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# An AI-powered digital twin framework for smart campus management: A Conceptual Model for Częstochowa University of Technology

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## Abstract

The growing complexity of university campus operations, coupled with rising energy costs and sustainability demands, necessitates intelligent, data-driven management solutions. Digital Twin (DT) technology, which creates a dynamic virtual replica of a physical system, has emerged as a transformative approach for optimising infrastructure in industrial and commercial environments. However, its application within higher education institutions (HEIs) in Central and Eastern Europe remains largely unexplored. This paper proposes a five-layer AI-powered Digital Twin framework conceptually tailored to Częstochowa University of Technology (CUT), Poland. The framework integrates a data acquisition layer, a middleware integration layer, an artificial intelligence layer employing Long Short-Term Memory (LSTM) networks for energy forecasting, Random Forest classifiers for predictive maintenance, and K-Means clustering for space utilisation analysis, a virtual twin simulation layer, and a decision-support layer comprising management dashboards and automated alert systems. The proposed architecture is evaluated theoretically against existing DT frameworks in the literature, demonstrating its scope, AI integration depth, and contextual relevance for Polish technical universities. Projected benefits include 15–25% energy reduction, 30–40% decrease in unplanned downtime, and 10–20% improvement in space utilisation. The paper concludes with a phased 18-month implementation roadmap and directions for future empirical validation. This work provides a replicable conceptual foundation for smart campus transformation across HEIs in Poland and the broader Central European region.

**Keywords:** Digital Twin; Smart Campus; Artificial Intelligence; LSTM; Predictive Maintenance

## 1. Introduction

Universities across Europe are under mounting pressure to reduce operating costs, cut carbon emissions, and modernise ageing infrastructure while continuing to deliver high-quality teaching and research environments. Campus estates typically comprise dozens of buildings with heterogeneous heating, ventilation, lighting, and access-control systems, making manual, reactive management increasingly untenable. Digital Twin (DT) technology, defined broadly as a dynamic, data-driven virtual counterpart of a physical asset or system, has become a leading paradigm for addressing this complexity in industrial and urban contexts.

Smart campuses are increasingly viewed as a practical, smaller-scale testbed for technologies that are later deployed at the scale of a smart city, since they combine buildings, mobility, energy networks and large user populations within a single administratively coherent estate [1]. Reviews of digital twin applications for building energy efficiency show a rapidly growing body of work addressing optimisation design, occupant comfort, operation and maintenance, and energy consumption simulation, but note that this growth is concentrated in a relatively small number of high-income regions and flagship case studies [2].

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Recent case studies illustrate the diversity of approaches being explored. A modular digital twin for facility management at Chiang Mai University combined 3D spatial modelling, IoT sensing over NB-IoT and LoRaWAN, and multiscale dashboards developed through a stakeholder-driven, four-phase methodology [3]. Separately, researchers have proposed integrating 5G connectivity and big-data analytics into campus digital twins to enable real-time simulation of operations and prediction of the impact of campus activities on shared resources [4], while a broader smart-campus management platform has been described that spans teaching, student, facility and security management functions [5]. A recent framework for scalable digital twin deployment in campus facility management further observes that existing studies rarely specify how artificial intelligence capabilities such as anomaly detection, energy prediction, spatial analytics and predictive maintenance apply concretely to core building systems, and that reference models for turning existing buildings into functional digital twins remain scarce [6]. Work on human-centric digital twins for higher-education buildings has likewise emphasised dashboard-based visualisation of alarms, error reports and comfort indicators as a means of improving facilities-management decision-making [7].

