 2026) and of nonprofit resource allocation more generally (Aliliele et al., 2025) highlight that mission-driven

providers must balance service commitments against solvency, which is precisely the trade-off represented by the mission floor in the model developed below. Related work shows that administrative governance is often the missing link in continuity of care (Ogundipe & Ominde, 2024), that access models can expand coverage when delivery is redesigned (Ilodigwe & Adesemoye, 2020), and that innovation fails to improve outcomes when system-level organization is neglected (Ilodigwe & Adesemoye, 2019b).

1.3.2 Operational Finance in ECE: The Iron Triangle

Stoney (2010) summarized provider finance in three linked conditions: classrooms must be fully enrolled, fees must be fully collected, and tuition plus third-party revenue must cover the per-child cost of care. Because labor is committed per classroom rather than per child, a single vacancy in a ratio-constrained room reduces revenue without reducing cost. The framework is widely used in technical assistance but is rarely expressed as a formal optimization or risk model, which makes it difficult to quantify trade-offs or the value of better data.

Each corner of the Iron Triangle has an analogue in the financial analytics literature. Revenue leakage from incomplete collection and process delay has been modeled through data-centric funnel optimization (Sanni & Wedraogo, 2024), lean re-engineering of revenue recovery (Ebisi et al., 2021), and DMAIC-based cost, pricing, and margin optimization (Ashore-Onisemo & Iziduh, 2024). Revenue optimization through integrated planning (Nnabueze et al., 2024) and predictive cash flow and working capital models (Oduleye & Medon, 2023a; Tonoyan et al., 2021b) address the timing of collections, while predictive budgeting from operational signals (Adesuyi et al., 2022), data-driven cost management (Oduleye & Medon, 2021), variance analytics (Aliliele et al., 2024), and data-led cost governance (Adesuyi et al., 2023) address the cost side. Further contributions frame the cost of poor quality as a governance metric (Ashore-Onisemo et al., 2021), link operational resilience to integrated risk and control analytics (Ashore-Onisemo & Unamma, 2022a), model regulatory compliance cost efficiency (Mensah et al., 2025), and develop predictive financial forecasting systems (Agu et al., 2025; Medon & Oduleye, 2023; Medon & Oduleye, 2024). In public and grant-funded settings, predictive analytics for financial oversight (Adelanwa et al., 2023b; Ashore-Onisemo & Unamma, 2022b), automated close controls in public sector enterprise systems (Oyeleye et al., 2025), strategic accounting systems (Bola-Sadipe et al., 2019), financial reporting models for accountability (Medon & Oduleye, 2022), and big-data financial analytics in health care (Atakpa et al., 2026) indicate the reporting infrastructure that subsidy-dependent childcare providers increasingly need.

1.3.3 Operations Research for Workforce Scheduling and Resource Allocation

Shift scheduling as a covering problem dates to Dantzig (1954), who formulated the assignment of toll booth operators to shifts as an integer program. Subsequent reviews document a large literature on personnel scheduling and rostering in health care, call centers, transportation, and retail (Ernst et al., 2004; Van den Bergh et al., 2013). These settings share key features with ECE: demand varies by time of day, staffing floors are mandated, and labor is the dominant cost. Classroom-to-group allocation resembles facility and capacity assignment problems that are routinely solved with MILP (Hillier & Lieberman, 2021). Despite this mature toolkit, applications to childcare are sparse, and published cost models such as those of Workman and Jessen-Howard (2018) typically assume a fixed staffing pattern rather than optimizing it.

Applied optimization research from adjacent sectors offers further methodological precedent. Studies integrate critical path scheduling with resource optimization (Makut et al., 2021), review simulation modeling for cost reduction and financial impact assessment (Tonoyan et al., 2022b), and develop predictive cost optimization models (Tonoyan et al., 2022c). Predictive forecasting for operational resource allocation (Unamma et al., 2018b), machine learning demand forecasting (Tonoyan et al., 2021a), algorithmic routing (Tonoyan et al., 2025), constraint-based resource allocation (Ahmed & Odejobi, 2018b), and capacity-constrained materials planning (Ebisi et al., 2023) each solve allocation problems structurally similar to assigning children, rooms, and staff. Queueing models for throughput and capacity (Akinola et al., 2024), recovery-value optimization (Obukadata, 2025), predictive maintenance scheduling for public infrastructure (Uduokhai et al., 2025b), capital efficiency and capital allocation models (Lawal & Oduleye, 2021a; Walawalkar, Kalu, et al., 2025), and procurement cost optimization (Akinleye & Adeyoyin, 2022a; Akokodaripon et al., 2023; Nwangwu et al., 2025; Tonoyan et al., 2024a) extend the toolkit, while lean and digital supply chain cost control frameworks (Akin-Oluyomi & Akhigbe, 2023c; Efobi et al., 2022b; Okonkwo et al., 2024e) and big-data business intelligence for procurement (Akinleye et al., 2023) show how optimization can be embedded in routine operations. AI-assisted synthesis of stakeholder and survey data has also been proposed as a way to enrich operations research models with qualitative evidence (Obukadata et al., 2024).

Workforce scheduling in health and human services is the closest analogue to ratio-constrained childcare staffing. Omaghomi et al. (2023) proposed a governance-driven framework for workforce planning and nurse-patient ratio optimization in public facilities, and related work reviews the digital transformation of workforce and scheduling systems

(Okwesa et al., 2023), frameworks for addressing staffing volatility (Falemi et al., 2023b), and the operational effects of alternative work schedules such as the compressed workweek (Oparah et al., 2024a). Studies of diagnostic laboratories show how workflow optimization and staff capacity building reduce turnaround time (Ayinde et al., 2026; Yusuf et al., 2025). Business intelligence for resource allocation in mental health and public health programs (Anioke & Atima, 2023b; Owoade et al., 2022), AI-based decision support for health care operations and resource planning (Adelanwa et al., n.d.), and governance models built on process optimization and performance metrics (Anioke & Atima, 2023a) demonstrate that ratio-like service standards can be met at lower cost when staffing is matched to measured demand. Broader work on health system data architecture, real-world evidence, and organizational resilience (Ilodigwe & Adesemoye, 2021; Ilodigwe & Adesemoye, 2024a; Ilodigwe & Adesemoye, 2024b) and on executing service transformation at scale (Ilodigwe & Adesemoye, 2025b) provides the system-level context for such changes.

1.3.4 Data-Driven Decision Making and Project Management

Firms that base decisions on data and analytics report higher productivity than comparable firms that do not (Brynjolfsson et al., 2011; Davenport & Harris, 2007). Realizing those benefits, however, requires organizational change: data must be integrated, staff trained, and new routines piloted. Project management standards emphasize value delivery, tailoring, and stakeholder engagement as much as schedule control (Project Management Institute [PMI], 2021; Kerzner, 2017). PERT, developed for complex research and development programs (Malcolm et al., 1959), remains a practical tool for estimating schedule risk when task durations are uncertain. Time-driven activity-based costing (Kaplan & Anderson, 2004) offers a complementary way to attach costs to the hours that staff actually spend on activities.

