From Data to Cultural Response: A Machine Learning–Driven Digital Twin Model for Smart Heritage Precincts in Urban Context

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SUMMARY: *In the context of Smart Cities, Smart Heritage has emerged as a forward-oriented strategy aimed at enhancing the construction, management, accessibility, and sustainability of culturally significant environments. Yet, within Smart Heritage discourse, the distinction between basic digital representations and truly responsive, sensor-informed systems remains underdeveloped. This study addresses this gap by proposing a machine learning–enhanced digital twin simulation framework that enables both real-time and anticipatory heritage interventions. Using Chinatown Melbourne as an urban heritage case study, five open-access urban datasets, pedestrian counting, on-street parking, microclimate conditions, dwelling functionality, and Microlab sensor data (CO_2, sound level, and accelerometer), were evaluated, with three integrated into a pilot simulation model. A key contribution is the inclusion of a conceptual 'Heritage Layer' that overlays cultural significance and symbolic meaning across all stages of system logic and design response. The model also incorporates a dedicated machine learning layer, trained on full-year 2024 sensor data, to forecast environmental and behavioural triggers such as crowd build-up. This predictive capability enables the system to shift from reactive monitoring to proactive design interventions aligned with cultural rhythms. A December 2024 simulation validated the frequency and relevance of trigger-based activations. Rather than relying on platform-specific code, the framework is designed for adaptability across construction informatics environments and heritage precincts globally. Findings demonstrate how Smart Heritage systems can bridge environmental sensing, cultural identity, and post-construction evaluation, offering a scalable methodology for digitally responsive, culturally attuned urban heritage management.*

KEYWORDS: *Smart Heritage, Digital Twin Framework, Urban Sensor, Machine Learning for Heritage Sites, Heritage Site Construction Informatics, Environmental Monitoring, Heritage-Aware Design, Chinatown Melbourne.*

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1. INTRODUCTION

The global emergence of Smart Cities has unlocked new possibilities for applying autonomous technologies to the built environment, particularly through the convergence of real-time data, automation, and artificial intelligence (AI) (Geng et al., 2024b). Within this broader transformation, Smart Heritage has emerged as a critical subdomain, extending the ambitions of smart urbanism to the cultural and historical strata of cities. Rather than focusing solely on digitisation for archival purposes, Smart Heritage foregrounds the dynamic activation of heritage precincts as responsive, data-enriched environments, supporting objectives of cultural sustainability, operational adaptability, and civic engagement (Batchelor et al., 2021). Melbourne, internationally recognised for its progressive smart city agenda, offers a fertile testbed for exploring Smart Heritage implementations. Its open-access data infrastructure provides a wealth of urban datasets capable of supporting heritage-sensitive monitoring and management through real-time metrics (Geng et al., 2024a). Yet, despite this technical potential, Smart Heritage remains underdeveloped in both theoretical framing and practical application, especially in ways that intersect with the construction sector's increasing emphasis on lifecycle performance, adaptive reuse, and post-occupancy intelligence (Song and Selim, 2022, Song et al., 2023).

Concurrently, digital twin (DT) technologies, now firmly embedded in construction informatics, have received limited attention within heritage contexts, often seen as a possible outcome of Smart Heritage. While DTs have advanced in areas such as HVAC optimisation, asset management, and performance simulation, their potential to embed cultural intelligence into data-driven decision-making remains largely unexplored (Song and Selim, 2022, Song et al., 2023, Geng et al., 2024a). This paper responds to this gap by proposing a multi-sensor DT simulation framework tailored to culturally significant urban precincts in the hope of achieving a Smart Heritage environment. As urban heritage sites are often situated within complex, gentrified contexts marked by frequent new construction, this study aims to address both heritage preservation and construction-related concerns through the application of Smart Heritage strategies. Taking Chinatown Melbourne as a heritage case study in an urban context, the study operationalises open access sensor data, including pedestrian counts, environmental conditions, and acoustic measurements, to model heritage-responsive interventions that are context-sensitive and construction-informed. To further enhance system responsiveness, a DT framework is proposed with a machine learning (ML) layer that predicts environmental and behavioural triggers before they occur, enabling anticipatory heritage interventions aligned with cultural contexts. This study does not treat DT technology as an end in itself but as an evolving cultural infrastructure, a mechanism through which environmental performance, spatial storytelling, and heritage values can be co-optimised. By embedding cultural responsiveness into post-construction workflows, the proposed framework reframes Smart Heritage as a forward-oriented, operational system integrated across the lifecycle of urban heritage environments.

2. LITERATURE REVIEW

2.1 Smart Heritage: From Digitisation to Autonomous Responsive Systems

Smart Heritage has evolved from the foundational practices of digital heritage, such as 3D documentation, GIS-based mapping, and digital archives, towards more interactive and responsive systems that integrate real-time data, AI, and urban informatics. While early efforts emphasised conservation and virtual representation (Song and Selim, 2022, Geng et al., 2023a, Borda and Bowen, 2017). There is a growing shift towards systems that are operational, participatory, and embedded within smart city infrastructures (Chianese and Piccialli, 2014, Piccialli and Chianese, 2018, Alkhafaji et al., 2020, Brusaporci and Maiezza, 2021). This shift reflects an expanded understanding of heritage environments, not merely as passive sites of memory but as dynamic urban interfaces capable of interaction, adaptation, and co-creation. As Luo et al. (2024) argues, Smart Heritage mirrors the broader evolution of smart cities, transitioning from efficiency-centric technologies to culturally responsive infrastructures. Similarly, Geng et al. (2023a) highlight how Smart Heritage practices increasingly rely on real-time data to support context-sensitive preservation and identity reinforcement. These practices employ tools such as Internet of Things (IoT) sensors, mobile interfaces, and DTs to facilitate responsive lighting, soundscapes, and storytelling that reflect both environmental and social rhythms (Amato et al., 2021, Capece et al., 2024).