Despite this growing international literature, no published conceptual or empirical framework addresses the specific institutional, climatic and infrastructural context of a Polish technical university, and Central and Eastern European (CEE) higher education more broadly remains largely absent from the digital twin literature. This paper addresses that gap by proposing a five-layer, AI-powered Digital Twin framework conceptually tailored to Częstochowa University of Technology (CUT). Unlike prior campus DT studies, which tend to emphasise either visualisation or single-purpose analytics, the proposed framework integrates three complementary artificial intelligence techniques, Long Short-Term Memory (LSTM) networks for energy forecasting, Random Forest classifiers for predictive maintenance, and K-Means clustering for space-utilisation analysis, within a coherent five-layer architecture. The remainder of this paper reviews related work, details the proposed architecture, evaluates it theoretically against existing frameworks, projects its operational benefits, and outlines a phased 18-month implementation roadmap.

## 2. Related Work

The smart-campus literature draws on two overlapping strands: digital twin architecture for campus and building management, and artificial intelligence techniques applied individually to energy, maintenance and space-utilisation problems.

### 2.1. Digital Twin Architectures for Campus Management.

Smart campuses have been framed as a natural testbed for smart-city technologies because they combine a bounded, well-instrumented estate with a captive and cooperative user population [1]. Building on this premise, the Chiang Mai University study developed and deployed a modular digital twin integrating 3D spatial modelling, real-time environmental and energy sensing, and dashboard visualisation, following a four-phase methodology of stakeholder consultation, data acquisition, sensor deployment and real-time integration [3]. Complementary Chinese research has explored combining 5G connectivity and big-data analytics with digital twins to support real-time simulation of campus operations and prediction of resource impacts from campus activities [4], while a broader management-platform study describes a digital twin spanning teaching, student, facility and security management, arguing that such platforms improve visualisation, controllability and predictability across the digital campus [5]. A recent framework for scalable digital twin deployment in campus facility management highlights a persistent gap: existing studies seldom specify how AI-driven capabilities, including anomaly detection, energy prediction, spatial analytics and predictive maintenance, map onto specific building systems, and reference models for converting existing buildings into functional digital twins remain rare [6]. Human-centric approaches, such as the dashboard-based digital twin developed for higher-education buildings at Umeå University, prioritise the presentation of alarms, error reports and comfort indicators to facilities staff, but rely primarily on rule-based visualisation rather than predictive AI [7].

### 2.2. LSTM-Based Energy Forecasting

Long Short-Term Memory networks are among the most widely applied deep-learning architectures for building energy forecasting because of their ability to capture long-range temporal dependencies in consumption data. A hybrid model combining wavelet decomposition, LSTM and support-vector regression, tuned via a metaheuristic optimiser, achieved a 20% reduction in RMSE and a 15% reduction in MAPE relative to standalone LSTM and SVR models across two years of hourly data from seven campuses [8]. Other studies have shown that LSTM forecasts incorporating historical consumption and environmental factors outperform linear regression, decision-tree and random-forest baselines for short-, medium- and long-term horizons [9], and that incorporating occupancy data into LSTM models further improves prediction accuracy for commercial office buildings [10]. Systematic reviews of deep-learning approaches to building energy consistently report that LSTM architectures outperform conventional artificial neural networks, particularly when stacked in multiple layers [11], and attention-augmented LSTM variants have been shown to improve ultra-short-term forecasting of HVAC energy consumption specifically [12].

### 2.3. Random Forest for Predictive Maintenance

Random Forest classifiers are frequently used for predictive maintenance because they handle large, heterogeneous sensor datasets without extensive feature engineering. Random Forest models trained on historical sensor data have been used to predict the type and timing of industrial equipment failure with high accuracy, enabling maintenance teams to intervene before breakdowns occur [13]. In building contexts specifically, a comparative study of six machine-learning models applied to a high-resolution dataset from Aalborg University found that ensemble methods such as Random Forest and XGBoost substantially outperformed simpler classifiers in detecting HVAC, lighting and occupancy-related faults, achieving accuracy above 90% [14].