The conditions under which data improves decisions have been examined in detail. Building analytics capacity at institutional and national levels (Unamma et al., 2021), predicting technology adoption in emerging economies (Oteri & Chibwaye, 2022), and designing executive decision systems (Lawal & Oduleye, 2019b) are recurring themes. Financial planning analytics aligned with strategy (Lawal & Oduleye, 2021b; Lawal & Oduleye, 2026), executive dashboards for real-time oversight (Walawalkar, Adesuyi, et al., 2025), quantitative models of the strategic value of financial analysis (Oduleye & Medon, 2023b), behavioral financial analytics (Lawal & Oduleye, 2023b), analytics-driven value creation (Lawal & Oduleye, 2018a), decision analytics for sustainable profitability (Lawal & Oduleye, 2023a), AI-enabled financial analytics (Walawalkar et al., 2026), data-driven financial decision making (Oluwo et al., 2025), and machine-learning-augmented scenario analysis under

uncertainty (Unamma, 2022) all bear on how a center director or board might use the models presented here. Quantitative policy models in other public-interest sectors show how such analytics translate into resource efficiency (Michael & Ogunsola, 2021c; Michael & Ogunsola, 2023a), and forecasting and segmentation models illustrate methods for anticipating demand (Basnet et al., 2021). Risk-focused contributions model compliance risk quantitatively (Akomolafe et al., 2023b; Akomolafe et al., 2025) and allocate risk in public-private partnerships (Ike et al., 2024a), which is relevant where childcare is delivered through mixed public and private funding. Enterprise analytics that align risk mitigation with process improvement (Adeniji et al., 2023), standardized reporting workflows (Alieme et al., 2022), and digital transformation in operations management (Agboada et al., 2018) complete the picture. Studies of capital planning for service infrastructure and equipment (Aminu-Ibrahim et al., 2018; Okoli et al., 2020), machine-learning risk dashboards (Filani et al., 2022), predictive logistics for resilient service delivery (Anene & Clement, 2022), and trust and privacy in digitally delivered services (Akintola et al., 2025) show that these principles extend to the facility and technology investments that a data-driven center must make.

Project management research emphasizes that analytic tools deliver value only when implementation is governed well. Studies of project governance in complex multinational settings (Akhigbe et al., 2025; Amayo et al., 2023a; Amayo et al., 2024b), lifecycle project management (Amayo et al., 2024a), and project strategies in resource-constrained emerging markets (Amayo et al., 2024c; Amayo et al., 2025b) stress clear accountability, stakeholder alignment, and staged delivery. Work on risk management and compliance in health care project delivery (Amayo et al., 2023b; Amayo et al., 2025c) and on health IT project delivery through integrated data governance and continuous improvement (Stephen-Kings et al., 2022) is especially pertinent because childcare management system deployments share their data protection and regulatory concerns. Predictive schedule-risk methods (Zhou et al., 2024; Zhou et al., 2025), data-driven lifecycle performance management (Adelanwa et al., 2023a), KPI-driven portfolio optimization (Edivri & Oteri, 2024), incentive-aligned contracting (Abdulhadi & Hamdan, 2026c), and multi-dimensional evaluation of change programs (Obukadata et al., 2022) inform the PERT model and the pilot evaluation stage. Related contributions address cross-departmental alignment during expansion (Ekelemu & Adikwu, 2026a), evidence standards and corrective action governance in publicly funded projects (Dogbatsey et al., 2026), the use of digital information models to improve project performance (Uduokhai et al., 2023a), leading indicators of safe project performance (Obriki et al., 2025), multi-stakeholder governance in joint ventures (Eyetsemitan et al., 2020),

strategic finance in partnerships (Isiekwu et al., 2021), supply chain governance for quality and compliance (Akin-Oluyomi & Akhigbe, 2022), and performance optimization of high-demand programs (Olagunju et al., 2024).

Lean and process improvement methods provide the operational counterpart. Standard operating procedures can serve as change infrastructure (Agboada et al., 2019) and as strategic assets for small businesses (Eyetsemitan et al., 2022); structured user acceptance testing reduces deployment risk (Eyetsemitan et al., 2023b); and workflow automation improves efficiency in small health care practices (Eyetsemitan et al., 2024a), a setting close to childcare in scale and staffing. Lean Six Sigma has been adapted for small, resource-constrained enterprises (Ambali et al., 2021; Ezeugwa et al., 2023a), for onboarding cycle time in small professional service firms (Oyeleye et al., 2022), for high-velocity operations (Nwangwu et al., 2024a), and for integrated quality management systems (Okoli et al., 2022). Further studies analyze first pass yield and defect drivers (Okoli et al., 2023), throughput bottlenecks and workflow redesign (Nwangwu et al., 2024b), translation of regulatory requirements into small-business compliance workflows (Eyetsemitan et al., 2021), organizational learning maturity (Arumosoye & Obriki, 2021), and training-based operational risk reduction (Obriki et al., 2022a). Together these works suggest that the efficiency gains estimated in this paper are achievable only if new schedules, enrollment routines, and billing processes are standardized and embedded in daily practice.

1.3.5 Data Use, Workforce, and Leadership in Education Settings

Education research supplies direct evidence on how data can be used responsibly in settings that serve young and vulnerable learners. In special education, researchers have developed models for risk assessment of documentation and accountability systems (Oloto & Yeboah, 2025), monitoring IEP implementation fidelity (Yeboah & Oloto, 2023), data-driven IEP development (Yeboah & Oloto, 2022), and data-driven teaching that uses progress data to personalize instruction (Yeboah et al., 2022). Reviews of IDEA compliance frameworks (Oloto & Yeboah, 2022), procedural safeguards (Oloto & Yeboah, 2024), PBIS integration (Yeboah & Oloto, 2025a), behavior intervention plans (Oloto & Yeboah, 2023), and behavioral intervention approaches (Ogbona et al., 2023) show how service mandates, like childcare ratios, shape staffing and cost. Leadership models promoting equity and accountability (Oloto & Yeboah, 2026), inclusive instructional frameworks (Yeboah & Oloto, 2024), technology integration for engagement and accessibility (Ijiga et al., 2024; Yeboah et al., 2024), and pedagogical strategies for resource-constrained schools (Bobga et al., 2018) demonstrate how quality can be protected under budget pressure. Family

engagement is equally important: home-school partnership (Ogbona et al., 2020b) and structured parent engagement in case management (Yeboah & Oloto, 2025b) parallel the family communication functions of an ECE enrollment system.

The early childhood workforce problem has close counterparts in this literature. Studies of teacher professional development and competence (Joseph & Nwankwo, 2024; Yeboah et al., 2019), teacher resilience and retention under burnout risk (Yeboah et al., 2025), and reform of teacher education curricula for special learning needs (Bobga et al., 2025) show that workforce stability depends on training, support, and working conditions as much as on pay. Work on advising, mentorship, and belonging as levers for retention (Githinji & Atobatele, 2025a; Githinji & Atobatele, 2025b; Githinji & Atobatele, 2026), predictive analytics for student retention and institutional risk (Aliliele et al., 2023c), and structured mentorship for on-the-job development (Amarahobu et al., 2025a) offers transferable models for retaining early educators. Leadership and coaching studies in education and sport (Ogbona et al., 2020a; Ogbona et al., 2024), strategic management education (Onwuzulike et al., 2024), simulation-based professional education (Ebhojie et al., 2023b), and research on professional ethics in educational workplaces (Onche & Ogbonna, 2021) further inform the change management stage of implementation.

Digital and AI-enabled learning systems raise both opportunities and governance questions relevant to childcare management platforms. Frameworks for AI-powered personalization and localization in basic education (Seun et al., 2023; Seun, Ajayi, Elumilade, et al., 2024; Seun, Ajayi, Yeboah, et al., 2024), AI-human collaboration in learning (Fawehinmi et al., 2026), adaptive learning systems (Onwubuya et al., 2026), AI and machine learning in STEM education (Joseph & Uzondu, 2024a), and data-informed and offline-first digital learning platforms (Orise & Niniola, 2020; Unamma et al., 2018) show the potential of data systems in education. Learning analytics and data governance in health professional education (Orise & Niniola, 2024a; Orise & Niniola, 2025; Orise & Niniola, 2026), ethical data practices and safeguarding in education technology (Orise & Niniola, 2023), digital equity in access (Orise & Niniola, 2024b), and transitional training in low-resource settings (Peteranaba et al., 2023b) underline the need for privacy protection when child-level attendance data are analyzed. Concerns about critical thinking and assessment integrity in the age of generative AI (Adams, 2023; Adams, 2024), and about the risks of AI as a force multiplier in professional services (Ilodigwe & Adesemoye, 2025a), caution against automating judgments that should remain with educators.