Scholars have also emphasised the socio-technical nature of Smart Heritage, its capacity to preserve not just physical fabric but also intangible cultural narratives (Cook and Hill, 2019). Responsive systems may be designed to interact with users through participatory platforms, supporting diverse narratives while ensuring inclusivity and interactivity (Batchelor et al., 2021, Udeaja et al., 2020). Casillo et al. (2022) point to the increasing use of environmental metrics, such as air quality and noise levels, to inform heritage design decisions, such as acoustic zoning or ventilation optimisation. Against the backdrop of a complex heritage environment, Smart Heritage offers a timely framework for adapting cultural sites into forward-looking, data-informed ecosystems. This paper contributes to the discourse by operationalising open-access urban data in a DT simulation tailored to Chinatown Melbourne as an urban heritage site. By embedding a 'Heritage Layer' into a sensor-based model, the study advances Smart Heritage from concept to application, connecting cultural significance with real-time urban intelligence. The concept of a ‘Heritage Layer’ proposed in this study refers to a non-automated, cross-cutting interpretive component embedded within a digital twin framework. Rather than functioning as a structural layer, it provides cultural and symbolic logic that shapes how environmental data is interpreted and how system responses are activated (Geng et al., 2024b). It draws on local knowledge, rituals, spatial memory, and socio-cultural narratives to contextualise digital outputs.

2.2 Open-Access Urban Data and Sensor Networks

The integration of open-access urban datasets and sensor networks has redefined how cities understand, monitor, and manage their built environments. These systems contribute to the emerging field of urban informatics, where environmental sensing and public data availability converge to produce actionable knowledge for governance and design (Angelidou and Stylianidis, 2020, Allam and Newman, 2018). In the context of Smart Heritage, this convergence enables dynamic interpretations of cultural precincts and supports informed decision-making based on real-time conditions. Environmental and behavioural measurements are now frequently collected through publicly accessible platforms, transforming once-static heritage precincts into sites of sensor-augmented interaction. The Melbourne Smart City Strategy demonstrates how such datasets can be used for adaptive planning, real-time navigation, and environmental management. Beyond city-led initiatives, crowdsourced and volunteered geographic information (VGI), such as OpenStreetMap and community-sensing platforms, offer a complementary layer of insight, particularly in marginalised or under-mapped urban areas (Geng et al., 2024b, Goodchild, 2009, Goodchild, 2007, Chakraborty et al., 2015). These developments challenge traditional top-down data regimes by fostering decentralised, participatory models of data production and use (Elwood, 2008, Liu et al., 2017). Tools such as Open Data Kit and geocoded citizen surveys further this shift by enabling local actors to document conditions, participate in planning, and advocate for change (Anokwa et al., 2009).

The expansion of cloud infrastructure, including services like Google Cloud, has improved access to analytical environments, accelerating the development of dashboards, simulations, and AI-driven applications even in low-resource contexts (Talari et al., 2017). Yet, as Chakraborty et al. (2015) argue, open datasets also carry risks, ranging from representational bias to privacy concerns. For example, informal settlements and culturally sensitive areas may be misrepresented or omitted altogether, creating planning blind spots. Integrating diverse data sources, from satellite imagery and municipal databases to local knowledge and civic complaints, is therefore critical for ensuring equitable and inclusive smart systems (Hao et al., 2015). In the current Smart Heritage practices, these tools remain underutilised (Geng et al., 2023a). Despite the growing interest in open government data and urban sensing, heritage-focused applications often lack the infrastructure or theoretical grounding to incorporate such information meaningfully. This paper responds to that gap by proposing a multi-sensor DT framework that links open-access data with cultural responsiveness, lifecycle workflows, and participatory heritage governance.

2.3 Sensor-Based Environmental and Cultural Modelling

Environmental sensors are increasingly deployed in urban environments to support performance-based design and planning. In construction informatics, these sensors inform strategies such as ventilation optimisation, acoustic mitigation, and pedestrian flow management (Lenzi et al., 2021, Fan and Loo, 2021, Mitro et al., 2022, García Diego et al., 2015). For instance, these sensors are integrated into Heritage-Building Information Modelling (H-BIM) systems to support conservation-friendly HVAC operations (Casazza and Barone, 2024). IoT-based platforms further allow tracking of VOC levels and temperature to monitor material health and microclimate stability (Laohaviraphap and Waroonkun, 2024). Sound sensors, meanwhile, enable the mapping of urban noise corridors, guiding acoustic zoning and supporting façade retention in mixed-use areas (Klein et al., 2017, Deng et al., 2021). Pedestrian sensing technologies, including Wi-Fi probes, UWB tracking, and GPS heatmaps, offer granular insights into movement patterns (Fan and Loo, 2021). These data can inform responsive design strategies, from crowd-based cultural programming to quiet zone designation. Within DTs, pedestrian data feed into simulations that test user flow, event planning, and spatial activation in heritage spaces. Collectively, these sensors offer a foundation for evidence-based spatial programming, where environmental data and cultural heritage use converge. However, very few frameworks have integrated them meaningfully within heritage systems. Hence, this paper proposes such integration, not as a technical add-on but as a cultural infrastructure, situating sensors within both Smart City and heritage paradigms to support co-productive, responsive, and story-rich environments.

