From Assessment to Action: Prioritizing Energy Investments in Building Portfolios With Advanced Analytics

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Abstract

This study explores the innovative use of artificial intelligence to analyze large-scale building datasets for Chicago Public Schools. By harnessing advanced analytical tools and leveraging existing assessment data, school administrators and facility managers can make effective data-driven decisions for planning capital investments to achieve substantial energy reductions without the need for further data collection efforts. Instead, advanced analysis techniques are used to integrate and study diverse data, such as energy consumption patterns, equipment inventories, and facility conditions, to uncover trends and deliver actionable insights. These insights help identify the business case for energy efficiency investments while aligning with broader facility planning objectives. By providing a repeatable and resource-efficient framework, this approach enables building owners to prioritize investments and maximize the impact of budgets across multiple facilities, while saving energy, reducing operational costs, and enhancing occupant environments. The results demonstrate the potential of advanced analytics to streamline technical assistance and transform capital planning, empowering stakeholders to achieve impactful outcomes.

Introduction

Across the public and private building sectors in the United States, there is a massive backlog of deferred maintenance, estimated to exceed $1 trillion (Sarmiento, Yashodhar, and Zhao 2025). For large portfolio owners, such as public school districts, this challenge is often magnified by budget constraints that create a barrier to achieving ambitious energy savings goals and result in a reactive cycle of fixing failing equipment rather than taking a proactive approach to building investments. Along with this challenge, there exists a frustrating paradox—the crucial data needed for strategic decision making is often locked in hundreds to thousands of pages of static documents. Making sense of this information and analyzing details to make informed decisions can be overwhelming and impractical to manage due to the scale.

This paper explores how leveraging artificial intelligence (AI) capabilities, specifically large language models (LLMs) and multi-agent AI architecture,[1] allows for the rapid ingestion and processing of large volumes of unstructured data. Through the U.S. Department of Energy (DOE) Better Buildings & Better Plants (BBBP) Initiative, the National Laboratory of the Rockies (NLR) piloted an AI-powered approach for supporting building owners with a large inventory of buildings as they develop the business case for saving energy at scale. By synthesizing details across multiple data streams, this model transforms static reports into a

[1] Large language models (LLMs) are AI systems trained on vast amounts of text that can understand and generate human-like language. A multiagent architecture extends this by coordinating multiple such models, each handling specialized subtasks, to pursue more complex goals.

dynamic and easily accessible decision engine for building owners to develop useful insights for reducing energy use while maximizing available capital funds. For single buildings as well as large portfolios, the use of AI to analyze building data accelerates portfolio-wide analysis, reduces administrative overhead, and lowers the barrier to capital deployment.

Background

As part of the BBBP Initiative, the Better Buildings Challenge invites commercial and institutional building owners to voluntarily commit to reducing site energy use in their facilities by at least 20% over a 10-year period (BBBP 2025). With BBBP Partners representing more than 10% of the total commercial floor area in the United States, many of the solutions developed can be scaled to support energy savings investments across the remaining building stock (BBBP 2025). Although some energy efficiency improvements can be achieved through operational efforts such as aligning building schedules with occupancy, many strategies for achieving larger energy savings involve investing in capital improvements to buildings. Informational and educational materials help communicate critical knowledge and best practices to support these decisions. However, we learned through partner engagement that a common challenge partners face is prioritizing where and how to invest in their buildings, and budget limitations exacerbate this issue. One of the keys to addressing this challenge is leveraging existing capital projects to maximize energy efficiency opportunities. An objective of this effort is to develop innovative strategies for partner organizations to make it easier and more cost-effective to achieve their energy goals.

Chicago Public Schools (CPS) is one of the largest public school systems in the United States, serving more than 300,000 students across more than 600 schools (NCES n.d.). As a participant in BBBP, CPS has committed to a 20% reduction in energy use from a 2022 baseline by 2032. Meeting this goal is a significant challenge for this partner, but they are not alone. School districts across the country are facing a $90 billion annual shortfall in school facility funding, with deferred maintenance backlogs far exceeding annual capital and maintenance budgets (Filardo 2025). Figure 1 shows examples of what this backlog looks like for the five largest school systems in the country, based on public budgetary and planning information for each school system.[2]

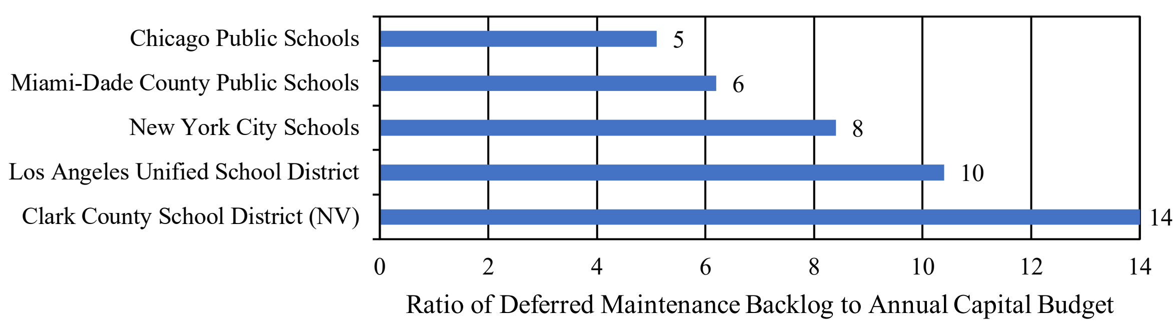

Figure 1. Deferred maintenance ratio for the five largest public school systems in the United States as of 2025

[2] Sources include: CPS FY2025/26 Capital Plan, CPS FY2025-26 Budget Overview, M-DCPS State of the Schools Infrastructure Audit, M-DCPS 2025-26 Budget Summary, NYC DOE Five-Year Capital Plan (FY 2025-2029), NYC Council FY2026 Adopted Budget, LAUSD FCA Data, LAUSD 2025-26 Adopted Budget and Fiscal Stabilization Plan, CCSD Capital Improvement Plan Updates, and CCSD 2025-26 Amended Final Budget.

