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A Novel Integrative Framework for Hybrid Energy Modeling in Non-Domestic Buildings: Bridging Data-Driven and Physics-Based Approaches for Global Sustainability

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Abstract: The building sector is a predominant contributor to global energy consumption and carbon dioxide emissions, with non-domestic buildings presenting unique challenges due to their operational complexity and heterogeneous profiles. While advancements in data-driven (DD) and physics-based (PB) modeling have independently progressed, a siloed approach persists, limiting scalable and robust energy performance forecasting and optimization. This paper presents a comprehensive review and, subsequently, proposes a novel integrative framework for hybrid energy modeling tailored for non-domestic buildings. We conduct a systematic analysis of DD methods—spanning statistical models, classical machine learning (ML), deep learning (DL), and ensemble techniques—and PB approaches, including simulation tools and engineering calculations. The review critically evaluates each paradigm's strengths regarding accuracy, interpretability, scalability, and data dependency, revealing a significant research gap in Africa and a need for standardized, transferable solutions. Synthesizing these insights, we introduce the *Integrated Hybrid Modeling and Transfer Learning Framework (IHM-TLF)*. This framework architecturally couples PB and DD models through sequential calibration, surrogate-assisted optimization, and physics-informed learning pathways. It explicitly incorporates adaptive transfer learning modules and data fusion strategies to overcome pervasive data scarcity and heterogeneity challenges. Furthermore, the framework is contextualized within a policy-supportive structure, aligning technical model outputs with actionable energy efficiency measures (EEMs), retrofit planning, and benchmarking protocols. The paper delineates a detailed validation pathway for the IHM-TLF, discusses its implementation barriers, and posits its potential to significantly enhance energy resilience, reduce operational costs, and support decarbonization targets, particularly in underrepresented and rapidly developing regions. This work aims to provide researchers, building managers, and policymakers with a unified, pragmatic roadmap for advancing building energy science toward global sustainability goals.

Keywords: *building energy efficiency; hybrid energy modeling; data-driven models; physics-based simulation; transfer learning; non-domestic buildings; sustainable infrastructure; machine learning*

1. Introduction

Anthropogenic climate change, driven predominantly by greenhouse gas emissions from energy production and consumption, represents the defining global challenge of the 21st century (IPCC, 2023). The built environment is a critical focal point in this crisis, responsible for approximately 30% of global final energy consumption and 26% of energy-related emissions (International Energy Agency [IEA], 2023). Within this

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sector, non-domestic buildings—encompassing commercial, institutional, and industrial structures—are particularly significant due to their intensive energy use profiles, complex systems, and diverse occupancy patterns (Santamouris & Vasilakopoulou, 2021). The imperative to decarbonize the global economy has thus placed unprecedented emphasis on optimizing the energy performance of these buildings through accurate forecasting, intelligent management, and effective retrofitting.

Accurately modeling and predicting building energy performance is the cornerstone of effective energy management systems (BEMS). Historically, two principal methodological streams have evolved: physics-based (PB) and data-driven (DD) modeling. PB models, also known as white-box models, utilize first principles of thermodynamics, heat transfer, and fluid dynamics to simulate building behavior. Tools like EnergyPlus, TRNSYS, and IDA ICE enable detailed simulation of energy flows, offering high accuracy and valuable insights into system interactions (Mazzeo et al., 2020). However, their utility is often constrained by the need for extensive, high-quality input data (e.g., detailed geometric, material, and operational schedules), significant computational resources, and expert knowledge for calibration—factors that limit their scalability for large building stocks or real-time applications (Azar et al., 2020).

Conversely, DD models, or black-box models, employ statistical and machine learning (ML) techniques to discern patterns directly from historical operational data. This category includes regression models, support vector machines (SVM), artificial neural networks (ANN), random forests (RF), and deep learning architectures like long short-term memory networks (LSTM) and convolutional neural networks (CNN) (Fan et al., 2019). DD models excel in contexts with abundant data, offering flexibility, computational efficiency for forecasting, and the ability to model non-linear relationships without explicit physical knowledge (Deb & Schlueter, 2021). Their primary limitations include a reliance on large, high-fidelity datasets, poor performance in data-scarce scenarios, lack of interpretability ("black-box" nature), and limited generalizability beyond their training conditions (Himeur et al., 2023).