2.4 DT Applications in Construction with Heritage Considerations

Originally developed for manufacturing and engineering, the concept of the DT has gained traction in the Architecture, Engineering, Construction, and Operations (AECO) industries as a means to simulate, monitor, and optimise building performance (Jeannot, 2019, Aheleroff et al., 2021). A DT typically comprises a five-layer structure: physical (sensor-enabled environment), virtual (data and simulations), control logic (rules and automation), application (interventions), and feedback (monitoring and refinement) (Al-Ali et al., 2020). In AECO, DTs have become central to post-occupancy evaluation (POE), predictive maintenance, and energy management, particularly when combined with IoT, BIM, and AI technologies (Barrientos et al., 2021, Rasheed et al., 2020), enable dynamic scenario testing and real-time decision-making, offering insights into façade retrofitting, HVAC performance, and space utilisation (Xie et al., 2020, Lydon et al., 2019).

Lu et al. (2020) and Liu et al. (2021) highlight the capacity of DTs to integrate construction data with environmental sensing, creating responsive infrastructures that learn and evolve. However, their application in heritage contexts remains underexplored. Several emerging studies advocate for DTs in conservation and adaptive reuse, where monitoring environmental stress, occupancy levels, or structural behaviour can guide retrofits and preventive maintenance (Dore and Murphy, 2017, Jordan-Palomar et al., 2018, Jouan and Hallot, 2020). Heritage-focused DTs, often linked with Heritage-BIM, present an opportunity to embed cultural intelligence into lifecycle planning and align post-occupancy insights with historical preservation goals (Khajavi et al., 2019, Guen, 2017). This study builds on that literature by operationalising a multi-sensor DT model within an urban heritage precinct. The model incorporates a dedicated 'Heritage Layer' to ensure that cultural value informs simulation rules and responses, offering a novel contribution to Smart Heritage practice within construction informatics.

2.5 ML, AI, and Smart Heritage in Cultural Heritage Sites

The integration of ML and AI into Smart Heritage systems marks a critical progression towards autonomous, context-aware cultural infrastructure. While traditional heritage informatics focused on static digitisation or remote sensing, recent advances increasingly leverage predictive and adaptive capacities to inform both preservation and spatial planning (Altaweel et al., 2023, Luo et al., 2024). AI is now increasingly applied to heritage data for classification, anomaly detection, event prediction, and spatial-temporal analysis, enabling both conservation and public engagement (Fiorucci et al., 2020). Deep learning techniques, such as convolutional neural networks (CNNs), have been used for image recognition in artefact digitisation and monitoring physical degradation in historical structures (Matrone et al., 2020, Altaweel et al., 2023). In cultural heritage contexts, AI enables heritage sites to be not only observed but also interpreted through behavioural and environmental inputs. For example, Casillo et al. (2022) introduced an AI-powered system that predicts stress triggers in heritage environments using adaptive models trained on CO_2, sound, and occupancy data. This predictive layer supports proactive interventions, especially for vulnerable cultural assets in high-traffic urban zones. Similarly, Matrone et al. (2020) argue for "semantically-aware" predictive maintenance in historic buildings by combining knowledge graphs with ML-based sensor analysis.

Smart Heritage applications have also expanded towards the use of semantic segmentation and deep feature extraction. Semantic segmentation (a computer vision technique that classifies each pixel of an image into predefined categories) is used in heritage to identify architectural features, detect deterioration, or map spatial functions within complex urban environments (Matrone et al., 2020). These tools help link architectural patterns with conservation status, as seen in transfer learning applied to unmanned aerial vehicle (UAV) imagery for looting detection in archaeological landscapes (Altaweel et al., 2023). Meanwhile, Geng et al. (2024b) demonstrated how real-time sensor data could be used in ML workflows to model context-sensitive heritage activation across urban precincts to embed the Smart Heritage concept. A key development is the integration of ML into DT systems. Fiorucci et al. (2020) stress the role of semi-supervised models in annotating underrepresented cultural data domains where labelled samples are sparse. The concept of cultural-event-aware DTs, trained to distinguish between routine and ritual events, shows promise for transforming cultural triggers into input variables for both spatial planning and narrative design (Fiorucci et al., 2020). More specifically, cultural-event-aware' DTs refer to simulation systems trained to differentiate between routine urban patterns and culturally significant events, such as festivals or parades. These DTs adjust their activation logic based on the cultural meaning of sensor inputs rather than treating all peaks in data equally. While challenges remain around data representativeness and explainability, emerging frameworks propose integrating AI with co-creation models, allowing stakeholders to adjust thresholds or retrain models based on cultural values rather than pure statistical optimisation. Overall, ML and AI represent a new computational frontier for Smart Heritage. They offer scalable and adaptive capabilities while challenging practitioners to consider the interpretive layers of cultural space. Future Smart Heritage systems may well rely on continual learning models, those that adapt over time to both environmental conditions and evolving cultural narratives.