For many school systems, including CPS, the objective is to maximize the value of capital and maintenance budgets. This includes making progress towards energy goals realizing that a common barrier is that there is simply not enough money. Although saving energy is important, the priority for the building owner is keeping their schools clean, safe, and operational for an educational environment. Saving energy mostly occurs either through small steps like replacing failed equipment or making operational changes, or through isolated large steps like building a new school building. The key is how to identify solution pathways to maximize budgeted funds to achieve educational and energy goals.

To illustrate this, consider two pathways to achieving 20% energy savings across the CPS portfolio. First is the example of large capital investment in new buildings or major renovations. Assuming these projects reduce energy use by 50% in each instance, CPS would have to do this to their top 93 energy-consuming schools (Figure 2). Alternatively, a second example is the distributed investment across the portfolio to reduce energy use by 20% on average in each school (Figure 3). These examples are both extreme and neither one is particularly easy to implement. A strategic, optimized approach with accurate and reliable data is needed to bridge the gap between these extremes.

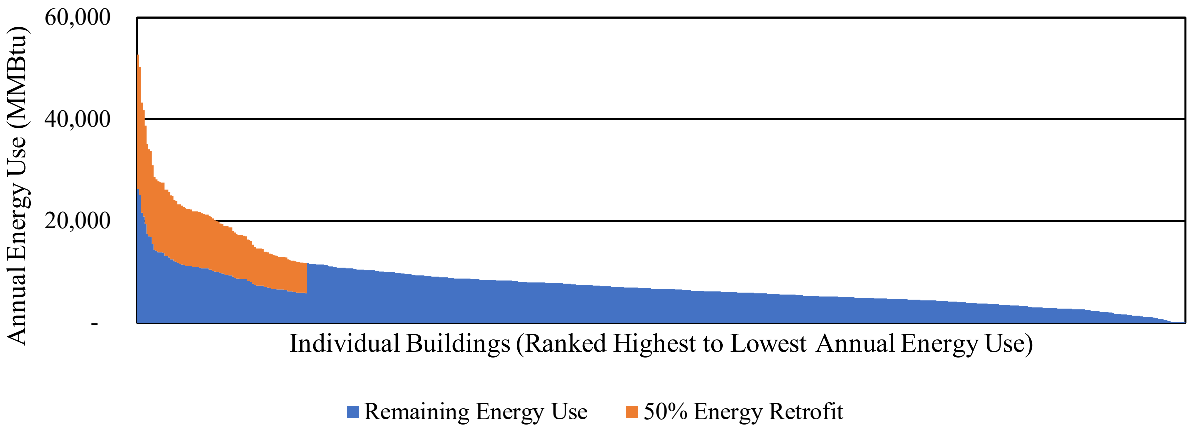

Figure 2. An illustrative example of achieving 20% energy savings across the Chicago Public Schools portfolio by completing 50% energy retrofits in the top 93 energy-consuming buildings

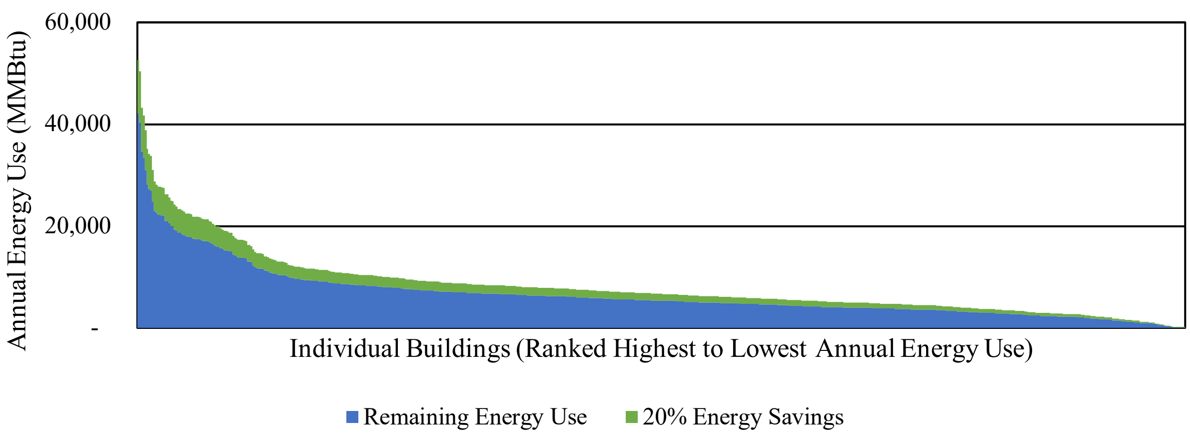

Figure 3. A second illustrative example of achieving 20% energy savings across the Chicago Public Schools portfolio by distributing investments across smaller energy savings measures in each school, averaging 20% energy savings per building

In pursuit of its energy savings goal for BBBP, CPS complies with external requirements such as Illinois Public Act 097-0474. This legislation was passed in 2011 and requires CPS to produce capital improvement plans for near-term investments as well as ten-year educational facilities master plans (Public Act 097-0474 2011). The law also requires CPS to conduct facility condition assessments (FCAs) of its schools at least once every two years to help inform the planning processes. The biennial FCA serves as a primary data-gathering mechanism, capturing information on the existing building features and systems and evaluating their condition and remaining useful life.

The facility assessment process generates an enormous volume of data about the building portfolio. Across all schools in 2023, CPS assessed more than 700,000 items. Despite this amount of data, FCA reports are typically not designed to capture energy audit detail, which creates a disconnect between existing data and energy improvements. This overwhelming amount of data can result in "paralysis by analysis" and resorting to ignoring energy savings opportunities and only focusing on critical needs in the short- and long-term planning processes.