The dichotomy between PB and DD approaches has led to parallel research tracks. While recent review articles have comprehensively surveyed one domain or the other, few have successfully synthesized them into a coherent, actionable framework that leverages their complementary strengths (Grillone et al., 2020; Sun et al., 2020). Furthermore, existing literature exhibits a pronounced geographical bias. Significant research originates from North America, Europe, and parts of Asia, where data infrastructure and policy frameworks are mature (see Figure 1). In contrast, regions like Africa, which face acute energy challenges, rapid urbanization, and unique climatic conditions, remain critically understudied (Adom, 2019; Tachega et al., 2021). This gap not only represents a scientific oversight but also a missed opportunity to develop resilient, context-appropriate solutions for a significant portion of the global building stock.

This paper addresses these gaps through two primary contributions. First, it provides a systematic, comparative review of PB and DD modeling techniques for non-domestic buildings, updating the state-of-the-art with recent advances in hybrid modeling and transfer learning. Second, and more significantly, it proposes a novel *Integrated Hybrid Modeling and Transfer Learning Framework (IHM-TLF)*. This framework is not merely conceptual; it provides a structured architectural blueprint for combining PB and DD models through specific coupling mechanisms. It integrates adaptive transfer learning and data fusion cores to tackle data scarcity, and it embeds these technical components within a policy-aware structure to ensure practical relevance and impact.

The remainder of this paper is organized as follows: Section 2 presents a detailed literature review, analyzing PB models, DD models (statistical, ML, DL, ensemble), and nascent hybrid approaches. Section 3 critically discusses persistent challenges, including data issues, model generalizability, and regional disparities. Section 4 introduces the proposed IHM-TLF, detailing its core components, architecture, and operational workflows. Section 5 outlines a validation pathway and discusses the framework's implications for research, practice, and policy. Finally, Section 6 concludes with a summary of key findings and future research directions.

2. Literature Review

2.1. Physics-Based (White-Box) Modeling

PB modeling relies on fundamental physical laws to describe the energy dynamics of a building and its systems. This approach is embodied in whole-building energy simulation (BES) tools.

2.1.1. Simulation Tools and Methods

Prominent BES engines include EnergyPlus (U.S. Department of Energy), TRNSYS (Transient System Simulation Tool), and IDA ICE (EQUA). These tools solve intricate sets of differential equations governing heat transfer (conduction, convection, radiation), air flow, and HVAC system performance on sub-hourly timesteps (Crawley et al., 2001). Their strength lies in their ability to model hypothetical scenarios, such as new building designs or deep retrofit packages, where historical data does not exist. They are indispensable for code compliance, design-phase optimization, and understanding the sensitivity of energy use to specific parameters (e.g., insulation level, window glazing) (Lam, 2020).

2.1.2. Strengths and Limitations

The primary strength of PB models is their *interpretability* and *physical consistency*. Results are traceable to input parameters, fostering trust among engineers and allowing for causal analysis. They are also *extrapolation-robust*; a well-calibrated model can make reliable predictions under conditions not present in the training data (e.g., extreme weather events).

However, critical limitations hinder their widespread operational use. They suffer from the *"performance gap,"* where simulated energy use deviates from actual measured consumption, often due to uncertain input parameters (e.g., occupant behavior, actual equipment efficiency) and simplification errors (Coakley et al., 2014). The *computational cost* of detailed simulations can be prohibitive for real-time control or optimization loops requiring thousands of evaluations. Most critically, they are *data-intensive to configure*, requiring a vast array of inputs that are often unavailable for existing buildings, making large-scale stock modeling challenging (Pan et al., 2023).

2.2. Data-Driven (Black-Box) Modeling

DD models bypass physical principles, instead learning mapping functions between input features (e.g., weather, time, occupancy signals) and output energy consumption from historical data.