3. METHODOLOGY

This study adopts a case study method to develop and test a DT simulation framework tailored for Smart Heritage applications. The aim is to integrate multi-sensor urban data with both heritage-responsive and construction-informatics perspectives. The selected case study, Chinatown Melbourne, is situated within the City of Melbourne's Hoddle Grid and serves as a high-potential testing ground due to its rich cultural identity and dense urban sensor network (Anderson, 1990, Chau et al., 2016). Known for its historic architecture, symbolic significance, and vibrant street life, Chinatown has in recent years experienced increasing pressures from tourism, identity crisis, gentrification, conflicts between stakeholders and evolving public realm needs (Geng et al., 2023b). These factors, combined with extensive real-time data on pedestrian movement, air quality, and acoustic conditions, position the precinct as a suitable environment for piloting data-driven Smart Heritage strategies.

3.1 Dataset Collection and Analysis

This study began by identifying open-access datasets relevant to environmental and behavioural monitoring from the City of Melbourne's data portal. A targeted search was conducted to locate sensor-enabled datasets that could support Smart Heritage simulations within culturally significant precincts, such as Chinatown Melbourne. Priority was given to datasets that offered proximity to the chosen case study, time-stamped records, enabling integration into a rule-based simulation framework. These datasets were then classified according to their applicability to heritage-informed urban design and construction informatics objectives, including ventilation design, acoustic zoning, and cultural programming, as suggested in the literature review.

Once selected, the datasets were downloaded and initially processed to conduct descriptive statistical analysis. A year-round scan of 2024 data was used to identify contextually meaningful thresholds with a quartile method that signalled peak activity or environmental stress, focusing on time-series patterns across sensor types and aligning them with culturally significant periods such as weekends, meal hours, and festive dates. These thresholds formed the basis of a rule-based logic for system activation. A pilot test using December 2024 data was then conducted to assess the frequency and overlap of trigger events under real-world conditions. Python was used for initial data cleaning, validation of patterns, scalability testing and automation potential. The results then informed the development of a six-layer DT simulation architecture that integrates technical performance with culturally responsive heritage interventions to reflect both technical integration and cultural responsiveness.

3.2 ML and DT Simulation Model Development

Following the pilot testing of activation thresholds, the study introduced an ML component to enhance the predictive capacity of the Smart Heritage system. Table 1 provides a summary of the proposed methodology for the DT framework development. Using full-year 2024 sensor data, Random Forest models were trained to forecast environmental and behavioural triggers, such as elevated CO_2, sound intensity, and pedestrian flow, before they surpassed threshold levels. To validate the predictive models, standard performance metrics were used, including accuracy, F1-score, and mean absolute error (MAE). Confusion matrices were also generated to evaluate classification performance. Model reliability was tested using five-fold cross-validation, ensuring robustness across temporal subsets of the data. These metrics are detailed in the results section (Table 6 and Figure 3). The ML pipeline incorporated engineered features such as three-hour rolling averages, cross-sensor relationships, and temporal indicators, enabling the system to operate in both reactive and anticipatory modes. Building on the threshold rules and ML outputs, the study established a six-layer DT simulation framework capable of translating sensor-derived insights into culturally responsive design actions, including physical, virtual, control logic, ML, application and feedback layers. While the six layers provide the structural and functional foundation for real-time sensing, prediction, activation, and feedback, a non-structural Heritage Layer can be introduced as a cross-cutting conceptual lens. It does not operate through computation or automation but rather guides how data is interpreted and acted upon in culturally meaningful ways. This layer can potentially help ensure that cultural meaning, heritage collective memory, and community identity inform system logic and design decisions. In the case of Chinatown Melbourne, this means recognising traditional festivals, events and key architectural heritage on site. The Heritage Layer thus mediates between environmental intelligence and cultural legitimacy, reinforcing the simulation framework's dual aim: to advance operational performance while upholding heritage values. The involvement of the heritage layer is thus tested in this study.

Table 1: Methodological Framework for Smart Heritage DT Simulation.

Step	Methods	Data Source	Expected Outcomes	Theoretical Alignment
1	Case Study Selection	City of Melbourne urban heritage records and prior literature	Context-specific heritage site for Smart Heritage prototyping	Case study methodology; cultural-technical integration
2	Dataset Identification and Classification	City of Melbourne open data portal, including Micro-Labs	Structured dataset matrix supporting DT inputs	Open-data urbanism; Smart Heritage data infrastructure
3	Data Analysis and Threshold Definition	Python-based statistical analysis (2024 sensor data)	Defined rules for Smart Heritage activation based on real conditions	Environmental responsiveness; cultural threshold logic
4	Pilot Testing of Sensor Thresholds	December 2024 hourly sensor data	Evidence of threshold validity; identification of multi-sensor triggers	Adaptive urban modelling; performance-based heritage design
5	ML for Trigger Forecasting	Full-year 2024 sensor dataset + engineered features	Predictive logic for anticipatory system activation	Data-driven urban intelligence; AI-enabled Smart Heritage
6	DT Simulation Model Development	All processed data, thresholds, and ML outputs	Fully integrated DT architecture with both rule-based and predictive layers	DT theory; lifecycle-informed cultural infrastructure

4. RESULTS

This section presents the results of a multi-sensor DT simulation developed to model real-time heritage responsiveness using publicly available urban datasets. The aim was to identify key activation thresholds and test the responsiveness of the ML system to real-world conditions to justify the proposal of the DT model. The data was sourced primarily from the City of Melbourne's open data platform and focused on Chinatown Melbourne's main street (Little Bourke Street) and southern boundary (Bourke Street).