To maximize limited capital funds, CPS cannot invest in a limited number of high energy-use building retrofits while the rest of the portfolio becomes more inefficient. Similarly, they cannot apply generic energy conservation measures at random across the portfolio. The strategic "sweet spot" is identifying the specific instances in which urgent deferred maintenance needs align with energy savings opportunities. Manually identifying these overlaps across a portfolio as large as CPS, however, is prohibitively complex. However, with support from the AI-enabled automation strategy presented in this paper, CPS can maximize the effectiveness of its capital investments to achieve its multifaceted goal of reducing energy use across its portfolio while complying with legislative requirements and maintaining a high standard for its educational facilities.

Approach and Methodology

The objective of this work is to create a strategy to support Chicago Public Schools' energy reduction goal. This started with documenting each available source of data about the building portfolio. Table 1 below describes the purpose of each data source.

Table 1. Data categories reviewed for large school system portfolio

Data category	**Purpose and value to portfolio-wide planning**
Building names and addresses	Data validation and reference for building-specific data
Historical utility data	Building-level insights into energy performance
Facility condition assessment reports	Detailed inventory of components, equipment, and systems in each building, along with assessed condition and remaining useful life
Budgetary and planning documents	Budget details, historical spending, capital planning documents, and long-term master planning documents provide pertinent details regarding the school system's existing constraints and future plans.
Building imagery	Visual inspection of building from satellite and street-level/façade perspectives provides detail on architectural style, building layout, and materials.

Analyzing this information for any single building, or small group of buildings, is relatively simple and a standard practice for planning and prioritizing investments in single building retrofits. A building engineer can use these data to identify energy efficiency opportunities that align with capital needs and building deficiencies outlined in the FCA reports. However, this becomes a much more complex and challenging task when scaled to a large building portfolio.

Each one of these schools is documented through detailed facility assessment reports averaging fifty pages covering heating, ventilating, and air-conditioning (HVAC) systems; building envelopes; lighting; controls; and equipment inventories. At roughly 30,000 pages of technical documentation across the full portfolio, extracting targeted answers about any single school, let alone comparing and finding trends across the portfolio, is a task that exceeds practical manual effort. Historically, facilities teams and consultants manually reviewed assessment reports, cross-referenced spreadsheets, and produced prioritization recommendations over several weeks per cluster of schools.

To address this, we built a retrieval-augmented generation (RAG) system on a cloud computing platform that makes the entire corpus searchable through natural language. Facility reports are ingested through an automated pipeline and segmented into meaningful chunks, enriched with contextual metadata, and converted into semantic representations using modern AI embedding models. These representations are stored in a cloud-hosted vector database, enabling fast similarity search across the full document set. When a user poses a question, the system retrieves the most relevant chunks, re-ranks them for precision, and a large language model generates a citable answer. The system does not rely on assessment data alone. It cross-references external knowledge sources covering ASHRAE guidelines, building performance standards, heat pump applications, lighting best practices, available incentive and financing programs, and documented case studies, so that responses are informed by both site-specific findings and current domain expertise.

It is important to note that although external knowledge sources are used, the system is self-contained and data from the school system are not used outside this environment—in other words it is not used to train other systems as an open data source. At the moment, this tool is only available to the technical laboratory staff developing the system. The long-term vision is to make an interface available to school systems. This end goal would allow other school districts to upload information and query the engine. The RAG architecture meets industry standards and can be deployed with any retrieval and embedding system.

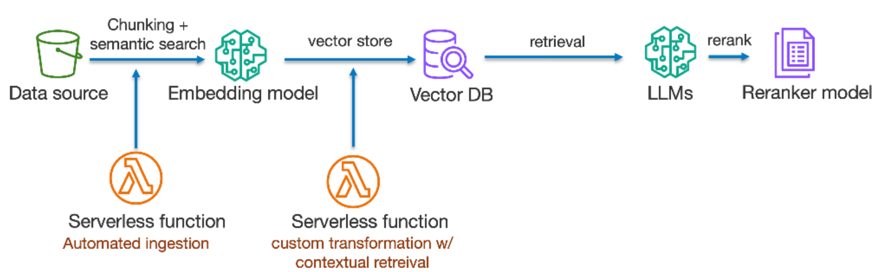

Figure 4. Architecture of RAG Knowledge Base

The system's primary purpose extends beyond question-and-answer. Our goal is to generate structured, actionable reports on energy savings opportunities, cost reduction potential, and building efficiency, scoped to an individual school or a cluster of schools grouped by geography, building archetype, or system type. For example, a report might include every school running aging steam boilers with pneumatic controls, rank them by replacement urgency, and cross-reference financing options and applicable code requirements, all synthesized from assessment data and external knowledge without manual compilation.

Every generated report goes through human-in-the-loop validation. We actively review the system's outputs and compare them against baseline assessments, ensuring accuracy and reliability before recommendations reach decision makers. This step is critical due to the well-known shortcomings of AI-enabled analysis (Tabassi 2023). The model's performance is inherently limited by the completeness and quality of the underlying data, and without human review and validation the AI model can misunderstand contextual nuance and produce erroneous output. The intended consumer is the building owner's leadership and facilities teams who need to allocate capital where it will have the greatest impact, particularly in schools where deferred maintenance has compounded over decades. By automating the analysis that currently requires weeks of consultant review, the system compresses the path from data to decision and helps reveal disparities in building conditions that might otherwise remain buried in documentation.