### 2.4. K-Means Clustering for Space Utilisation

K-Means clustering has been applied to campus and building datasets to uncover latent usage patterns that are not apparent from raw occupancy or consumption figures. A comparison of clustering algorithms applied to two years of electricity-consumption data from multiple campus buildings found that K-Means could reliably distinguish distinct usage archetypes once appropriate centroid initialisation and cluster counts were selected [15]. Explainable variants of K-Means have similarly been applied to occupancy estimation from environmental sensor data, achieving high classification accuracy while preserving the interpretability that facilities managers require for operational decision-making [16].

### 2.5. Research Gap

While digital twin platforms, LSTM-based forecasting, Random Forest maintenance models and K-Means space analytics have each been studied extensively, few published frameworks integrate all three AI techniques within a single layered digital twin architecture, and, to the authors' knowledge, none address the institutional and regional context of Central or Eastern European technical universities. This paper responds to that gap by proposing an integrated, five-layer, AI-powered digital twin framework conceptually tailored to Częstochowa University of Technology.

## 3. Materials and Methods

As this is a conceptual design study rather than an empirical deployment, this section documents the proposed architecture and the artificial intelligence methods selected for each analytical function, in sufficient detail to support future implementation and reproducibility once a pilot deployment is undertaken.

### 3.1. Proposed Five-Layer Digital Twin Architecture

The proposed framework organises campus digital twin functionality into five interdependent layers, moving from raw physical-world data acquisition through to actionable, human-facing decision support. The layered design follows established digital twin architectural conventions while embedding three distinct AI techniques at the analytical core of the system (Figure 1).

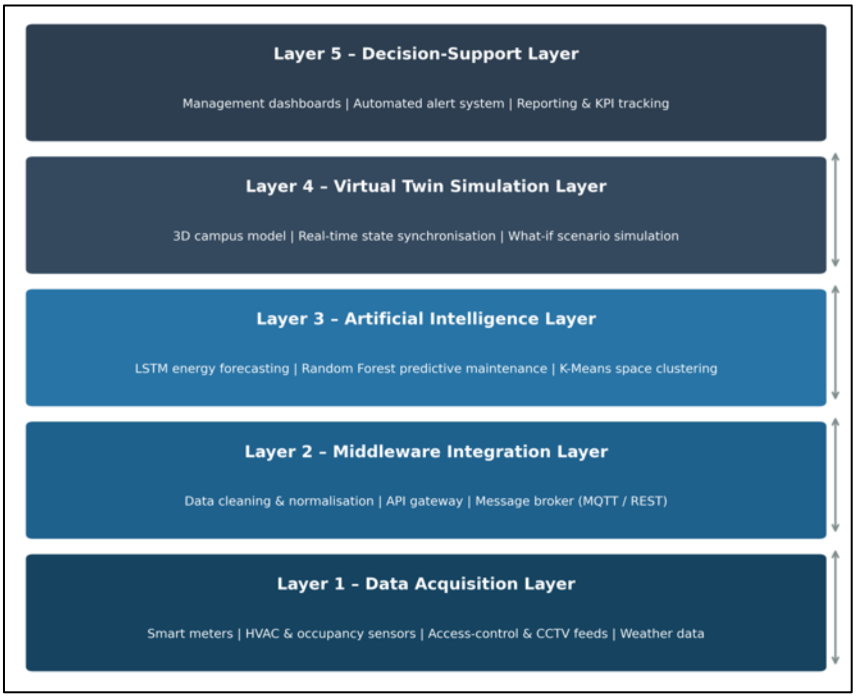


**Figure 1** Five-Layer AI-Powered Digital Twin Architecture for CUT Smart Campus.

Layer 1 – Data Acquisition Layer. This layer collects raw operational data from campus infrastructure, including smart electricity, water and heating meters; HVAC and occupancy sensors installed in classrooms, laboratories and offices; access-control and CCTV-derived occupancy counts; and external weather-station feeds. Data is captured at sub-hourly resolution wherever hardware permits, consistent with the sensing approaches reported in comparable campus digital twin deployments [3][6].