4.1 Identification of Available Datasets

A foundational step in this study involved identifying and assessing open-access datasets relevant to operationalising Smart Heritage in Chinatown Melbounre. Five datasets were selected based on their relevance to both cultural heritage management and construction lifecycle evaluation within DT frameworks: on-street parking, pedestrian counting, microclimate conditions, dwelling functionalities and Microlab datasets (CO_2, sound level and accelerometer). The microclimate dataset was initially eliminated due to the distance of the sensor to Chinatown Melbourne. These datasets were accessed via the City of Melbourne's open data platform and each offers unique insights into how the precinct performs spatially, environmentally, and experientially. Datasets related to pedestrian counts, ambient sound and CO_2 were shortlisted based on their data availability consistency, sensor location proximity to case study, granularity and spatial relevance to Chinatown Melbourne, and potential to inform spatial, environmental, and cultural modelling. Table 2 provides a map of sensor locations and its spatial relevance to Chinatown Melbourne. Also, although not all data initially identified were used in this study, Table 3 is made to summarise the potential use of these data for Smart Heritage and construction informatics, which can inform future studies with similar data types.

Table 2: Sensor location in relation to Chinatown Melbourne (site highlighted in green).

Dataset	**Sensor Location**	**Dataset**	**Sensor Location**
On-Street Parking		Dwelling Functionality	
Pedestrian Counting		Microlab Sensor (CO_2, Sound level and Accelerometer)	

On-Street Parking Data: Originally addressed in the *Chinatown Action Plan* (1985), the design of the precinct's main street reflects a desired level of congestion, considered culturally symbolic of traditional Chinese urban vibrancy. This strategy influenced the widening of streets to accommodate both pedestrian flows and intermittent on-street parking. Open-access parking data now enables real-time tracking of bay availability around the precinct. Such data is valuable for urban designers and policymakers, who can model temporal zoning strategies, e.g., transforming parking areas into al fresco dining zones during evenings or weekends. This dynamic use of space promotes operational sustainability while retaining the precinct's cultural ambiance and liveliness. It also supports the adaptive reuse of streetscapes in ways that honour both functional flexibility and symbolic heritage.

Pedestrian Counting Data: As a key indicator of urban vitality, pedestrian data provides critical insights into heritage precinct performance. Given Chinatown Melbourne's location within the Hoddle Grid, footfall metrics help distinguish between incidental passersby and intentional cultural visitors. This differentiation is central to designing meaningful Smart Heritage responses. For instance, foot traffic data can inform peak-hour lighting, cultural programming, or digital storytelling activations, enhancing tourism appeal and energy efficiency. Targeted activation not only increases visitor engagement but also allows cultural institutions to optimise resource allocation. In this study, hourly pedestrian data from March 2025 was used as a core input for DT modelling.

Microclimate Data: Environmental data, particularly temperature, humidity, and solar radiation, is vital for heritage site preservation and visitor comfort. Although Chinatown Melbourne currently lacks embedded microclimate sensors, proxy data from nearby Argyle Square was analysed to represent broader environmental conditions. Such data, if expanded city-wide, could support climate-sensitive design decisions, including shading strategies, ventilation design, or misting systems for laneways. When integrated into DT simulations, microclimate data can facilitate responsive comfort management, reduce energy use, and enhance material conservation efforts, especially important in heritage settings exposed to seasonal stress.

Dwelling Functionality Data: Current land-use classifications suggest that Chinatown Melbourne is dominated by commercial activity, particularly restaurants, with a noticeable lack of buildings designated for cultural or community purposes. This imbalance contributes to the precinct's identity dilution, a challenge faced by many Chinatowns worldwide. At present, only basic residential data is available through open-access sources, creating a significant data gap in terms of cultural land-use mapping. Expanding these datasets to include mixed-use, cultural, and institutional uses would allow policymakers to develop heritage-supportive planning strategies.

Identifying these ‘magnet’ functions is critical for maintaining cultural resilience and precinct distinctiveness amidst commercial pressures.

Micro-Labs Sensor Data: As part of the City of Melbourne’s Micro-Labs initiative, temporary sensor installation, including CO_2, sound, temperature, and accelerometer sensors, was deployed to assess how emerging technologies could enhance public space design and urban responsiveness. These sensors, placed in select urban laneways and open spaces, collect real-time environmental and behavioural data relevant to Smart Heritage applications. The CO_2 sensors capture ventilation performance and crowd density, while acoustic sensors track ambient soundscapes to support acoustic zoning and identity mapping. Accelerometers provide subtle insights into vibrations and human activity patterns, which are valuable for identifying public realm usage and stress points. Though not permanently installed in Chinatown Melbourne, the Micro-Labs data offers a transferable prototype for precincts with similar cultural and environmental dynamics. This type of sensor-rich dataset supports evidence-based spatial programming, cultural storytelling, and climate-responsive interventions, aligning with the goals of heritage preservation and urban adaptability.