The breakdown of the assessment reports into computer-digestible fragments of data became the core information model. Coupling this with other data sources, such as historical energy consumption and specific subject matter expertise, the CPS building portfolio[3] became readily accessible for detailed analyses of energy savings opportunities aligned with building needs. We tested several prompts and queries, which were grouped into the categories shown in Table 2. Each category also exists on a spectrum of retrieval-dominant to reasoning-dominant queries, which can be defined in terms of "orders," where:

- **First Order [Retrieval → Answer]:** This is pure lookup and retrieval of discrete information from source documentation in the model's knowledge base. Minimal reasoning is required.
- **Second Order [Retrieval → Reasoning → Answer]:** Answers to these types of queries are not in the model's knowledge base verbatim. The model is forced to do something with retrieved content (e.g., summarize, compare, or reframe), but the desired answer is still relatively simple.
- **Third Order [Retrieval → Reasoning → Retrieval → Reasoning → Answer]:** Information is needed from multiple sources to answer the queries. The output of one retrieval typically informs what to retrieve next, and then the model reasons across the combined context.
- **Nth Order [(Retrieval ↔ Reasoning)^n → Answer]:** As retrieval and reasoning loops become more iterative, the model starts exhibiting more agentic behavior. These queries require the model to plan, retrieve, evaluate what it obtained, decide on additional information it needs, retrieve again, and iterate on this potentially many times before it can answer. With agentic behavior, the model runs an internal loop in which each reasoning step potentially triggers new retrieval.

[3] The analysis presented in this paper covers a sample size of 20 schools. However, the plan is to continue scaling the model to eventually cover the full CPS portfolio.

Table 2. Categories and descriptions of artificial intelligence model queries

Category	Description	Query type
Building-specific information	Retrieves information about a specific building (or group of buildings) defined in the query.	First order
Building deficiencies and maintenance needs	Focuses on identifying and summarizing critical needs across the portfolio.	Second order
Building archetypes	Identifies key characteristics in each building (found in the FCA reports) and categorizes the portfolio into X representative groups/archetypes. This serves dual purposes: (1) empowering the artificial intelligence model to determine representative characteristics and define the archetypes, and (2) using the outputs as humans to consider scalable retrofit packages that could be deployed across all buildings in each archetype.	Third order
Energy savings opportunities	Prompts the model to consider the energy consumption impacts associated with components/systems in each building and use its reasoning capabilities to identify and prioritize retrofit projects that would address critical deficiencies and improve energy performance.	Third order
Strategic planning	Synthesizes several data streams to build staged project plans based on information retrieved from FCA reports and reasoning on energy savings opportunities.	Nth order

Results and Findings

Review and Validation of Data

Before any information from CPS school buildings could be analyzed with our model, we conducted an initial data review and validation exercise to ensure the correct list of schools and associated assessment reports was being used as the "source of truth" for building the model.[4] Publicly available FCA reports were accessible with a standardized file naming convention that included the school's name and an ID number. Beginning with a small sample set of reports, we piloted the use of a RAG model to read each PDF report and extract the school's name to compare against the file name. Scaled to the entire dataset, this approach identified a handful of mismatched reports with incorrect file names and ultimately enabled the validation of which reports were accurately linked to the corresponding schools. Following this exercise, we generated a list of the expected file names for each school's FCA report using a master list of 649 schools and associated ID numbers from the city's data portal. We tested each file name against the library of publicly available reports to determine which file names failed – indicating schools that did not have an FCA report under their name.

[4] "Source of truth" refers to the information used by an artificial intelligence model that is considered to be true and accurate. It is often based on direct measurement and observation.

By automating this process with an AI model, we quickly found that 130 schools, or 20% of the portfolio, did not have a corresponding assessment report in the CPS database. Further validation revealed that more than 100 of these schools are not owned or managed by the CPS facilities team. An additional 15 schools were co-located with other schools and therefore represented in assessments under a different name. Ultimately, this data validation process resulted in a verified list of 534 schools owned and controlled by CPS, for which they pay the utility bills, and which are represented by 519 unique facility assessment reports. These 519 reports became the source of truth for the model's knowledge base, enabling the team to proceed with trusted data to be used in the AI model. The non-verified schools were not analyzed as the effort and number of staff to engage in correcting these problems was not easily accomplished. Using AI as a validation tool proved to be a valuable resource to identify the 80% of the schools that were ready for the next phase of analysis.

Testing and Performance of the Model

With our model, we tested more than 100 queries and prompts across all categories and types described above in Table 2. Each type of query was found to serve a specific purpose, with pros and cons that point to the overall benefit of a conversational large language model interface that allows a user to investigate and analyze the building portfolio data from various perspectives. Further detail on these findings is described below.

First order queries on building-specific information. Queries in this category are very direct and straightforward. Users can ask the model for information on a particular building or group of buildings, and the model will provide the information as long as it is in the model's knowledge base. In this use case, the information sought by CPS is included in the FCA reports for this portfolio, so the model is able to retrieve these details on building equipment, systems, condition ratings, and other statistical information when asked. However, these questions could likely also be answered by manually referencing the corresponding school's FCA report and other documentation, so the model we have built is overpowered for this "first order" type of query/search in isolation. The importance of this type of query is that it forms the foundation of higher-order types of queries.

Second order queries on building deficiency patterns and maintenance needs. With second order queries, the model is retrieving information from source documentation and doing something with it (i.e., summarizing, comparing, and reframing). In the application discussed here, we are mainly using second order queries to extract information about building deficiencies and maintenance needs across the school portfolio. Answers from the model rely on the accuracy of its fact retrieval and its understanding of context using natural language processing.

Across a portfolio of more than 500 buildings, it would be an impractical and inefficient use of time for a human to review every assessed item, organize and structure the data, and then compile summary information for each school. Automating the extraction and processing of information greatly reduces the level of manual effort required and allows for more strategic and efficient use of human resources. Queries like this could ask about specific building needs (e.g., how many buildings need an HVAC system replacement in the next 5 years; or which schools have single-pane windows), or they could ask about broader summaries of needs and deficiencies across the portfolio. The findings from these queries are greatly informative for decision makers who are not deeply knowledgeable about building details and could prove valuable when summarizing details to stakeholders. Many of the school's facilities managers and building engineers, however, may already be familiar with the general trends discussed in the model's answer. To attain strategic insights that inform decision making, higher order queries are needed.