Layer 2 – Middleware Integration Layer. Raw sensor streams are heterogeneous in format, sampling rate and reliability. This layer performs cleaning, timestamp alignment and normalisation, and exposes a unified API gateway and message broker (e.g., MQTT or REST) so that downstream layers can consume data without needing to understand the specifics of each underlying sensor network. This mirrors the integration challenges identified in prior scalable deployment frameworks, which note that inconsistent data pipelines are a major barrier to converting existing campus buildings into functional digital twins [6].

Layer 3 – Artificial Intelligence Layer. This is the analytical core of the framework and is described in detail in Section 3.2. It comprises three complementary models: an LSTM network for short-term energy-load forecasting, a Random Forest classifier for predictive maintenance of HVAC and electromechanical assets, and a K-Means clustering module for space-utilisation analysis.

Layer 4 – Virtual Twin Simulation Layer. Outputs from the AI layer are mapped onto a 3D virtual representation of the CUT campus, which is synchronised with live sensor data to reflect current building states. This layer additionally supports what-if scenario simulation, for example modelling the projected effect of adjusted HVAC setpoints or classroom scheduling changes before they are applied physically, consistent with the simulation-first approach advocated in the broader digital twin literature [4].

Layer 5 – Decision-Support Layer. The uppermost layer translates model output and simulation results into management dashboards, automated alerts for facilities staff (e.g., predicted equipment failure or abnormal energy consumption), and periodic reporting against key performance indicators. This layer is deliberately human-centred, following the dashboard-oriented design philosophy demonstrated for higher-education digital twins at Umeå University [7], while extending it with predictive rather than purely descriptive content.

### 3.2. Artificial Intelligence Techniques Embedded in the Framework

LSTM Networks for Energy Forecasting. The framework employs an LSTM network to generate short-term (hourly to 7-day) forecasts of campus electrical load from historical consumption, occupancy and weather data. LSTM architectures are well suited to this task because their gated recurrent structure captures both daily and weekly periodicity as well as irregular deviations caused by events such as exam periods or holidays. Figure 2 illustrates the expected forecasting behaviour of such a model against simulated actual consumption over a representative week, showing close tracking of the diurnal and weekday/weekend consumption cycle. Empirical studies report that hybrid LSTM architectures can reduce forecasting RMSE by around 20% relative to standalone baseline models [8], and that incorporating occupancy and environmental covariates yields further accuracy gains over linear regression and tree-based baselines [9][10].