Curriculum and system-level studies complete the education context. Research on interdisciplinary STEM curriculum development (Joseph & Uzondu, 2024b), mathematics curriculum reform (Boakye et al., 2021), ICT and mathematical thinking (Boakye et al., 2020), curriculum integration of sustainability topics (Michael & Ogunsola, 2025d), digital transformation strategies in education (Joseph et al., 2024), and bridging the digital divide (Joseph & Uzondu, 2024c) examines how institutions implement change. Studies of technical and vocational education address workforce readiness, work-integrated learning, government roles, and industry-academia collaboration (Joseph et al., 2025a; Joseph et al., 2025b; Joseph et al., 2025c; Joseph et al., 2025d; Joseph, 2022; Nwangwu et al., 2019; Ogunnowo et al., 2025a), while language and multilingual research (Amessouwoe et al., 2024; Amessouwoe et al., 2025; Lilian et al., 2025a; Lilian et al., 2025b) is pertinent to the linguistically diverse families that many ECE programs serve.

Finally, the human resource management literature informs the staffing dimension of the model. Research on gamified performance management (Ukadike, 2019), strategic recruitment and integration (Akhigbe et al., 2020), data-driven talent matching (Akhigbe, Wikiri, et al., 2023), HR-integrated enterprise risk management (Falemi et al., 2024), organizational readiness for AI in HR (Ukadike, 2025), talent development and pipelines (Falemi et al., 2020; Wikiri & Akhigbe, 2026; Wikiri, 2019), staffing performance scorecards (Wikiri et al., 2024), competency frameworks and onboarding redesign (Ukadike, 2018), employee retention linked to productivity (Falemi et al., 2023a), career progression (Okafor et al., 2025), technology adoption readiness (Akhigbe et al., 2024), and responsible AI governance and workforce readiness (Unamma et al., 2018a; Unamma et al., 2025b) offers tools for building and retaining a stable teaching team. Studies linking workforce behavior to service experience (Akhigbe, Falemi, et al., 2023), leadership to operational growth (Akin-Oluyomi & Akhigbe, 2023b; Falemi et al., 2025), diversity and inclusion to team performance (Amayo et al., 2023c; Amayo et al., 2025a; Uchechi et al., 2022), inclusive decision making (Oguntegbe et al., 2023), and integrated legal, quantitative, and operational disciplines (Ominyi et al., 2026a) reinforce the view that staffing models must account for people, not only for hours.

1.3.6 Literature Synthesis and Research Gap

Table 1 synthesizes the six literature streams reviewed above, identifying for each the central insight and how it is used in this study. Read together, the streams converge on three points. First, the cost of childcare is dominated by ratio-bound labor, so efficiency must come from how labor is deployed rather than from reducing it below mandated levels. Second, the

financial position of providers is more sensitive to vacancy and collection than to most structural costs, which makes data on enrollment and billing especially valuable. Third, analytic tools create value only when embedded in governed implementation and routine monitoring, and only when safeguards for staff, children, and families are respected.

Table 1. Synthesis of literature streams and their role in the study.

Literature stream	Representative sources	Synthesized insight	Use in this study
Childcare economics and affordability	Helburn (1995); Blau (2001); Herbst (2023); Workman & Jessen-Howard (2018); Asiedu & Asiedu (2023b); Ilodigwe & Adesemoye (2019a); Odeyemi & Idowu (2025)	Labor-intensive, ratio-bound services cost more than many families can pay; market prices understate true cost.	Cost structure, 7% benchmark, subsidy gap
Operational finance and revenue integrity	Stoney (2010); Adesuyi et al. (2022); Aliliele et al. (2024); Ashore-Onisemo & Iziduh (2024); Ebisi et al. (2021); Oduleye & Medon (2021); Sanni & Wedraogo (2024)	Vacancy and uncollected fees erode margins faster than structural costs; leakage is measurable and recoverable.	Fill and collection levers, Model C
Optimization and workforce scheduling	Dantzig (1954); Ernst et al. (2004); Van den Bergh et al. (2013); Ebisi et al. (2023); Makut et al. (2021); Okwesa et al. (2023); Omaghomi et al. (2023); Unamma et al. (2018b)	Covering and assignment models meet mandated staffing floors at minimum cost when demand is measured.	Models A and B
Data-driven decision making and analytics	Brynjolfsson et al. (2011); Davenport & Harris (2007); Efobi et al. (2021); Lawal & Oduleye (2019b); Orise & Niniola (2022); Tonoyan et al. (2024b); Unamma (2022)	Dashboards and predictive models improve decisions only when tied to routine management cycles.	KPI system, feedback loop
Project management, lean, and change	PMI (2021); Kerzner (2017); Malcolm et al. (1959); Agboada et al. (2019); Amayo et al. (2023a); Ambali et al. (2021); Obukadata et al. (2022); Zhou et al. (2024); Zhou et al. (2025)	Analytic gains depend on governed implementation, piloting, and standardized processes.	Model D, PM lifecycle
Education workforce, equity, and data ethics	Whitebook et al. (2018); Orise & Niniola (2023); Orise & Niniola (2024b); Yeboah & Oloto (2023); Yeboah et al. (2019); Yeboah et al. (2022); Yeboah et al. (2025)	Staff retention, family engagement, and privacy safeguards condition whether efficiency gains are sustainable.	Constraints and safeguards

The literature therefore offers a strong account of why childcare is expensive, a mature set of optimization methods for labor-intensive services, and established project management practice for organizational change. What is missing is an integrated, reproducible model that connects these elements for an ECE institution: one that optimizes allocation and staffing under licensing constraints, quantifies financial risk, translates savings into family affordability, and specifies how the change would be implemented. This paper is designed to fill that gap.

1.4 Conceptual Model and Propositions

1.4.1 Conceptual Model

Drawing on the synthesis above, this study proposes the conceptual model in Figure 1. The model treats data-driven project management as the mechanism that converts routinely collected operational data into resource decisions, and treats the Iron Triangle levers as the pathway through which those decisions affect institutional and family outcomes. It integrates four strands of the literature: the cost economics of childcare (Blau, 2001; Helburn, 1995), operations research on staffing and allocation (Makut et al., 2021; Okwesa et al., 2023; Omaghomi et al., 2023), data-driven decision systems (Efobi et al., 2021; Lawal & Oduleye, 2019b; Tonoyan et al., 2024b), and project lifecycle governance as codified by the Project Management Institute (2021) and applied in complex delivery settings (Amayo et al., 2023a; Obukadata et al., 2022).

The model has five components. **Data inputs** comprise enrollment and waitlist records, hourly attendance, payroll and shift records, billing and collections, and facility and licensing data, consistent with performance intelligence frameworks for service institutions (Adelanwa et al., 2024; Orise & Niniola, 2022). The **data-driven project management layer** organizes adoption through initiation, planning, piloting, KPI monitoring, and closure, reflecting governance and change program evaluation research (Amayo et al., 2023a; Obukadata et al., 2022; Stephen-Kings et al., 2022). The **optimization engine** contains the four quantitative models specified in Section 2. The **Iron Triangle levers** of full enrollment, full fee collection, and cost coverage (Stoney, 2010) mediate between decisions and outcomes. The **outcomes** are operational efficiency, cost per paying child, financial resilience, family affordability, workforce stability, and the residual public funding gap. A feedback loop returns KPI results to the planning stage so that models are recalibrated as conditions change (Ezeako et al., 2024; Tonoyan et al., 2024b).

The whole system is moderated by contextual constraints that the institution cannot optimize away: staff-to-child ratios and group sizes (NAEYC, 2018), wage levels and labor markets (Whitebook et al., 2018), public subsidy rules (HHS, 2024), quality and continuity-of-care safeguards (Yeboah et al., 2019; Yeboah et al., 2025), and data privacy obligations (Oloto & Yeboah, 2025; Orise & Niniola, 2023). These moderators appear in the quantitative models as hard constraints or fixed parameters rather than as decision variables.