Third order queries on building archetypes and energy saving opportunities. One of the central objectives of developing this AI-powered model is the ability to overlay energy analysis onto the FCA findings, which is where the third order queries demonstrate their impact. Building owners, facility managers and engineers, and other decision makers can benefit from using third order queries to dig deeper into the building data and uncover trends and opportunities related to energy use. By our definition, these queries retrieve information (first order), apply reasoning (second order), then retrieve more information and reason again before finally providing an answer. One of the primary ways this process can be used is to task the model with identifying key characteristics of each building and sorting schools into representative archetypes that allow humans to plan retrofits across a smaller set of groups rather than 500+ individual schools. Another way this process generates impact is through identifying energy savings opportunities that align with deferred maintenance needs across the portfolio.

In the example provided in Figure 5 below, we show how this approach can be used to produce valuable insights. The model we developed produced a report outlining opportunity areas for energy savings that align with deferred maintenance needs found across the 20-school cohort used for our pilot. Using the FCA reports for each school, some subject matter expertise developed for BBBP, and other general knowledge, the model identified these opportunities and outlined potential strategies for addressing each one. Even with this smaller sample size, it is clear how the automation of extracting, analyzing, and organizing these data allow human decision makers to focus more on what they can do with this information (i.e., strategize investments and budget allocations, bundle projects for bidding, etc.)

Our model is not limited to these examples. One can imagine a range of other queries along this spectrum that would probe the assessment reports and other supporting documentation for guidance on strategizing capital planning to address deferred maintenance and energy efficiency simultaneously.

Energy Savings Aligned with Deferred Maintenance

CPS 20-School Cohort | Based on 2023 Facility Assessment Documents

This brief identifies areas across the CPS 20-school portfolio where deferred maintenance needs and energy-savings opportunities overlap. For each area, the document describes the maintenance condition driving the need, explains why that condition also represents an energy opportunity, and lists a range of potential strategies for further evaluation. Aligning energy upgrades with already-scheduled maintenance work maximizes capital efficiency: labor, scaffolding, and downtime are shared, and the incremental cost of a higher-efficiency replacement is typically a fraction of a standalone retrofit.

Portfolio Snapshot

- 20 schools | 2.5M **total sq ft**
- 11 schools on steam heat | 13 relying on window A/C | 9 with pneumatic controls
- Construction dates span 1881–2013; 14 of 20 buildings pre-date 1965

Opportunity Areas

1. Aging Steam Heating Infrastructure (11 schools)

Maintenance need: 11 campuses rely on steam boiler plants, distribution piping, and condensate-return systems that are approaching or past their expected useful life. Average HVAC condition rank[5] across these schools is 6.0/10, and many components are flagged in the 0–5-year replacement window.

Energy opportunity: Steam heating systems typically operate at 65–75% distribution efficiency due to standby losses, condensate leaks, and uninsulated piping. The scheduled replacement of this infrastructure creates a natural decision point to evaluate whether higher-efficiency heating alternatives could reduce long-term operating costs.

Potential strategies: High-efficiency condensing boilers; conversion to hot-water hydronic distribution; air-source heat pumps; ground-source heat pumps; hybrid heating systems combining multiple technologies. The optimal path depends on building-specific factors including electrical service capacity, available space, and heating-load profile.

School	ID	Built	Sq Ft	HVAC Rank	0–2 yr	Notable Condition
Addams	609772	1948	62,043	5.9	5	—
Alcott ES	609774	1937	84,193	6.2	1	Abandoned rooftop cooling unit
Alcott HS	610524	1895	51,852	6.0	2	Feed-water tank leaking steam
Amundsen HS	609695	1930	218,950	6.1	8	DHW tank/pumps corroded
Armour	609777	1901	82,842	6.0	7	500 LF uninsulated condensate; leak history
Ashburn	610287	1953	58,580	6.0	10	200 LF condensate; leak history
Ashe	610268	1963	55,335	6.1	8	Units deteriorated / abandoned in place
Audubon	609782	1894	86,989	6.2	0	Poor performance due to leaks
Austin CCA HS	610518	1930	397,258	6.3	5	Half exhaust-hood coverage
Avalon Park	609786	1915	87,101	5.9	6	317 LF uninsulated condensate
Avondale-Logandale	610325	1881	138,900	5.9	18	No outside air source

0–2 yr = items flagged for replacement within 0–2 years from the 2023 assessment.

2. End-of-Life Window Cooling Units (13 schools)

Maintenance need: 13 campuses cool with window-mounted air conditioning units. These units have a typical service life of 5–8 years, and many are at or past replacement age. Several FADs note units that are non-functional, deteriorated, or abandoned in place.

Energy opportunity: Legacy window A/C units typically operate at EER 8–10. Replacing at end-of-life is an opportunity to improve cooling efficiency (modern units achieve EER 12–15+) and potentially add heating-season capability, reducing load on the primary heating plant during shoulder seasons. No additional ductwork or structural work is typically required for a unit-for-unit swap.

Potential strategies: Higher-efficiency window A/C units; window-mount heat pumps (providing both cooling and heating); ductless mini-split systems; centralized cooling solutions where existing ductwork permits. Selection depends on building configuration, electrical capacity, and whether dual-mode (heating + cooling) capability is desired.