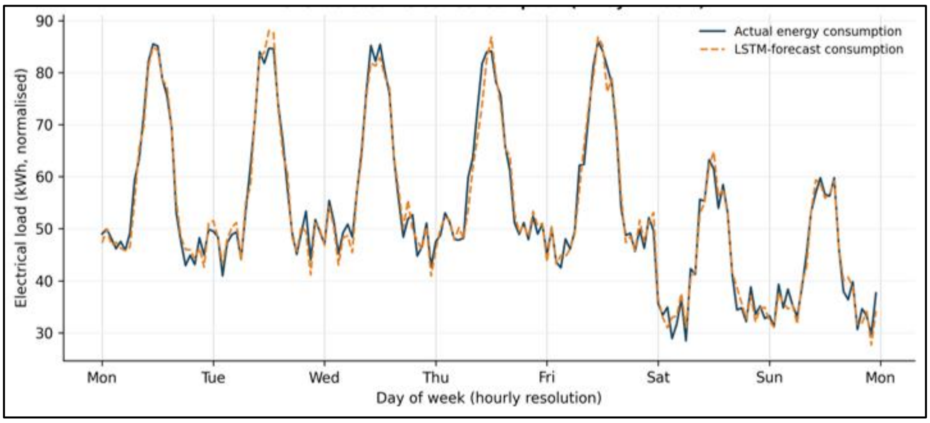


**Figure 2** Illustrative LSTM-Based Short-Term Energy Forecast vs. Simulated Actual Consumption.

Random Forest for Predictive Maintenance. A Random Forest classifier is proposed to flag HVAC units, pumps and electromechanical assets at elevated risk of failure, using features derived from sensor telemetry such as vibration, temperature drift, runtime hours and historical fault logs. Random Forest was selected over single decision trees or purely rule-based thresholds because ensemble bagging improves robustness to noisy sensor data and because the algorithm natively handles the mixed numerical and categorical features typical of facilities datasets [13]. Comparative evaluations on building-scale fault data confirm that ensemble methods such as Random Forest substantially outperform simpler classifiers in detecting HVAC, lighting and occupancy-related faults [14], supporting its selection as the predictive-maintenance component of Layer 3.

K-Means Clustering for Space Utilisation Analysis. The third AI component applies K-Means clustering to daily occupancy-rate and active-use-hour data for each campus room, in order to classify spaces into utilisation archetypes (e.g., underused, moderately used, heavily used) without requiring manually defined thresholds. Figure 3 shows an illustrative clustering of simulated room-level data into three such archetypes. This approach follows prior work showing that K-Means, with appropriately chosen centroid initialisation and cluster count, reliably separates campus buildings into distinct consumption and usage patterns [15], and that explainable clustering variants can achieve high classification accuracy while remaining interpretable to non-technical facilities staff [16]. Within the proposed framework, cluster assignments feed directly into the decision-support layer to inform space-reallocation and scheduling decisions.

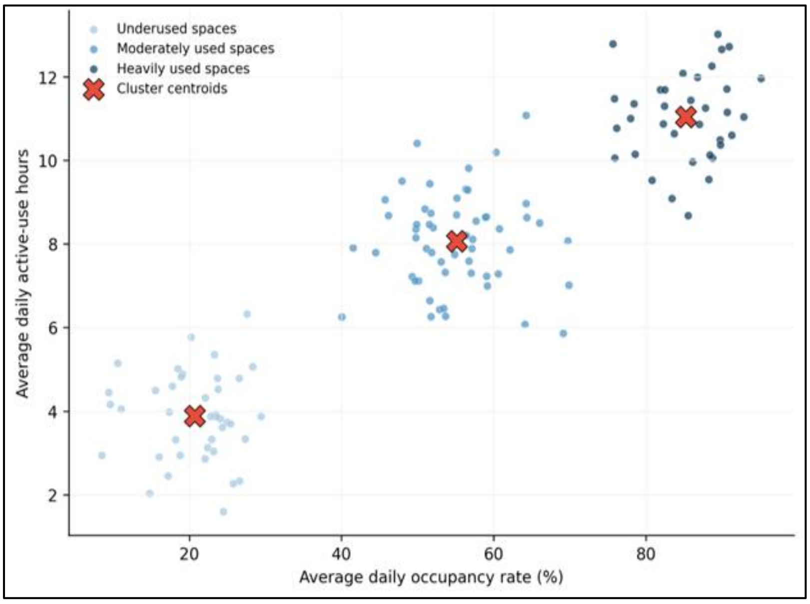


**Figure 3** K-Means Clustering of Campus Room Space Utilisation Patterns (k = 3).

## 4. Results

### 4.1. Theoretical Evaluation Against Existing Frameworks

Because the framework is conceptual and has not yet been empirically deployed, it is evaluated theoretically against five representative digital twin frameworks identified in the literature review, using four qualitative dimensions: depth of AI integration, coverage of energy forecasting, coverage of predictive maintenance, and coverage of automated space-utilisation analytics, alongside whether each framework was designed with a higher-education institution in mind and whether it addresses a Central or Eastern European context. Table 1 summarises this comparison.