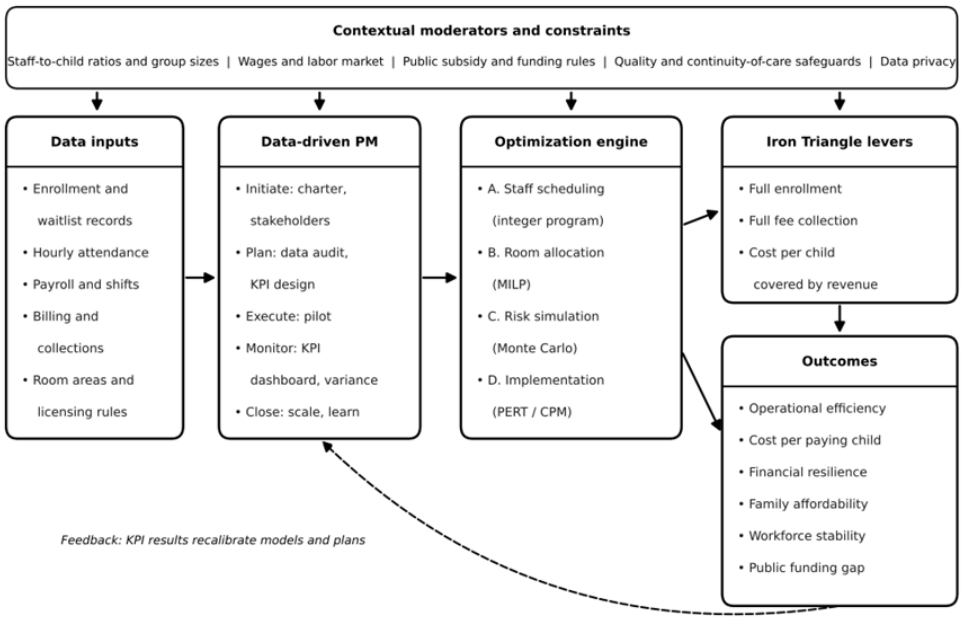

Figure 1. Conceptual model of data-driven project management and resource optimization in an early childhood education institution.

1.4.2 Propositions

The conceptual model implies five propositions, each of which is examined by one or more of the quantitative models in Section 2 and evaluated against the results in Section 3:

- **P1.** Demand-driven scheduling that matches staff hours to measured hourly attendance reduces teaching labor cost without relaxing ratio compliance (tested by Model A).
- **P2.** Data-driven assignment of classrooms to age groups increases licensed capacity and lowers cost per child without reducing access (tested by Model B).
- **P3.** Improvements in enrollment fill and fee collection produce larger financial gains than structural changes to space or staffing (tested by the scenario decomposition and Model C).
- **P4.** Operational efficiency lowers, but does not eliminate, the gap between cost-based tuition and the 7% affordability benchmark; the residual gap is largest for infant care (tested by the affordability analysis).

- **P5.** The adoption of data-driven management is a bounded project whose duration and risk are concentrated in data integration and model building (tested by Model D).

2. RESEARCH METHOD

2.1 Research Design and Modeling Framework

The study uses a quantitative modeling design. Rather than estimating relationships from observational data, it constructs normative optimization and simulation models of a representative institution, calibrates their parameters to ranges reported in the cost-of-care literature, solves them, and evaluates outcomes under alternative management scenarios. The four models are linked as shown in Table 2. Models A and B constitute a hierarchical, two-stage optimization: Model B chooses the classroom layout using a linear proxy for labor cost derived from Model A, after which Model A is re-solved for the chosen layout to obtain exact labor cost. Model C stress-tests the resulting financial position, and Model D plans the project that would deliver it.

Table 2. Components of the integrated modeling framework.

Model	Decision level	Method	Key output
A. Staff scheduling	Operational (daily)	Integer programming (set covering)	Minimum-cost shift mix by age wing
B. Classroom allocation	Tactical (annual)	Mixed-integer linear programming	Room-to-age assignment, enrollment
C. Financial risk	Strategic (annual)	Monte Carlo simulation (20,000 draws)	Surplus distribution, probability of loss
D. Implementation	Project	PERT / Critical Path Method	Expected duration, critical path, risk

2.2 Representative Institution and Parameter Calibration

The representative institution is a single-site, full-day center open 11 hours (7:00 to 18:00), 250 days per year, with six classrooms of 420, 420, 560, 600, 700, 750 square feet of usable space. It serves three age groups whose ratios and maximum group sizes follow common licensing and accreditation norms (National Association for the Education of Young Children [NAEYC], 2018). Prices, wages, and costs are calibrated to a high-cost metropolitan market and are consistent in magnitude with published cost-of-quality estimates (Workman & Jessen-Howard, 2018). Because the purpose is to demonstrate method and estimate relative effects, parameters are synthetic and stated explicitly so that any institution can substitute its own data. Table 3 lists the main parameters.

Table 3. Calibrated model parameters.

Parameter	Infant	Toddler	Preschool
Staff-to-child ratio (1 : ρ)	1 : 4	1 : 6	1 : 10
Maximum group size	8	12	20
Annual list tuition (USD)	$19,500	$16,500	$12,800
Variable cost per child-year (USD)	$2,100	$1,900	$1,700
Waitlist-adjusted demand (children)	20	30	60
Mission floor (minimum children)	8	12	0

Additional shared parameters are a blended teaching wage of $16.50 per hour; benefit and payroll loads of 1.22 for full-time and 1.08 for part-time staff; annual fixed costs (occupancy, leadership, administration, insurance) of $285,000; a licensing space standard of 35 square feet per child; and a median family income benchmark of $80,000, which implies an affordability threshold of $5,600 per year at 7%. The hourly attendance profile p(h), expressed as the share of enrolled children present, is 0.25, 0.60, 0.90, 1.00, 1.00, 1.00, 1.00, 1.00, 0.90, 0.60, 0.30 for the eleven hourly blocks beginning 7:00. It reflects the staggered arrival and departure patterns that attendance systems typically record.

2.3 Model A: Demand-Driven Staff Scheduling

Let H be the set of hourly blocks and J the set of permissible shift types, each defined by a contract type (full-time or part-time), a start time, and a length L_j. Let $a_{hj} = 1$ if shift j covers hour h. The decision variable $x_j \in \mathbb{Z}^+$ is the number of staff assigned to shift j. For an age wing g containing rooms k with enrollment n_k and ratio ρ_g, the model is:

$$\text{minimize} \quad \sum_j c_j x_j, \quad \text{where } c_j = w \cdot L_j \cdot \lambda_j \qquad (1)$$

$$\text{subject to} \quad \sum_j a_{hj} x_j \geq r_h \quad \text{for all } h \in H \qquad (2)$$

$$\sum_{j \in FT} a_{hj} x_j \geq \ell_h \quad \text{for all } h \in H \qquad (3)$$

$$\sum_{j \in PT} L_j x_j \leq 0.4 \cdot \sum_j L_j x_j \qquad (4)$$

Here w is the hourly wage and λ_j the benefit load for the shift's contract type. Constraint (2) enforces the licensing ratio in every hour, constraint (3) requires a full-time lead teacher in every open room during core hours (9:00 to 15:00) and at least one full-time employee at all times, and constraint (4) limits part-time hours to 40% of the total to protect continuity of care. The hourly requirement r_h depends on the staffing policy:

$$\text{Room-level:} \quad r_h = \sum_k \lceil n_k \cdot p(h) / \rho_g \rceil \qquad (5)$$

$$\text{Pooled edges:} \quad r_h = \lceil \sum_k n_k \cdot p(h) / \rho_g \rceil \quad \text{for } h \in \{7{:}00, 16{:}00, 17{:}00\} \qquad (6)$$

Three policies are compared. **P0 (baseline)** uses room-level requirements and a traditional template of full-time eight-hour shifts with fixed opener (7:00 to 11:00) and closer (14:00 to 18:00) part-time blocks. **P1** keeps the same shift template but allows same-age rooms to combine during the first and last hours of the day, as permitted by many licensing codes when group size limits are respected. **P2** adds flexible part-time shifts of four or six hours at any start time. All three policies satisfy identical ratio rules; they differ only in how efficiently they meet them.