Table 3: Identified Initial Open Access Sensor Datasets and Their Dual Applications in Smart Heritage and Construction Informatics.

Dataset	Smart Heritage Application	Construction Informatics Use
On-Street Parking	Dynamic zoning (e.g., al fresco), time-based cultural programming	Streetscape repurposing; off-peak functional retrofits
Pedestrian Counting	Time-based activation of events, lighting, and digital storytelling	Public realm planning; pedestrian flow modelling
Microclimate Conditions	Climate-responsive heritage conservation; environmental storytelling	Ventilation planning; material durability assessment
Dwelling Functionality	Cultural identity mapping; detection of underrepresented heritage functions	Land-use analysis; adaptive reuse forecasting
Urban Sound	Acoustic identity zones; sound-responsive storytelling and event planning	Acoustic zoning; façade and buffer design for noise mitigation

4.2 Trigger Identification from Year-Round Sensor Data

To support robust rule-setting, a full year (2024) of sensor data was analysed to determine statistically meaningful thresholds for activating Smart Heritage interventions. Hourly pedestrian, CO_2, and sound datasets, sourced from the central Little Bourke Street and the Bourke Street boundary of Chinatown Melbourne, were cleaned and processed using Python to reveal recurring patterns and moments of intensified activity or environmental stress. These patterns provided the empirical basis for defining responsive thresholds that reflect both cultural activation and environmental discomfort. A quartile-based approach was used to determine the third quartile (Q3), representing high values, to identify appropriate thresholds and triggers (Figure 1).

The results show that pedestrian flow displayed a bimodal hourly distribution, with peaks around 12:00–14:00 and again from 18:00–21:00, aligning with typical retail and dining hours. While weekday counts remained moderate, weekends and public holidays recorded elevated flow, often exceeding the updated Q3 threshold of 984 people per hour. These thresholds identify when the precinct becomes socially and commercially vibrant, suggesting strong alignment with cultural storytelling or event programming opportunities. CO_2 concentrations surpassed the Q3 value of 452 ppm most commonly during early to mid-afternoon on warmer days, especially in narrow laneways where ventilation is constrained. This pattern signals potential thermal discomfort and the need for responsive airflow interventions. Sound levels, particularly the ‘soundAvg’ values, exceeded 43 dBA during the evening period, frequently coinciding with the hospitality-driven character of the precinct (Geng et al., 2023b). This indicates rising acoustic intensity during cultural clustering and commercial activity, supporting zoning or buffering design for both vibrancy and mitigation.

These Q3-based thresholds shown in Table 4 were not selected to drive constant interventions but rather to mark peak moments warranting context-sensitive, culturally meaningful, and environmentally aware responses. They also help form the logic for activating Smart Heritage tools within a rule-based DT, linking real-time sensing with adaptive urban design.

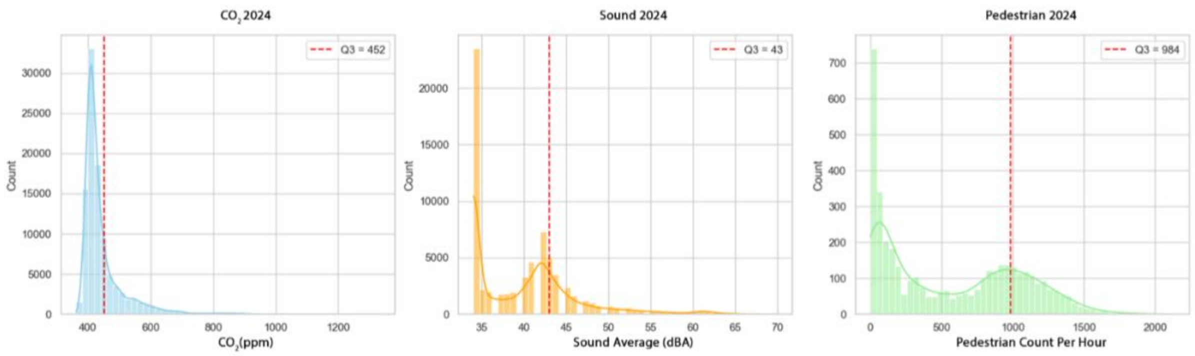


Figure 1: Quartile Distribution and Q3 (Trigger Value) of the Identified Three Datasets.

Table 4: Sensor Thresholds and Their Interpretive Value for Smart Heritage Activation.

Sensor Type	**Threshold**	**Peak Periods**	**Smart Heritage Insight**
Pedestrian Flow	> 984 people/hour	Weekends, holidays, 12:00–14:00 & 18:00–21:00	Signals cultural activity and crowd movement for events and storytelling
CO_2 Concentration	> 452 ppm	Warm days	Indicates environmental discomfort; supports responsive ventilation interventions
Sound Level	> 43 dBA	Evening values tended to be higher, and the variation between evening and daytime readings remained modest	Marks vibrant acoustic zones; informs zoning and quiet area design

Table 5: Trigger Exceedance Interpretation – December 2024.