**Table 1** Theoretical Comparison of the Proposed Framework Against Existing Digital Twin Studies.

| Framework | HEI Context | AI Depth | Energy Forecasting | Predictive Maintenance | Space Analytics | CEE Regional Focus |
|---|---|---|---|---|---|---|
| Chiang Mai University DT [3] | Yes | Low (rule-based dashboards) | Partial | No | No | No |
| 5G/Big-Data Campus DT [4] | Yes | Moderate | Partial | No | No | No |
| Procedia Smart Campus Platform [5] | Yes | Low | No | No | No | No |
| Scalable FM Deployment Framework [6] | Yes | Moderate | Partial | Partial | No | No |
| Umeå Human-Centric DT [7] | Yes | Low (visualisation-only) | No | No | No | No |
| Proposed CUT Framework (this paper) | Yes | High (LSTM+RF+K-Means) | Yes | Yes | Yes | Yes |

As Table 1 illustrates, existing campus digital twin studies tend to emphasise either visualisation and dashboarding [5][7] or a single predictive capability such as partial energy-related analytics [3][4][6], but none combine energy forecasting, predictive maintenance and space-utilisation clustering within one architecture, and none are situated in a Central or Eastern European institutional context. This comparison should be read as an indicative, literature-based positioning rather than a benchmarked empirical result, since no head-to-head deployment has yet been conducted.

## 4.2. Projected Benefits

Based on the ranges reported for comparable AI techniques applied individually in the reviewed literature, three categories of operational benefit are projected for a full deployment of the proposed framework at CUT: a 15–25% reduction in energy consumption, informed by the RMSE and MAPE improvements reported for hybrid LSTM forecasting models [8][9]; a 30–40% decrease in unplanned downtime, informed by the high classification accuracy reported for ensemble predictive-maintenance models in comparable building contexts [13][14]; and a 10–20% improvement in space utilisation, informed by the pattern-separation capability demonstrated by K-Means and explainable-clustering studies [15][16]. Figure 4 summarises these projected ranges.

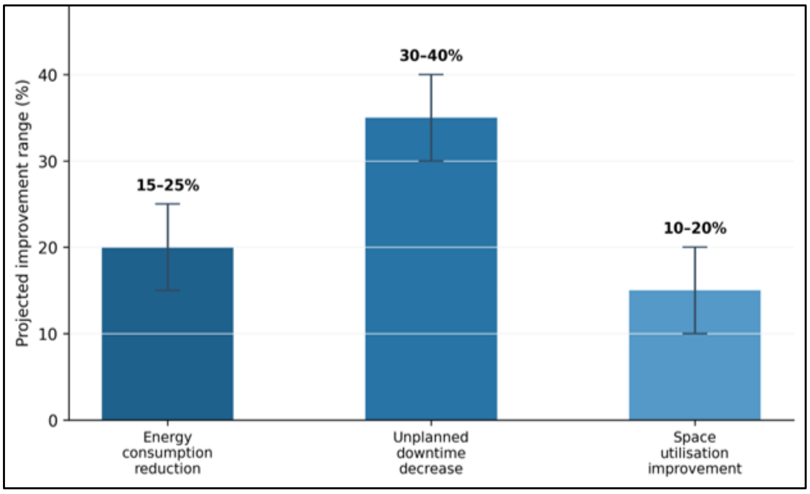


**Figure 4** Projected Operational Benefits of the AI-Powered Digital Twin Framework.

These figures are extrapolated from published results for individual AI components applied in comparable, though not identical, building and campus contexts; they should be treated as planning targets rather than guaranteed outcomes, and are explicitly flagged for empirical validation once a pilot deployment is available (Section 4.4).