2.2.1. Statistical and Classical Machine Learning Models

Early DD approaches employed statistical models. Linear and multivariate regression provide simple benchmarks but often fail to capture non-linearities (Chung & Yeung, 2017). Time-series models like ARIMA and SARIMA are effective for capturing temporal autocorrelation in stationary data (Box et al., 2015). Classical ML techniques marked a significant advancement. Support Vector Regression (SVR) demonstrated robust performance, particularly for short-term load forecasting (STLF) with limited data (Chen et al., 2017). Artificial Neural Networks (ANN), especially multilayer perceptrons (MLP), became popular for their universal approximation capabilities, successfully applied to forecasting loads at various time scales (Karatasou et al., 2006). Tree-based ensembles, namely Random Forests (RF) and Gradient Boosting Machines (e.g., XGBoost), gained prominence for handling heterogeneous data types, automatic feature importance ranking, and generally high predictive accuracy (Wang et al., 2018).

2.2.2. Deep Learning and Ensemble Models

The advent of accessible computational power and large datasets propelled deep learning (DL) to the forefront. Recurrent Neural Networks (RNN), and specifically their variant Long Short-Term Memory (LSTM) networks, are explicitly designed to model long-term dependencies in sequential data, making them exceptionally suitable for load forecasting (Rahman et al., 2018). Convolutional Neural Networks (CNN), applied to 1D sequences or transformed 2D representations of time-series data, excel at extracting local temporal patterns (Sadaei et al., 2019). Transformers, with self-attention mechanisms, are emerging for capturing complex, long-range dependencies but require vast datasets (Vaswani et al., 2017).

Ensemble methods, which combine predictions from multiple base models (e.g., via bagging, boosting, or stacking), are consistently shown to enhance accuracy and robustness by reducing variance and bias (Wang et al., 2018). Hybrid ensemble-DL models represent the current cutting edge in pure DD forecasting.

2.2.3. Strengths and Limitations

DD models shine in *predictive accuracy* when ample, high-quality data is available. They are typically *fast to execute* once trained, enabling real-time applications. Furthermore, they can seamlessly integrate diverse data streams from the Internet of Things (IoT), including non-traditional data like Wi-Fi connection counts or footfall sensors (Fotopoulou et al., 2017).

Their weaknesses are the inverse of PB strengths. They are largely *uninterpretable*; understanding *why* a model made a specific prediction is difficult, hindering trust and troubleshooting. They are prone to *overfitting* on noisy or limited data and are generally *poor at extrapolation* beyond the range of their training data. Their most significant constraint is *data hunger*: performance degrades sharply with insufficient or poor-quality data, a common scenario for new buildings or in regions with limited metering infrastructure.

2.3. Hybrid (Gray-Box) Modeling: The Convergent Path

Recognizing the complementary nature of PB and DD paradigms, the field has gradually shifted towards hybrid, or gray-box, modeling. These approaches seek a pragmatic middle ground.

2.3.1. Current Hybrid Strategies

1. **Sequential Calibration:** A PB model is first run, and a DD model (often a simpler regression or MLP) is trained to predict the residual error between the simulation and actual measurements. The final prediction is the simulation output plus the learned correction (Heo et al., 2012).
2. **Surrogate Modeling:** A DD model is trained to emulate the input-output relationship of a high-fidelity PB simulation. This fast-running "surrogate" or "meta-model" can then be used in place of the slow simulation for tasks like design optimization or uncertainty quantification, where thousands of evaluations are needed (Rastogi et al., 2017).
3. **Physics-Informed Machine Learning (PIML):** This is a more profound integration. Physical laws (e.g., conservation of energy) are embedded into the ML model's loss function or architecture as soft

constraints. Physics-Informed Neural Networks (PINNs) are a prominent example, guiding the model towards physically plausible solutions even with sparse data (Raissi et al., 2019).

2.3.2. Addressing Data Scarcity: Transfer Learning and Data Fusion

A pivotal challenge for DD and hybrid models in practice is data scarcity. Two key strategies have emerged:

- **Transfer Learning (TL):** A model pre-trained on a *source* building or region with abundant data is fine-tuned using a small dataset from a *target* building. This leverages learned general patterns (e.g., daily or weekly load shapes) to accelerate and improve learning on the new task (Weiss et al., 2016). Studies show TL can reduce prediction error by 11-20% compared to training from scratch on limited target data (Fang et al., 2021; Chaudhary et al., 2025).
- **Data Fusion:** This involves intelligently combining multi-source, heterogeneous data (sensor readings, weather forecasts, building management system logs, categorical building attributes) to create a richer, more informative feature set for modeling (Himeur et al., 2023).