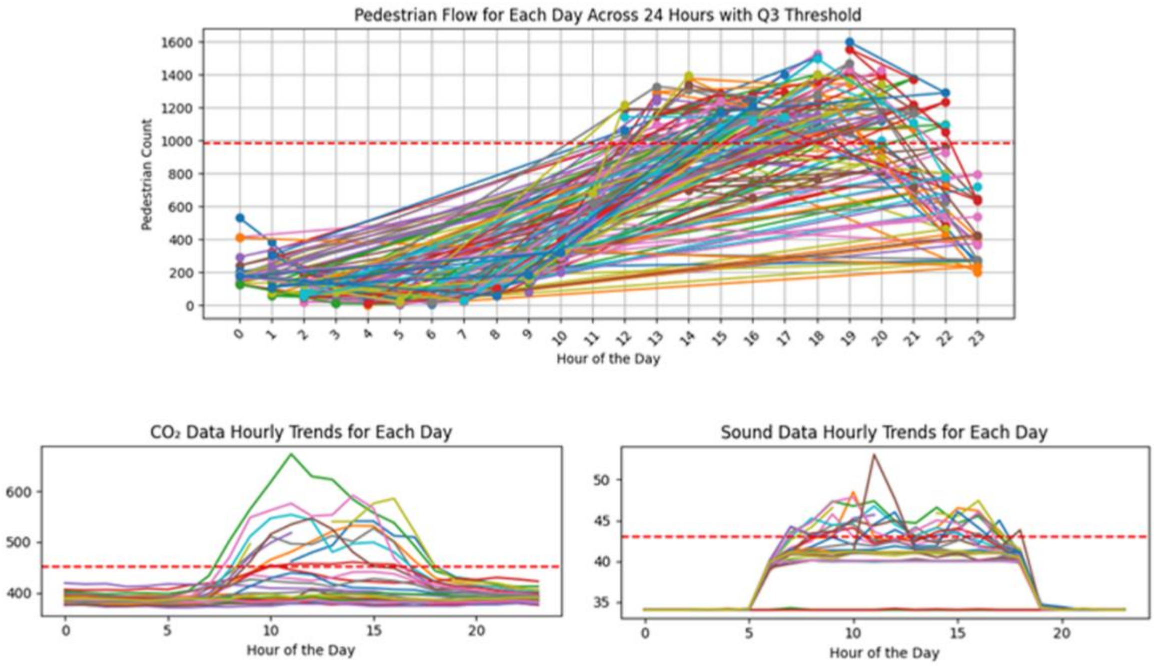
Sensor Type	**Days Exceeded (Dec)**	**Frequent Peak Hours**	**Example Smart Heritage / Construction Informatics Action**
Pedestrian Count	9 of 31 days	12:00–14:00, 18:00–21:00	Dynamic lighting, pop-up cultural events, interactive signage for construction projects
CO_2 Concentration	19 of 31 days	13:00–15:00, warm afternoons	Airflow design review, vertical greening, ventilation retrofits
Sound Level	11 of 31 days	18:00–22:00	Acoustic zoning, buffer design, noise-tolerant programming

4.3 Pilot Testing of Triggers

A pilot simulation using Python was conducted using December 2024 sensor data to test the real-world applicability of the identified thresholds. This exercise assessed how frequently triggers would activate across different temporal scales, providing insights into system responsiveness and confirming practical moments for Smart Heritage engagement. Using the Q3 thresholds (CO_2: 452 ppm, Sound: 43 dBA, Pedestrian: 984/hour), analysis showed that multiple days throughout December recorded overlapping exceedances across two or more sensors (Figure 2). Notable days included December 6, 14, 21, and 24, coinciding with heightened cultural or commercial activity. These days emerged as ideal for temporary installations, responsive lighting, acoustic interventions, or community-engaged storytelling.

- Pedestrian counts exceeded 984/hour on 9 out of 31 days, mostly during lunchtime and evening peaks;
- CO_2 levels were triggered on 19 out of 31 days, showing sustained exceedance during midday hours and warm periods;
- Sound levels surpassed 43 dBA on 11 out of 31 days, especially on hospitality-active evenings, reflecting environmental and acoustic intensity.

Based on the results, Table 5 outlines several potential strategies that can be integrated to support Smart Heritage implementation. Once appropriate strategies are in place, the next objective is to enable real-time responses when Q3 thresholds (trigger values) are reached. This represents a key goal for Smart Heritage activation within the precinct. Also, this study presents the methodological framework above to guide heritage precincts in identifying relevant datasets and establishing trigger conditions. The ML-enhanced DT model developed can further support precincts with similar aims by helping precincts identify context-sensitive strategies and implement smart strategies in culturally informed ways.



*Pedestrian (count/hour); CO2 (ppm); Sound level (dBA)

Figure 2: Trigger Exceedance Summary by Day and by Hour – December 2024.