This covering formulation follows the personnel scheduling tradition and mirrors recent applications to ratio-constrained health care staffing (Okwesa et al., 2023; Omaghomi et al., 2023), staffing volatility (Falemi et al., 2023b), and alternative shift structures (Oparah et al., 2024a).

2.4 Model B: Classroom Allocation and Enrollment

Let R be the set of rooms with usable area A_r and G the set of age groups. Decision variables are $y_{rg} \in \{0,1\}$ (room r assigned to group g), $n_{rg} \in \mathbb{Z}^+$ (enrollment), and $s_{rg} \in \mathbb{Z}^+$ (ratio positions). With list tuition τ_g, expected fill rate u, fee collection rate κ, variable cost v_g, and a per-position annual labor proxy π_g obtained from Model A, the model is:

$$\text{maximize} \quad \sum_r \sum_g \left[(\tau_g u \kappa - v_g u)\, n_{rg} - \pi_g s_{rg} - \varepsilon_{rg} y_{rg} \right] \qquad (7)$$

$$\text{subject to} \quad \sum_g y_{rg} \le 1 \quad \text{for all } r \qquad (8)$$

$$n_{rg} \le \min(G_g, \lfloor A_r / 35 \rfloor) \cdot y_{rg} \quad \text{for all } r, g \qquad (9)$$

$$n_{rg} \le \rho_g \cdot s_{rg} \quad \text{for all } r, g \qquad (10)$$

$$M_g \le \sum_r n_{rg} \le D_g \quad \text{for all } g \qquad (11)$$

$$\sum_r \sum_g n_{rg} \ge N_0 \qquad (12)$$

Constraint (8) assigns at most one age group per room; (9) imposes the group size limit and the space standard; (10) enforces ratios; (11) bounds enrollment between a mission floor M_g (the center's commitment to serve infants and toddlers, which are typically loss-making) and waitlist demand D_g; and (12) is an access-preservation constraint requiring that the optimized layout serve at least as many children as the baseline N_0. The small coefficient ε_{rg} breaks ties by placing younger groups in smaller rooms. After solving, exact labor cost for the selected layout is recomputed with Model A, so reported results do not depend on the linear proxy.

Structurally, Model B is a capacity-constrained assignment problem related to those used in critical-path resource optimization (Makut et al., 2021), capacity-constrained materials planning (Ebisi et al., 2023), and constraint-based resource allocation (Ahmed & Odejobi,

2018b), adapted here to the mission-driven objectives of a nonprofit or community provider (Aliliele et al., 2025).

2.5 Model C: Monte Carlo Financial Risk Simulation

Annual operating surplus S is modeled as a function of four uncertain quantities: the fill rate U, the collection rate K, a wage shock W, and a fixed cost shock Φ:

$$S = \Sigma_g \tau_g N_g \cdot U \cdot K - \text{Labor} \cdot W - \Sigma_g v_g N_g \cdot U - F \cdot \Phi \qquad (13)$$

U and K follow Beta distributions parameterized by mean μ and precision φ, so that both remain on the unit interval and become less dispersed as management improves. $W \sim N(1, 0.04)$ and $\Phi \sim N(1, 0.05)$. Under baseline practice, U has mean 0.86 ($\varphi = 60$) and K has mean 0.95 ($\varphi = 150$). Under data-driven practice, informed by waitlist analytics, automated billing, and enrollment forecasting, U has mean 0.95 ($\varphi = 150$) and K has mean 0.985 ($\varphi = 500$). Each scenario is simulated with 20,000 independent draws.

Simulation-based financial assessment of this kind is consistent with recent reviews of simulation modeling for cost reduction (Tonoyan et al., 2022b), scenario analysis under uncertainty (Unamma, 2022), predictive financial forecasting (Medon & Oduleye, 2024), and quantitative risk allocation (Ike et al., 2024a).

2.6 Model D: PERT Model of the Implementation Project

The adoption of data-driven management is itself a project. Ten activities were defined with optimistic (a), most likely (m), and pessimistic (b) durations in weeks. Expected durations and variances follow the standard PERT approximations (Malcolm et al., 1959):

$$t_e = (a + 4m + b) / 6 , \quad \sigma^2 = ((b - a) / 6)^2 \qquad (14)$$

$$P(T \le d) = \Phi((d - T_{cp}) / \sigma_{cp}) \qquad (15)$$

where T_{cp} and σ_{cp} are the expected length and standard deviation of the critical path obtained by forward and backward passes, and Φ is the standard normal distribution function. Schedule risk analysis of this type is recommended in studies that combine critical path scheduling with resource optimization (Makut et al., 2021) and in reviews of predictive schedule-risk methods (Zhou et al., 2024; Zhou et al., 2025); the pilot and evaluation stages follow multi-dimensional evaluation practice for change programs (Obukadata et al., 2022).

2.7 Key Performance Indicator System

The models are operationalized through a small set of indicators that a center can monitor monthly from its management information system. These indicators connect the optimization outputs to routine project control (PMI, 2021) and are summarized in Table 4.

Table 4. Key performance indicators for data-driven ECE management.

Indicator	Definition	Iron Triangle link
Enrollment fill rate	Paid child-slots / licensed slots offered	Full enrollment
Fee collection rate	Tuition collected / tuition billed	Full fee collection
Cost per paying child	Total annual cost / paying children	Revenue covers cost
Labor cost ratio	Teaching labor cost / operating revenue	Revenue covers cost
Schedule efficiency	Ratio-required staff hours / paid staff hours	Revenue covers cost
Break-even fill rate	Fill rate at which surplus equals zero	All three
Affordability index	Cost-based tuition / median family income	Family affordability

The indicator set draws on real-time KPI tracking and dashboard frameworks (Ezeako et al., 2024; Tonoyan et al., 2024b; Walawalkar, Adesuyi, et al., 2025), institutional governance dashboards (Ashore-Onisemo et al., 2026), and educational performance dashboards (Orise & Niniola, 2022), and is kept deliberately small so that it can be maintained by a center director without specialist staff (Eyetsemitan et al., 2024b; Eyetsemitan et al., 2025).

2.8 Solution Approach and Scenarios

All integer programs were solved to proven optimality with the HiGHS branch-and-cut solver through the SciPy optimization library (version 1.18) in Python. Simulations used NumPy with a fixed random seed for reproducibility. Four cumulative scenarios were evaluated: **S0 (baseline)**, the legacy room layout with P0 staffing, 86% fill, and 95% collection; **S1**, the MILP-optimized room layout with P0 staffing; **S2**, which adds P2 scheduling; and **S3**, which adds enrollment and fee management (95% fill and 98.5% collection).

3. RESULTS AND DISCUSSION

3.1 Staff Scheduling (RQ1)

Table 5 reports the minimum daily teaching labor cost for each age wing of the baseline layout under the three staffing policies. Every solution satisfies the same ratio requirements, so differences are pure efficiency gains. Across the center, daily teaching cost falls from $2,645.28 under P0 to $2,502.72 under P1 and $2,448.60 under P2, a reduction of 7.4%. Over 250 operating days this equals $49,170 per year on the baseline layout.

Table 5. Daily teaching labor under alternative staffing policies. (baseline layout)

Wing (room enrollments)	P0 cost / hours	P1 cost / hours	P2 cost / hours	Saving P0 to P2
Infant (8)	$465 / 24 h	$465 / 24 h	$465 / 24 h	0.0%
Toddler (12, 12)	$929 / 48 h	$858 / 44 h	$858 / 44 h	7.7%
Preschool (12, 20, 20)	$1,251 / 64 h	$1,180 / 60 h	$1,126 / 58 h	10.0%
Center total	**$2,645 / 136 h**	**$2,503 / 128 h**	**$2,449 / 126 h**	**7.4%**

Note. Hours are paid teaching staff hours per day. All policies meet identical ratio and lead-teacher constraints.