2.4. Critical Research Gaps

Despite these advances, our review identifies persistent gaps:

1. **Lack of a Unified Framework:** Existing hybrid studies are often ad-hoc, combining specific models for a specific case. A generalized, architectural framework for selecting and coupling PB and DD components based on project goals, data availability, and building type is absent.
2. **Neglect of Underserved Regions:** The modeling literature disproportionately reflects contexts in the Global North. The unique challenges of regions like Africa—characterized by data poverty, distinct building typologies, different HVAC practices, and resource constraints—are rarely addressed, leading to a lack of transferable, context-sensitive solutions (Agradi et al., 2022).
3. **Disconnect from Policy and Implementation:** Many sophisticated models remain academic exercises. A clear pathway to translate model outputs into actionable energy conservation measures (ECMs), retrofit investment decisions, and policy instruments like building performance standards is frequently missing.

The proposed IHM-TLF, detailed in the next section, is designed to address these exact gaps.

3. Persistent Challenges and Barriers

Before introducing the framework, it is essential to crystallize the core challenges it must overcome.

3.1. The Data Trilemma: Scarcity, Quality, and Heterogeneity

The foundational barrier remains data. For many existing buildings, especially outside regulated markets, historical energy consumption data is sparse, non-existent, or inconsistently formatted. Sensor data is often noisy, contains gaps from transmission failures, and may lack crucial contextual metadata (Liu et al., 2023). Furthermore, data from different systems (electrical meters, gas meters, BMS, weather stations) operate at different temporal and spatial granularities, making fusion non-trivial.

3.2. The Generalizability Problem

Models trained on data from office buildings in temperate climates may fail spectacularly when applied to a hospital in a tropical region. This lack of generalizability across building types, usage patterns, and climatic zones is a major impediment to scalable solutions. It underscores the need for adaptive techniques like transfer learning and the inclusion of robust, context-descriptive features.

3.3. Interpretability vs. Performance Trade-off

There is an inherent tension between model complexity (and thus potential accuracy) and interpretability. While a deep neural network may achieve the lowest forecast error, its "black-box" nature makes it difficult for facility managers to trust or for engineers to diagnose faults. Simpler, more interpretable models are often preferred in operational settings, even at the cost of some accuracy.

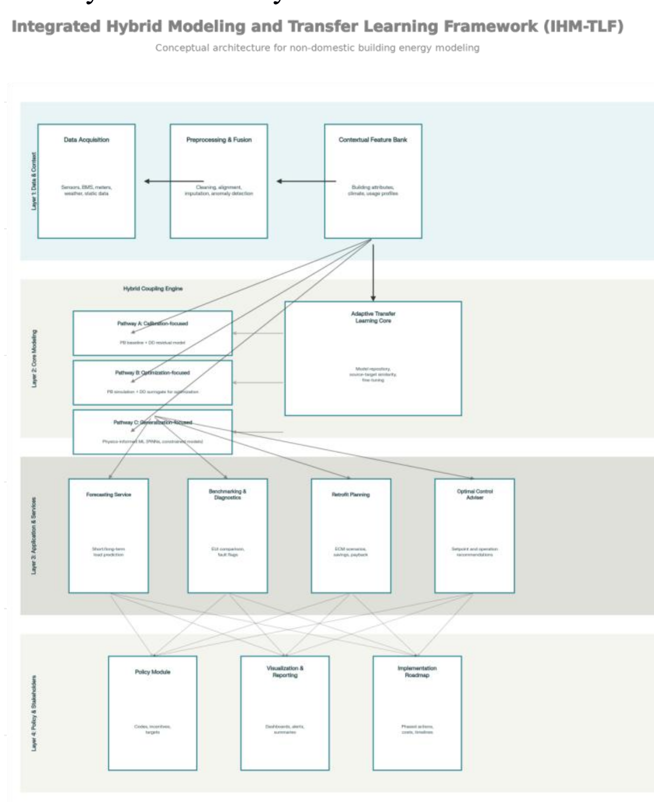
3.4. Integration into Real-World Workflows

The ultimate test of any model is its integration into decision-making processes. Barriers here include the cost and expertise required for model deployment and maintenance, alignment with existing BEMS protocols, and the ability to clearly communicate results (e.g., energy savings estimates, fault alerts) to non-expert stakeholders like building owners and financiers.