School	ID	Built	Heating Type	Controls	Notable Condition
Addams	609772	1948	Steam/HW	Pneum	Pneumatic controls not operational
Alcott ES	609774	1937	Steam	DDC	Abandoned rooftop cooling; DDC
Alcott HS	610524	1895	Steam	Pneum	Feed-water tank leaking; pneumatic
Aldridge	609848	1960	Hot water	DDC	Compressors non-functional; DDC
Amundsen HS	609695	1930	Steam	Pneum	Pneumatic; DHW corroded
Armour	609777	1901	Steam	Pneum	500 LF uninsulated pipe; pneumatic
Armstrong G	609779	1911	Hot water	DDC	Non-functional equipment per engineer
Ashburn	610287	1953	Steam	Pneum	200 LF leaking condensate; pneumatic
Ashe	610268	1963	Steam	Pneum	Units deteriorated/abandoned; pneumatic
Audubon	609782	1894	Steam	Pneum	Leaks, poor performance; pneumatic
Austin CCA HS	610518	1930	Steam	DDC	Half exhaust-hood coverage; DDC
Avalon Park	609786	1915	Steam	Pneum	317 LF uninsulated; pneumatic

[5] The FCA reports for Chicago Public Schools assessed the condition of items using a 7-point rank scale, where 1 indicates failure (i.e., immediate remediation required) and 7 indicates new or like-new condition (i.e., no work required).

Avondale-Logandale	610325	1881	Steam	Pneum	No outside air source; pneumatic

3. Uninsulated Steam / Condensate Piping (3 schools)

Maintenance need: Three campuses have documented runs of uninsulated steam or condensate-return piping totaling approximately 1,017 linear feet, compounded by active leak histories. These runs require repair and/or replacement to maintain system function.

Energy opportunity: Bare steam and condensate piping loses a significant fraction of delivered heat to unconditioned spaces. Addressing these runs during scheduled pipe-repair work captures energy savings at minimal incremental cost, as the piping is already being accessed.

Potential strategies: Mechanical insulation (fiberglass, mineral wool, or elastomeric) on all accessible runs; leak repair and/or full condensate-return replacement; steam-trap survey and repair to reduce system losses further.

School	ID	Documented Condition
Armour	609777	~500 LF of steam condensate piping not insulated; history of leaks
Avalon Park	609786	~317 LF of steam condensate piping not insulated
Ashburn	610287	~200 LF of steam condensate piping; history of leaks

4. Obsolete / Non-Operational Controls (9 schools)

Maintenance need: 9 schools operate pneumatic control systems, which rely on compressed-air tubing, actuators, and dedicated compressors. Multiple FADs note that these controls are non-operational (e.g., Addams) or that temperature regulation is unreliable. Maintaining pneumatic infrastructure is increasingly difficult due to parts scarcity and specialist-labor requirements.

Energy opportunity: Non-functional or poorly calibrated controls prevent effective scheduling, night/weekend setback, and demand-based ventilation—resulting in energy waste whenever spaces are conditioned but unoccupied or over-ventilated. Upgrading controls when other HVAC work is already planned avoids redundant wiring passes and commissioning cycles.

Potential strategies: Direct digital controls (DDC); building automation system (BAS) integration; wireless sensor and actuator retrofits; demand-controlled ventilation (DCV) tied to occupancy or CO_2 sensors. The controls upgrade should be coordinated with any heating/cooling plant replacement to avoid rework.

Affected schools: Addams (609772), Alcott HS (610524), Amundsen HS (609695), Armour (609777), Ashburn (610287), Ashe (610268), Audubon (609782), Avalon Park (609786), Avondale-Logandale (610325)

5. Building Envelope Deficiencies (15 schools with near-term items)

Maintenance need: Numerous schools have envelope deficiencies—roof membrane failures, masonry deterioration, window/door degradation—already flagged in the 0–2-year replacement window. These issues cause water infiltration and occupant-comfort problems that require remediation regardless of energy considerations.

Energy opportunity: Every envelope repair touches the building's thermal boundary. The labor, equipment access, and disruption required for a roof replacement or façade repair are largely the same whether the new assembly is code-minimum or higher-performance. The incremental cost of upgrading thermal performance during scheduled work is substantially lower than a standalone insulation or air-sealing project.

Potential strategies: Adding above-deck continuous insulation during re-roofing; specifying thermally broken frames during door/window replacement; air-sealing penetrations as part of masonry repointing; upgrading wall insulation where cavities are exposed during façade repair; cool-roof or reflective membrane options during roof replacement.

School	ID	Built	0–2 yr items	Documented Condition
Armour	609777	1901	16	Roof soft spots, vegetation; avg rank 5.7
Addams	609772	1948	8	Peeling paint, cracked, holes; avg rank 5.9
Ashe	610268	1963	8	Deteriorated sealant, sparse gravel; avg rank 5.5
Alcott HS	610524	1895	7	Nonfunctional roof hatches, cracking; avg rank 5.8
Ariel	609951	1893	7	Missing shingles, water infiltration; avg rank 5.7
Avondale-Logandale	610325	1881	6	Poor surface, leaks, damaged shingles; avg rank 5.8
Ashburn	610287	1953	5	Exposed bubbling tar, missing ballast; avg rank 6.1
Air Force HS	610513	1949	4	Nonfunctional roof hatches; avg rank 6.0
Armstrong G	609779	1911	4	Nonfunctional roof hatches; avg rank 6.3
Avalon Park	609786	1915	4	Roof soft spots; avg rank 6.0
Audubon	609782	1894	3	Exposed rafters, rust corrosion; avg rank 6.0

Aldridge	609848	1960	2	Bubbling; avg rank 6.3
Amundsen HS	609695	1930	2	Roof cracking; avg rank 5.8
Alcott ES	609774	1937	1	Roof cracking; avg rank 6.7
Aspira-Haugan	400017	2005	1	Green roof; avg rank 6.5

6. Failed / Aging Exit Signage (19 of 20 schools)

Maintenance need: 19 schools have exit signs flagged for immediate replacement due to failed lamps, broken housings, or end-of-life components. Exit signs operate 24/7/365 and legacy units draw ~25–50 W each. The portfolio total is approximately 653 signs requiring replacement.