Two findings stand out. First, the single infant room shows no saving, because a one-room wing has nothing to pool and its requirement is already met efficiently by the traditional template. Savings scale with the number of same-age rooms: 7.7% in the two-room toddler wing and 10.0% in the three-room preschool wing. Second, most of the saving comes from pooling at the edges of the day (P0 to P1); flexible part-time shifts (P1 to P2) add a smaller increment by trimming the idle overlap that fixed opener and closer blocks create. Figure 2 illustrates this for the toddler wing: the P2 requirement drops at 7:00 and 16:00 because combined rooms need fewer staff when only a fraction of children are present.

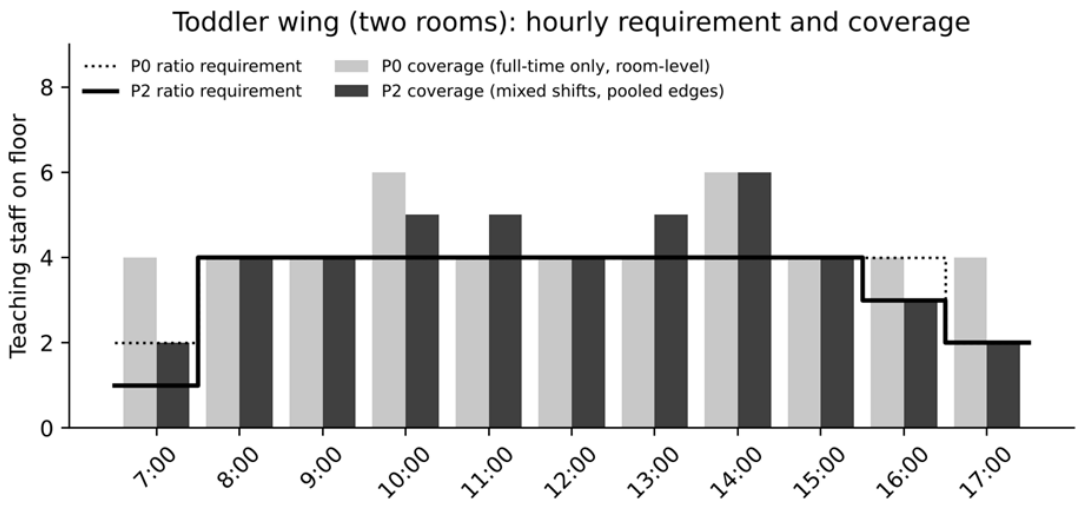

Figure 2. Hourly ratio requirement and scheduled staff coverage for the two-room toddler wing under the baseline (P0) and optimized (P2) policies.

3.2 Classroom Allocation and Scenario Results (RQ2)

The legacy layout placed a preschool group in a 420 square foot room, where the space standard limited it to 12 children, and toddlers in the 560 and 600 square foot rooms, where

the toddler group size cap of 12 left space unused. The MILP instead assigns the two smallest rooms to toddlers, the 560 square foot room to infants, and the three largest rooms to preschool groups of 17, 20, and 20. Licensed capacity rises from 84 to 89 children (6.0%) with no new space and with the infant and toddler commitments intact. Table 6 presents the full financial results for each cumulative scenario.

Table 6. Financial outcomes under cumulative optimization scenarios. (annual, USD)

Metric	**S0 Baseline**	**S1 Room realloc.**	**S2 + Shift opt.**	**S3 + Enroll./fee**
Children enrolled (capacity)	84	89	89	89
Paying children (fill-adjusted)	72.2	76.5	76.5	84.6
Operating revenue	$994,779	$1,047,067	$1,047,067	$1,199,257
Teaching labor	$661,320	$696,960	$629,970	$629,970
Variable costs	$129,688	$136,998	$136,998	$151,335
Fixed costs	$285,000	$285,000	$285,000	$285,000
Operating surplus	**-$81,229**	**-$71,891**	**-$4,901**	**$132,952**
Operating margin	-8.2%	-6.9%	-0.5%	11.1%
Cost per paying child	**$14,895**	**$14,619**	**$13,744**	**$12,612**
Labor cost ratio	66.5%	66.6%	60.2%	52.5%
Paid teaching hours per day	136	144	130	130
Schedule efficiency	86.8%	83.3%	87.7%	87.7%
Break-even fill rate	94.1%	92.8%	86.5%	82.9%

The surplus improves from -$81,229 to $132,952, a total gain of $214,181. Decomposing this gain shows the relative value of each lever: room reallocation contributes $9,338 (4.4%), shift optimization $66,990 (31.3%), and enrollment and fee management $137,853 (64.4%). Room reallocation on its own adds little net surplus because the additional children require additional ratio positions under the inefficient P0 template; its value is realized once staffing is optimized and the new seats are filled. The break-even fill rate, perhaps the most practical single indicator for a director, falls from 94.1% to 82.9%, which means the optimized center remains solvent with considerably more vacancy than the baseline center can tolerate. Figure 3 shows the corresponding decline in cost per paying child.

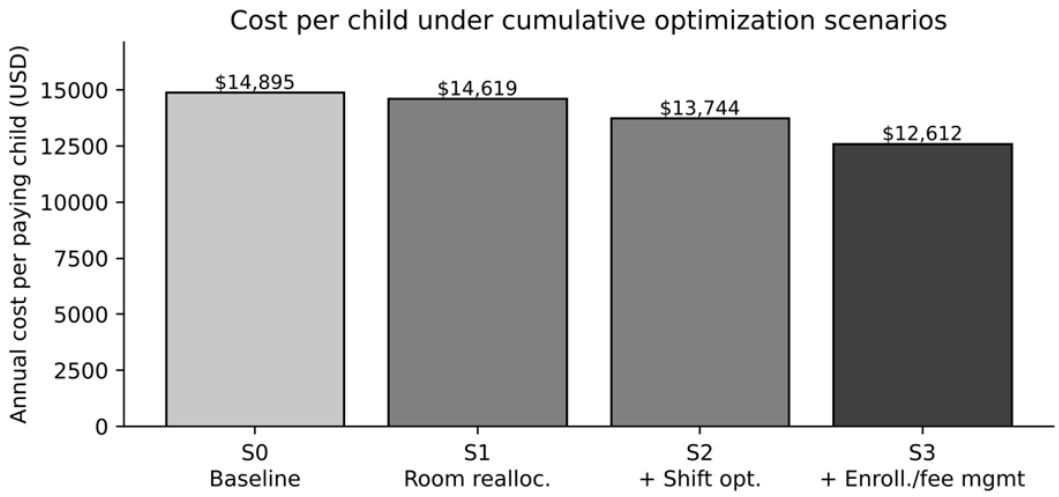

Figure 3. Annual cost per paying child across the four cumulative scenarios.

3.3 Affordability Outcomes (RQ3)

Table 7 converts costs into cost-based tuition, defined as the price each age group would need to charge to cover its own teaching labor, its variable cost, and an equal share of fixed cost, after accounting for vacancy and uncollected fees. This is compared with the market list price and with the 7% affordability threshold.

Table 7. Cost-based tuition and the affordability gap by age group.

Age group	List price	Cost-based tuition S0	Cost-based tuition S3	Share of median income (S3)	Gap to 7% (S3)
Infant	$19,500	$24,136	$21,071	26.3%	$15,471
Toddler	$16,500	$18,001	$14,902	18.6%	$9,302
Preschool	$12,800	$13,306	$10,760	13.4%	$5,160

Three results follow. First, operational improvement lowers cost-based tuition in every age group, by $3,065 for infants, $3,099 for toddlers, and $2,546 for preschoolers. Second, the cross-subsidy pattern documented in the literature is reproduced: at baseline, infant and toddler care cost more than their list prices, and preschool tuition carries part of the burden. After optimization, toddler and preschool care cover their costs at list price, while infant care still does not. Third, and most importantly for policy, no age group approaches the affordability benchmark. Cost-based infant tuition equals 26.3% of median family income even in the optimized center.