4. The Integrated Hybrid Modeling and Transfer Learning Framework (IHM-TLF)

To bridge the gaps identified, we propose the IHM-TLF—a modular, flexible architecture for developing and deploying energy performance models for non-domestic buildings. The framework is visualized in Figure 1 and consists of four interconnected layers.

Figure 1: Schematic of the Proposed Integrated Hybrid Modeling and Transfer Learning Framework (IHM-TLF). The diagram shows a four-layer architecture: Data & Context Layer, Core Modeling Layer (with Hybrid Coupling Engine and Transfer Learning Core), Application & Service Layer, and Policy & Stakeholder Interface Layer. Arrows indicate the flow of data, model outputs, and decisions.



4.1. Layer 1: Data & Context Layer

This layer is responsible for ingesting and harmonizing all relevant data. It includes modules for:

- **Data Acquisition:** Connectors to IoT sensors, smart meters, BMS, weather APIs, and static databases (e.g., building material properties, floor area).
- **Preprocessing & Fusion:** Robust pipelines for handling missing data (via advanced imputation), anomaly detection, normalization, and temporal alignment of heterogeneous data streams.
- **Contextual Feature Bank:** A structured repository that not only stores raw data but also engineered features critical for generalization (e.g., building vintage, climate zone classification, primary activity type, number of occupants). This bank is crucial for enabling effective transfer learning.

4.2. Layer 2: Core Modeling Layer

The heart of the IHM-TLF, this layer contains two central engines.

4.2.1. Hybrid Coupling Engine

This engine provides three distinct, structured pathways for combining PB and DD models, moving beyond ad-hoc hybridization.

1. **Pathway A (Calibration-Focused):** Employs the *Sequential Calibration* pattern. A configured PB model (e.g., a simplified RC-network model or a pre-configured EnergyPlus template) generates baseline predictions. A light-weight DD model (e.g., Gradient Boosting) is then dedicated to learning the systematic error (residual) between the physics-based simulation and observed data. This is ideal for scenarios where a reasonable PB model can be constructed but precise calibration is needed.
2. **Pathway B (Optimization-Focused):** Employs the *Surrogate-Assisted* pattern. For tasks requiring vast parameter exploration (e.g., finding the optimal setpoint schedule or retrofit package combination), a high-fidelity PB simulation is run for a designed sample of scenarios. A powerful DD model (e.g., a deep neural network) is trained as a surrogate on this input-output data. The fast surrogate is then coupled with an optimization algorithm (e.g., genetic algorithm) to rapidly identify optimal solutions.
3. **Pathway C (Generalization-Focused):** Employs the *Physics-Informed Learning* pattern. For applications where data is very limited but physical knowledge is strong, a PINN or a kernel-based model with physics-based constraints is constructed. The DD model's architecture or training regimen is explicitly designed to respect governing equations, ensuring predictions are physically plausible.

4.2.2. Adaptive Transfer Learning Core

This component is transversal, supporting all pathways in the Hybrid Coupling Engine. It manages a repository of pre-trained models (both DD and simplified PB) from the *Contextual Feature Bank*. When a new target building is introduced, the core:
a) Identifies the most similar source models based on contextual features (climate, building type, size).
b) Selects an appropriate transfer strategy: *feature-based transfer* (using learned representations), *parameter-based transfer* (fine-tuning model weights), or *instance-based transfer* (weighting relevant source data).
c) Executes the transfer and fine-tuning process, drastically reducing the target data required for accurate modeling.

4.3. Layer 3: Application & Service Layer

This layer translates model outputs into actionable services.

- **Forecasting Service:** Provides short-term (hourly/day-ahead) and long-term (monthly/annual) load forecasts for operational planning and demand response.
- **Benchmarking & Diagnostics:** Compares a building's energy use intensity (EUI) against a peer group generated by the model or identifies deviations from expected baselines, flagging potential faults or inefficiencies.
- **Retrofit Simulation & Planning:** Leverages the surrogate models (from Pathway B) to simulate the energy and financial impact of various ECMs, generating prioritized retrofit packages.
- **Optimal Control Adviser:** Suggests real-time or scheduled setpoint adjustments for HVAC and lighting systems to minimize energy use while maintaining comfort, using predictions from the model.