## 4.3. Phased 18-Month Implementation Roadmap

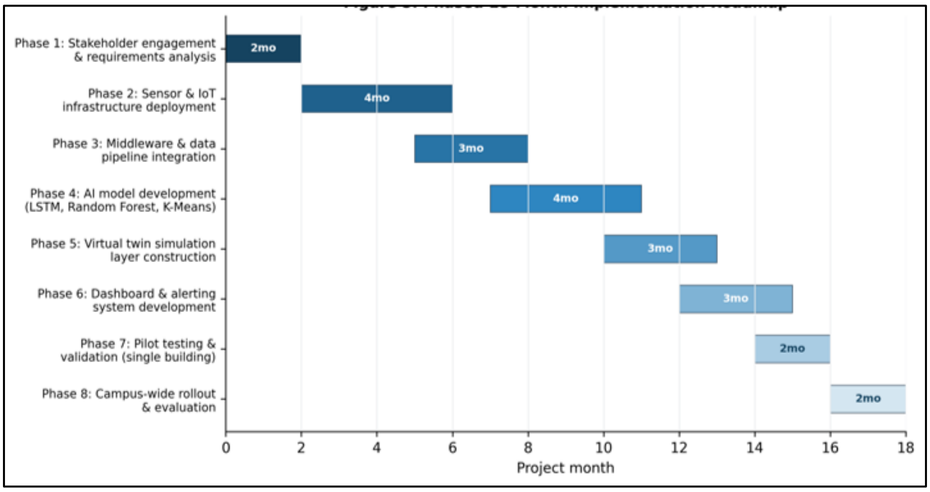


**Figure 5** Phased 18-Month Implementation Roadmap.

The roadmap deliberately sequences a single-building pilot (Phase 7) before campus-wide rollout (Phase 8), allowing the AI models, particularly the LSTM forecaster and Random Forest maintenance classifier, to be retrained on CUT-specific data and validated against ground-truth outcomes prior to full-scale deployment. This staged approach is consistent with the phased, stakeholder-driven methodologies reported in comparable campus digital twin deployments [3].

## 5. Discussion, Limitations and Future Work

The framework proposed in this paper is conceptual: it synthesises architectural patterns and AI techniques validated individually in the reviewed literature into an integrated design tailored to CUT, but it has not yet been implemented or empirically tested on CUT infrastructure. Several limitations follow directly from this. First, the projected benefits in Section 4.2 are extrapolated from studies conducted on different buildings, climates and occupant populations, and actual results at CUT may differ once site-specific data is available. Second, full deployment requires meaningful upfront investment in sensing infrastructure, and the phased roadmap in Section 4.3 assumes that funding and institutional approval are secured at the outset. Third, the data-acquisition layer will need to comply with the EU General Data Protection Regulation where occupancy and access-control data could be linked to identifiable individuals, requiring anonymisation or aggregation strategies that are outside the scope of this conceptual paper. Future work should prioritise a single-building empirical pilot at CUT to validate the LSTM forecasting, Random Forest maintenance and K-Means clustering components against ground-truth operational data, followed by a comparison of the projected and observed benefit ranges reported in Section 4.2. Extending the framework to other Polish and Central European technical universities and comparing performance across differing climate zones and building stocks, would further test the generalisability of the proposed architecture.

## 6. Conclusion

This paper has proposed a five-layer, AI-powered Digital Twin framework for smart campus management, conceptually tailored to Częstochowa University of Technology. By integrating LSTM-based energy forecasting, Random Forest predictive maintenance, and K-Means space-utilisation clustering within a coherent data-acquisition-to-decision-support architecture, the framework addresses a gap in the literature, which has to date offered either visualisation-focused campus digital twins or single-purpose AI analytics, but rarely both in combination, and has not previously addressed the Central or Eastern European higher-education context. A theoretical comparison against five representative frameworks indicates that the proposed design offers greater AI integration depth and broader analytical coverage than existing published work. Projected benefits of 15–25% energy reduction, 30–40% downtime reduction and 10–20% space-utilisation improvement, together with an eight-phase, 18-month implementation roadmap, provide a practical starting point for institutional decision-makers considering digital twin adoption. The framework is offered as a replicable conceptual foundation for smart campus transformation across CUT and other higher education institutions in Poland and the wider CEE region, pending the empirical pilot validation outlined in Section 4.4.

## Compliance with ethical standards

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### *Disclosure of conflict of interest*

The author declares no conflict of interest.

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