Two summary measures quantify what efficiency does and does not achieve. The **affordability dividend** is the surplus above a 3% operating reserve that could be returned to

families. In S3 it amounts to $96,974 per year, or $1,147 per paying child, a 8.0% reduction in average list tuition of $14,400. The **residual public funding gap** is the subsidy required to bring every family's payment down to 7% of median income. It falls from $728,096 ($10,079 per paying child) at baseline to $609,063 ($7,204 per paying child) after optimization, a 28.5% reduction in the per-child public cost of achieving affordability.

3.4 Financial Risk

Table 8 and Figure 4 summarize the Monte Carlo results. Under baseline practice, the center runs a loss in 93.2% of simulated years, with a mean surplus of -$81,117. Under data-driven practice, the mean surplus rises to $132,635 and the probability of a loss falls to 0.03%. The fifth percentile outcome, a reasonable stress case for reserve planning, improves from -$178,197 to $72,955. The improvement comes from two sources: a higher expected surplus and a narrower distribution, because better enrollment forecasting and automated billing reduce the variance of fill and collection rates.

Table 8. Monte Carlo simulation results. (20,000 draws per scenario)

Statistic	Baseline practice	Data-driven practice
Mean annual surplus	-$81,117	$132,635
5th percentile surplus	-$178,197	$72,955
95th percentile surplus	$8,773	$191,003
Mean operating margin	-8.4%	11.0%
Probability of annual loss	93.2%	0.03%

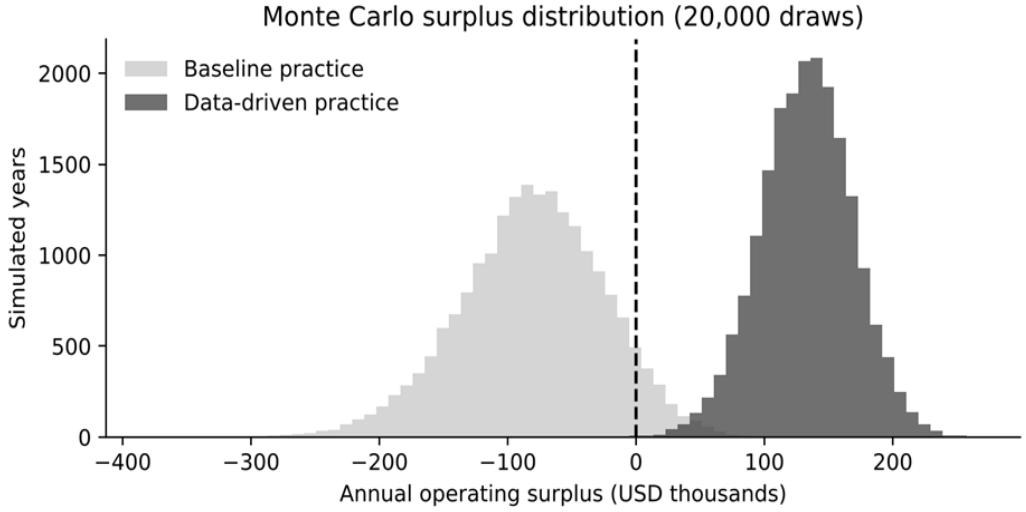

Figure 4. **Simulated distribution of annual operating surplus under baseline and data-driven practice. The dashed line marks break-even.**

3.5 Sensitivity Analysis

Figure 5 reports one-at-a-time sensitivity of S3 cost per paying child ($12,612) to its main drivers. The teaching wage produces the widest swing ($11,494 to $13,729), confirming that compensation is the dominant structural cost. The enrollment fill rate is a close second and is asymmetric: a fall to 85% raises cost by $1,273, while full enrollment lowers it by only $541. This asymmetry is the quantitative signature of the Iron Triangle: vacancies are expensive because ratio-driven labor cannot be shed child by child. Ratio stringency and fixed costs have intermediate effects, and variable costs matter least.

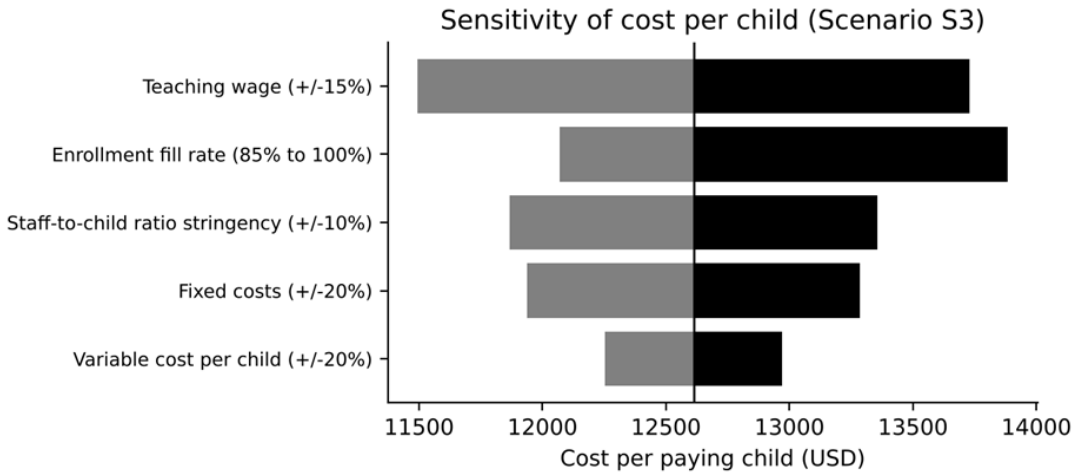

Figure 5. Tornado diagram of cost per paying child in Scenario S3. Grey bars show the favorable end of each range and black bars the unfavorable end.

An important implication concerns wages. Because the teaching wage is the most influential parameter, the savings from scheduling and enrollment management could alternatively be directed to compensation. In S3, the affordability dividend would fund roughly a 15% increase in teaching payroll while holding tuition constant, which would address the workforce dimension of the childcare problem rather than the price dimension. The model makes this trade-off explicit for governing boards.

3.6 Implementation Project Schedule (RQ4)

Table 9 lists the implementation activities and their PERT estimates. The critical path runs through A, C, D, F, H, I, J, that is, through system selection, data integration, model building, the pilot, its evaluation, and rollout. The expected project duration is 25.3 weeks with a standard deviation of 1.89 weeks. The probability of completing within 26 weeks (one half-year) is 63.8%, and within 30 weeks it is 99.3%. A 90% confidence completion date is 27.7

weeks. Data audit, dashboard design, and staff training carry slack and can absorb modest delays, whereas any slip in data integration or model building delays the whole project.

Table 9. PERT estimates for the implementation project. (weeks)

Activity	Pred.	a	m	b	t_e	ES	EF	Slack
A. Project charter and stakeholder mapping	None	1	2	3	2.00	0.00	2.00	0 (critical)
B. Data audit of enrollment, attendance, payroll	A	2	3	6	3.33	2.00	5.33	1.00
C. Select child care management system	A	2	4	8	4.33	2.00	6.33	0 (critical)
D. Data integration and cleaning	B, C	3	5	9	5.33	6.33	11.67	0 (critical)
E. KPI dashboard design	B	2	3	5	3.17	5.33	8.50	4.17
F. Build scheduling and allocation models	D	2	4	7	4.17	11.67	15.83	0 (critical)
G. Staff training and change management	C, E	2	3	5	3.17	8.50	11.67	4.17
H. Pilot in two classrooms	F, G	3	4	6	4.17	15.83	20.00	0 (critical)
I. Evaluate pilot and recalibrate	H	1	2	4	2.17	20.00	22.17	0 (critical)
J. Center-wide rollout	I	2	3	5	3.17	22.17	25.33	0 (critical)