4.4. Layer 4: Policy & Stakeholder Interface Layer

This layer ensures the framework's outputs are accessible and relevant to decision-makers.

- **Policy Module:** Translates technical outputs (e.g., "potential 25% savings with insulation upgrade") into policy-relevant metrics: carbon savings, peak demand reduction, cost-benefit analyses, and compliance with local building codes or energy performance certificates.
- **Visualization & Reporting Dashboard:** Presents insights through intuitive graphs, alerts, and reports tailored to different users (facility manager, sustainability officer, financier).
- **Implementation Roadmap Generator:** For retrofit scenarios, produces a step-by-step guide including estimated costs, savings, payback periods, and recommended contractors or technologies.

5. Validation Pathway and Discussion

5.1. Proposed Validation Pathway

The IHM-TLF requires rigorous, multi-stage validation.

1. **Component-Level Testing:** Individual modules (data preprocessing, TL core, each hybrid pathway) are tested on open benchmarks (e.g., ASHRAE Great Energy Predictor III dataset, Building Data Genome Project 2).
2. **Framework-Level Case Studies:** The full framework is applied to diverse case studies:
   - *Case A (Data-Rich, Developed Region):* A university campus in Europe, testing optimization (Pathway B) for HVAC control.
   - *Case B (Data-Scarce, Developing Region):* A hospital in Sub-Saharan Africa, testing the TL-enhanced calibration pathway (Pathway A + TL Core) to establish a baseline and identify low-cost ECMs.
   - *Case C (New Building Design):* A commercial building in design phase, using the surrogate pathway (Pathway B) to optimize façade and system selection.
3. **Comparative Metrics:** Performance will be evaluated against pure PB and pure DD baselines using standard metrics (CV-RMSE, MAE, NMBE) as well as novel metrics for stability,

generalizability cost, and interpretability.

5.2. Discussion of Implications

5.2.1. For Research

The IHM-TLF provides a standardized experimental platform, encouraging systematic comparison of hybrid strategies. It directs research attention towards understudied areas, particularly the development of robust TL methods for cross-climate/cross-typology applications and the creation of lightweight, interpretable gray-box models suitable for edge computing in BEMS.

5.2.2. For Industry and Practice

The framework lowers the barrier to entry for advanced modeling. By providing structured pathways and automating complex tasks like model selection and TL, it empowers consultants and energy managers. Its explicit link to retrofit planning and financial metrics can build a stronger business case for energy efficiency investments.

5.2.3. For Policy and Global Sustainability

By generating reliable, building-specific data on energy savings potential, the IHM-TLF can inform more effective and equitable building codes, incentive programs, and carbon reduction targets. Its focus on transferability is crucial for supporting the global South in leapfrogging to efficient building stocks, contributing directly to UN Sustainable Development Goals (SDG 7: Affordable and Clean Energy; SDG 11: Sustainable Cities; SDG 13: Climate Action).

6. Conclusion

This paper has presented a comprehensive review of energy performance modeling for non-domestic buildings, highlighting the complementary strengths and weaknesses of physics-based and data-driven paradigms. The convergence toward hybrid modeling is clear, yet efforts remain fragmented and lack a cohesive structure, particularly for addressing global challenges like data scarcity and regional inequity. In response, we proposed the *Integrated Hybrid Modeling and Transfer Learning Framework (IHM-TLF)*. This framework is a significant step beyond the current state-of-the-art by: (1) providing a clear architectural blueprint with distinct, purpose-built hybrid coupling pathways; (2) centralizing adaptive transfer learning and data fusion as core capabilities to overcome the data barrier; and (3) explicitly embedding the technical modeling process within a policy-aware and stakeholder-relevant workflow.

The IHM-TLF is not a single model but a versatile ecosystem. Its value lies in its ability to guide the development of context-appropriate, robust, and actionable energy models—from a data-scarce hospital in Malawi to a high-tech office tower in Singapore. Future work will focus on the computational implementation of the framework as an open-source toolkit and its rigorous validation through the proposed international case studies. By bridging the gap between sophisticated energy science and on-the-ground implementation needs, frameworks like the IHM-TLF are essential for accelerating the transition to a sustainable, resilient, and equitable built environment.

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