Energy opportunity: Because exit signs run continuously, the per-unit energy draw—while small—accumulates to a meaningful load across a large sign inventory. Replacing failed signs with modern units that draw ~5 W captures savings with zero coordination with other trades. Portfolio-wide, this represents an estimated 110,000–260,000 kWh/yr in aggregate.

Potential strategies: LED retrofit kits for existing housings; full LED exit-sign replacement; self-luminous (photoluminescent) signs where code permits. All options are commodity products with simple installation and rapid payback.

School	ID	Exit Signs	Est. Annual Savings (kWh)
Austin CCA HS	610518	146	30,000–60,000
Avondale-Logandale	610325	69	10,000–30,000
Armstrong G	609779	67	10,000–30,000
Audubon	609782	61	10,000–20,000
Albany Park	610212	58	10,000–20,000

Table shows the five largest single-school opportunities. Remaining 14 schools each have 1–45 signs flagged.

7. Deteriorated Domestic Hot Water Systems (4 schools with critical needs)

Maintenance need: Four schools have DHW systems rated at or below 5.6 (condition rank, 10 = new) with piping that is corroded, leaking, or past useful life. These systems require replacement to maintain basic function and water quality.

Energy opportunity: When DHW piping and/or water-heating equipment must be replaced, the project scope already includes demolition, new piping runs, and equipment selection. This is the lowest-cost moment to evaluate whether higher-efficiency water-heating alternatives could reduce operating costs over the new system's life.

Potential strategies: High-efficiency condensing water heaters; heat-pump water heaters; solar thermal preheat (where roof area and orientation permit); improved pipe insulation and recirculation controls; right-sizing replacement equipment to actual demand. Selection depends on available fuel, electrical capacity, and physical space.

School	ID	DHW Rank	Documented Condition
Aldridge	609848	4.5	Pipes beyond useful life, clamps, leaking
Avalon Park	609786	4.6	Galvanized pipes corroded
Armour	609777	4.9	120-yr-old piping; water-pressure loss
Austin CCA HS	610518	5.6	Deteriorated horizontal piping, pipe clamps

Cross-Cutting Priority View

The matrix below maps each school against all seven opportunity areas. Schools with the most overlapping needs offer the greatest potential for capital-efficient bundled projects, since multiple issues can be addressed within a single mobilization.

School	Steam Heating	Window Cooling	Pipe Insul.	Controls	Envelope	Lighting	DHW
Armour	✓	✓	✓	✓	✓	✓	✓
Avalon Park	✓	✓	✓	✓	✓	✓	✓
Ashburn	✓	✓	✓	✓	✓	✓	—
Addams	✓	✓	—	✓	✓	✓	—
Alcott HS	✓	✓	—	✓	✓	✓	—
Ashe	✓	✓	—	✓	✓	✓	—

Avondale-Logandale	✓	✓	—	✓	✓	✓	—
Amundsen HS	✓	✓	—	✓	—	✓	—
Audubon	✓	✓	—	✓	—	✓	—
Austin CCA HS	✓	✓	—	—	—	✓	✓
Alcott ES	✓	✓	—	—	—	✓	—
Aldridge	—	✓	—	—	—	✓	✓
Armstrong G	—	✓	—	—	✓	✓	—
Air Force HS	—	—	—	—	✓	✓	—
Ariel	—	—	—	—	✓	✓	—
Albany Park	—	—	—	—	—	✓	—
Aspira-Haugan	—	—	—	—	—	✓	—
Back of the Yards HS	—	—	—	—	—	✓	—
Art in Motion	—	—	—	—	—	—	—
Azuela	—	—	—	—	—	—	—

✓ = opportunity area applies. Envelope: schools with ≥4 items in the 0–2-year window. Lighting: schools with >1 exit sign flagged. Sorted by number of overlapping areas (descending).

Recommended Next Steps

- **Tier 1 — Immediate / low-capital maintenance items:** Address steam pipe insulation at Armour, Avalon Park, and Ashburn (combined ~1,017 LF) and replace failed exit signs portfolio-wide (~653 units). These are maintenance-driven actions that also yield energy savings; they require no design work and can be executed under routine maintenance budgets.
- **Tier 2 — Evaluate alternatives at point of equipment replacement:** When steam boilers, window cooling units, or pneumatic control panels reach end-of-life, conduct a brief alternatives analysis before specifying like-for-like replacements. Schools with the most overlapping needs (Armour, Avalon Park, Avondale-Logandale, Ashburn, Alcott HS, Ashe) offer the greatest return on this evaluation effort.
- **Tier 3 — Scope bundled envelope + mechanical projects:** For schools with simultaneous roof/envelope and HVAC deficiencies (Armour, Ariel, Avondale-Logandale, Ashe), explore whether a combined project scope could address multiple needs in a single mobilization, reducing overhead and disruption.
- **Tier 4 — DHW system evaluation:** At Aldridge, Avalon Park, Armour, and Austin CCA HS, pair mandatory pipe replacement with an evaluation of water-heating alternatives that may lower operating costs over the replacement system's life.

Methodology & Data Source

All findings are drawn from the 2023 CPS Facility Assessment Documents (FADs) for the 20-school cohort. Replacement timelines (0–1 yr, 1–2 yr, etc.) are relative to the 2023 assessment date. Condition ranks are on a 1–10 scale (10 = new). Energy-savings estimates for exit signs use the FAD methodology (24/7 operation, 25–50 W legacy → 5 W modern). Efficiency ranges cited for heating and cooling equipment are representative of currently available technology for ASHRAE Climate Zone 5A (Chicago) and are provided for context, not as design targets. No field verification or utility-bill calibration has been performed; a detailed engineering study is recommended before selecting specific technologies at any campus.