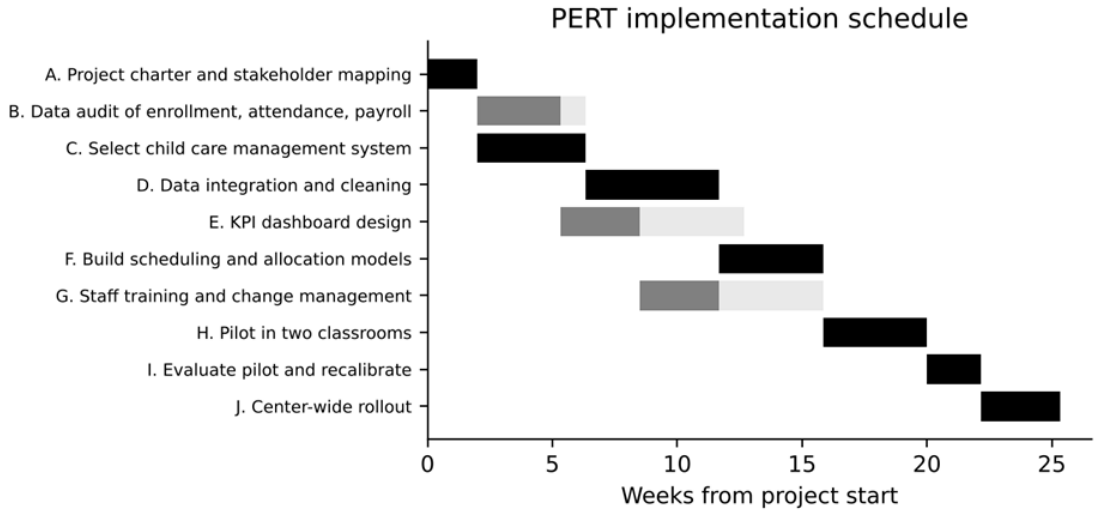

Figure 6. Gantt view of the PERT schedule. Black bars are on the critical path, dark grey bars are non-critical activities, and light grey extensions show available slack.

3.7 DISCUSSION OF FINDINGS

3.7.1 Interpreting the Results

The modeling results support a measured conclusion. Data-driven management produced a 15.3% reduction in cost per paying child, turned a -8.2% operating margin into a 11.1% margin, and nearly eliminated the risk of an annual loss. These are large changes for an organization whose margins are typically measured in single digits. Yet the same results show that cost-based infant tuition remains roughly 3.8 times the 7% affordability threshold. Efficiency narrows the affordability gap; it does not close it.

The decomposition of gains is also instructive. The largest single lever, enrollment and fee management, accounts for 64% of the improvement and requires no change to classroom practice. It depends instead on accurate waitlist data, timely re-enrollment, attendance-based forecasting, and automated billing. Scheduling improvements rank second and depend on hourly attendance data that many management information systems already collect but rarely analyze. Room reallocation creates capacity whose financial value is realized only in combination with the other two levers, which supports an integrated rather than piecemeal approach.

This pattern is consistent with process improvement research showing that revenue recovery and collection discipline often produce larger and faster returns than structural redesign (Ashore-Onisemo & Iziduh, 2024; Ebisi et al., 2021; Sanni & Wedraogo, 2024), and with evidence that dashboard-based monitoring sustains such gains (Ezeako et al., 2024; Tonoyan et al., 2024b).

3.7.2 Evaluation of the Propositions

Table 10 summarizes how the quantitative results bear on the five propositions derived from the conceptual model.

Table 10. Evaluation of propositions against model results.

Proposition	Evidence from the models	Assessment
P1. Demand-driven scheduling	Daily teaching cost fell 7.4% on the baseline layout and annual labor fell $66,990 in S2, with all ratios met	Supported
P2. Data-driven room allocation	Capacity rose from 84 to 89 children with the access floor and mission commitments intact	Supported
P3. Enrollment and fee levers dominate	Enrollment and fee management produced 64% of the surplus gain; loss probability fell to 0.03%	Supported

Proposition	Evidence from the models	Assessment
P4. Efficiency narrows but does not close the gap	Per-child funding gap fell 29%; infant cost-based tuition remains 26.3% of median income	Supported
P5. Implementation is a bounded project	Expected duration 25.3 weeks; critical path through data integration and model building	Supported

3.7.3 Safeguards for Quality and Workforce Wellbeing

Optimization can be misused. A scheduling model that minimizes cost without constraints on continuity of care, planning time, and predictable hours could harm children and staff. The formulation here includes a lead-teacher requirement and a cap on part-time hours for this reason, and institutions adopting similar tools should add constraints for guaranteed minimum hours, advance notice of schedules, and paid non-contact time. Ratios were treated as inviolable throughout. The intent of data-driven management in ECE is to remove waste around the ratio, not to erode the ratio itself.

Research on teacher retention (Yeboah et al., 2019; Yeboah et al., 2025), compressed and alternative work schedules (Oparah et al., 2024a), and responsible AI governance (Ilodigwe & Adesemoye, 2025a; Unamma et al., 2025b) supports these safeguards, as does work on ethical data practices for systems that hold information about children and families (Oloto & Yeboah, 2025; Orise & Niniola, 2023).

3.8 Implications

3.8.1 Implications for Practice

- **Measure the Iron Triangle monthly.** Fill rate, collection rate, and break-even fill rate should be standing agenda items for directors and boards, with explicit targets.
- **Schedule to attendance, not to the clock.** Pooling same-age rooms at the edges of the day and using flexible part-time shifts reduced labor cost by about 10% in this model without relaxing any ratio.
- **Revisit room assignments when enrollment patterns change.** A simple MILP, solvable on a laptop in seconds, increased capacity by 6.0% in the same building.
- **Manage the change as a project.** The PERT analysis implies a realistic horizon of roughly six to seven months, with data integration as the main schedule risk.
- **Decide deliberately how to use the dividend.** Lower tuition, higher wages, quality investment, and reserves compete for the same surplus; the model makes these trade-offs visible.

3.8.2 Implications for Policy

For policymakers, the results suggest that technical assistance and shared services that improve provider operations can reduce the public cost of affordability. In this model, the subsidy required to hold every family to 7% of median income falls by 29% per child after optimization. However, the large residual gap, especially for infants, confirms the view of the National Academies of Sciences, Engineering, and Medicine (2018) that sustained public investment is necessary. Funding formulas based on the cost of care, rather than on market prices that already reflect underpaid labor and cross-subsidies, would be more consistent with the cost structure revealed by the model.

Lessons from health system financing reform (Ilodigwe & Adesemoye, 2019a; Odeyemi & Idowu, 2025) and from inclusive financing for essential infrastructure (Komi & Adeniji, 2020; Komi & Adeniji, 2024a) suggest that blended funding and cost-based payment rates are more effective than any single instrument in reaching low-income families.

3.8.3 Theoretical and Methodological Implications

Theoretically, the study formalizes the Iron Triangle (Stoney, 2010) as a set of measurable levers embedded in an optimization and simulation framework, showing that the levers are not equally weighted: fill and collection dominate structural efficiency in their effect on solvency. It also extends personnel scheduling research (Ernst et al., 2004; Van den Bergh et al., 2013) to a setting in which demand is defined by regulatory ratios applied to fluctuating attendance. Methodologically, the two-stage linkage between a tactical allocation MILP and an operational scheduling program, followed by exact re-evaluation, offers a template for other ratio-regulated human services such as residential care, nursing, and special education, where comparable staffing mandates apply (Omaghomi et al., 2023; Yeboah & Oloto, 2023).

4. CONCLUSION

This paper developed and solved an integrated set of quantitative models that connect project management practice with operations research for early childhood education institutions. For a representative six-classroom center, data-driven classroom allocation, demand-driven scheduling, and disciplined enrollment and fee management increased capacity from 84 to 89 children, reduced cost per paying child by $2,283, and moved the institution from a probable annual loss to a stable surplus. The surplus could fund a tuition reduction of about 8% or a meaningful wage increase. At the same time, the analysis shows that infant care in particular cannot reach conventional affordability benchmarks through efficiency alone. Data-driven

management is therefore best understood as a necessary complement to, not a substitute for, public investment in affordable, high-quality early childhood education.

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