Figure 5. Sample output from the agentic artificial intelligence model for a third order query. All content in this sample was generated by the model in response to the following prompt: "Across all schools in the portfolio, summarize the opportunities for energy savings that align with building deferred maintenance needs."

Nth order queries on strategic planning. When the model can take all the information uploaded to its knowledge base and create project plans, generate procurement strategies, identify financing mechanisms, and more, the value to building owners and operators reaches a new level. We are prototyping a second-generation system built on an agentic AI architecture. Rather than a fixed retrieve-and-generate pipeline, the system operates as an autonomous AI agent equipped with a suite of computational tools. The agent can read and search the full corpus of facility assessments and external knowledge sources, but, critically, it can also write and execute code, perform calculations, manipulate data files, generate visualizations, produce formatted reports and structured templates—all within an isolated, secure computing environment provisioned for each user session. Secure web search capabilities also allow the model to find information that is not in the existing knowledge base.

The agentic system transforms the user interaction from question-and-answer to collaborative investigation. When a user poses a complex query, the agent formulates and executes a multi-step investigation plan rather than performing a single retrieval pass. This capability also extends to user-provided data. A facilities manager could upload a recent utility bill or a contractor proposal and ask the agent to incorporate that information into a retrofit prioritization for a specific school. The agent processes the uploaded document, extracts relevant data points, and weaves them into its analysis with citations that distinguish user-provided inputs from the canonical assessment record.

A distinguishing feature of the agentic architecture is the ability to produce presentation-ready deliverables on the fly. Rather than returning only text responses, the agent writes code that generates charts, data tables, comparison matrices, and formatted report documents within the session's computing environment. The agent can invoke command-line tools and work with document-generation libraries to apply consistent formatting, headers, logos, and branding appropriate for the intended audience (i.e., a school board briefing, a facilities planning meeting, or a technical memorandum for engineering staff). When visualizations require refinement, the agent can modify them iteratively within the same session, adjusting scales, annotations, color schemes, or layout in response to user feedback, then re-rendering and delivering an updated artifact. All generated files are immediately available for the user to download.

In parallel, we developed a prototype demonstrating geospatial analysis capabilities as a complement to the document-based investigation. This prototype integrates mapping services and satellite-derived building data to enable spatial reasoning about the school portfolio. Schools are plotted on an interactive map using geocoded addresses, providing a geographic view of the portfolio that reveals spatial patterns, such as clusters of aging infrastructure, geographic correlations with energy intensity, and proximity to utility incentive program boundaries, that are invisible in tabular data.

The retrieval system and the agentic capabilities described above represent sequential steps toward a broader architectural vision—a coordinated multi-agent platform that integrates document analysis, geospatial intelligence, and computational modeling into a unified decision-support environment.

Discussion

Although this study focuses within the context of a large public school system, the total accumulated deferred maintenance backlog across public and private sectors in the United States is estimated to exceed $1 trillion (Sarmiento, Yashodhar, and Zhao 2025). Combining this with the facts that commercial buildings represent 17% of total U.S. energy use (EIA 2026) and new buildings are being constructed at faster rate than the sector is saving energy,[6] there is significant

[6] Using EIA data on historic building sector energy consumption trends, we can determine that despite declining energy use intensities in buildings, overall building energy consumption remains flat because of new construction outpacing efficiency gains.

untapped energy savings potential locked up in the building stock. The nation's schools in particular represent a critical vulnerability, receiving a D+ grade from the American Society of Civil Engineers' 2025 Infrastructure Report Card (ASCE 2025).

FCAs are a common tool used to inventory building equipment and systems and quantify maintenance needs, with approximately two-thirds of public school districts reporting completed FCAs at least once in a ten-year period (GAO 2020). Although this is required in some locations—Chicago, for example—other schools conduct these assessments voluntarily. Either way, there are almost 70,000 schools across the country that could leverage these existing assessments using the AI model developed for this study. Beyond public schools, other institutional and municipal buildings share similar characteristics that expand the potential to save even more energy.

A typical ASHRAE level 2 energy audit evaluates a building from a different perspective than an FCA[7], so there are cases in which energy audits may still be needed to evaluate specific buildings. Our AI model provides a solution for avoiding the need for portfolio-wide energy audits and prioritizing those studies for the buildings that need them most. Using the typical FCA findings (that are already being completed for various reasons) as a new lens for energy strategy helps building owners overcome typical barriers like limited funding and the need for integrated planning tools. At scale, the capability highlighted here can inform facility planning and investment prioritization, making energy efficiency faster and easier for building owners to accomplish.

Conclusions

This work through the DOE BBBP Initiative found a significant opportunity to transform FCA data into powerful energy planning insights with AI models. Working with Chicago Public Schools and their portfolio of more than 500 buildings, we have demonstrated proof of concept with a large-scale dataset that we hope to replicate with other building portfolios of varying sizes. The core architecture is designed to be reproducible—the retrieval pipeline, agent framework, and reporting structure remain the same across deployments, with only the agent descriptions and tool configurations adapted on a case-by-case basis. Any school district or public building portfolio with facility assessment data could deploy a similar system to reveal energy savings opportunities at scale. The ambition is straightforward—turn 30,000 pages of static assessments into a living, searchable intelligence layer that helps the building owner direct resources where they matter most.

The limitations of AI-enabled analysis have already been discussed, but it is important to emphasize that the ability to scale this analysis capability relies on human-in-the-loop validation of source material. Additional model functionalities, such as detailed cost/benefit analyses or energy modeling, could be feasible with the right training inputs and model architecture.

By leveraging information that is already available, such as existing FCA reports, energy metering data, and more, there is significant opportunity to streamline capital planning processes without conducting new data collection (i.e., full energy audits) in every building. Saving any unnecessary costs and time is crucial to maximizing the effectiveness of available funds for the purpose of addressing maintenance backlogs and achieving energy savings goals.

[7] In general, FCAs do not focus on energy savings or operational costs.

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