4.4 ML for Trigger Prediction and Adaptive Heritage Simulation

While the threshold-based model confirmed cultural-intensity correlations, predictive models were tested to simulate anticipatory interventions, reducing system lag and overactivation. To address this limitation, an ML approach was introduced to enhance the predictive capacity of the Smart Heritage DT. Rather than relying solely on fixed thresholds, the system incorporates data-driven forecasting to anticipate trigger conditions, thereby improving cultural timing, energy efficiency, and operational adaptability. This study developed a supervised ML pipeline to predict three types of heritage-relevant triggers: elevated CO_2 levels, increased sound pressure, and high pedestrian footfall. Using full-year 2024 sensor data, three separate Random Forest classifiers were trained to detect whether a given hour would exceed pre-defined Q3 thresholds. Additionally, regression models were developed to estimate the actual sensor values, providing dual interpretive modes: probabilistic trigger detection and continuous condition forecasting.

The feature set for each model included:

- Direct sensor values (e.g. CO_2 concentration in ppm, average sound level in dBA, pedestrian count per hour)
- 3-hour rolling means to capture temporal trends and local context
- Cross-sensor predictors (e.g. estimating sound levels from CO_2 fluctuations)
- Temporal indicators such as hour of day, day of week, and weekend status

Each model was trained using the full-year 2024 dataset and tested using five-fold cross-validation to ensure reliability across different temporal subsets. The training process used scikit-learn's implementation of the Random Forest algorithm, with hyperparameters tuned via grid search to optimise performance. Classification models predicted whether each hour would exceed the identified thresholds, while regression models estimated actual sensor values. The validation metrics reported, including accuracy, F1-score, and MAE, demonstrate the models' robustness and predictive utility for Smart Heritage trigger forecasting. This hybrid feature design allowed the models to capture both intra-sensor patterns and cross-variable relationships, offering a more nuanced understanding of environmental and behavioural conditions in Chinatown Melbourne. Figure 3 presents the confusion matrices for the three Random Forest classifiers, illustrating how well the models distinguish between trigger and non-trigger conditions across CO_2, sound, and pedestrian datasets. Each matrix shows the count of true positives (correct trigger predictions), true negatives (correct non-trigger predictions), false positives, and false negatives.

- The CO_2 model demonstrates a balanced classification performance with low false positives, indicating reliable detection of ventilation-related stress.
- The Sound model shows strong separation between trigger and non-trigger classes, aligning well with temporal patterns of acoustic activity in hospitality zones.
- The Pedestrian model captures high-flow events accurately, reinforcing its value for real-time cultural crowd management.

The diagonal dominance in each matrix indicates strong predictive performance, with minimal false positives or negatives across all categories. These results confirm the suitability of the models for real-time or anticipatory deployment in Smart Heritage systems. As seen in Table 6, classification matrices (accuracy and F1-score) indicate the models' ability to detect whether thresholds are exceeded, while regression metrics (mean absolute error) measure precision in predicting actual values. Feature importance is also shown, highlighting which variables were most influential for each sensor target.

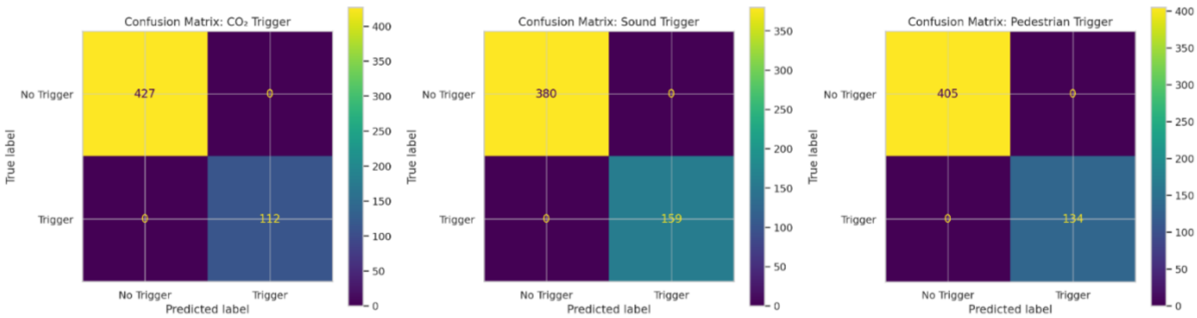


Figure 3: Confusion Matrix for Classifier Performance.

Table 6: Key Classification and Regression Results.

Key Classification Results				**Key Regression Results**		
Trigger Type	**Accuracy**	**F1-Score**	**Top Features**	**Variable**	**Model Type**	**MAE (Mean Absolute Error)**
CO_2 Trigger	0.89	0.84	CO_2, sound_from_CO_2, CO_2_roll3	CO_2 (ppm)	Random Forest	±14.2 ppm
Sound Trigger	0.91	0.86	soundAvg, ped_from_sound, roll3	Sound (dBA)	Random Forest	±3.8 dBA
Pedestrian Trigger	0.88	0.85	Total_of_Directions, co2_from_ped, hour	Pedestrian Count	Random Forest	±71 people/hour

These results confirm that ML methods can support both quantitative prediction and binary trigger identification, offering a dual mode of operation for Smart Heritage interventions. The importance of cross-sensor predictors, such as CO_2 readings improving sound predictions, or sound trends helping estimate pedestrian flow, underscores the interconnected complexity of urban heritage environments. These relationships are not readily captured by threshold logic alone. By embedding this predictive capacity into the DT, the system gains the ability to anticipate environmental and cultural thresholds before they are breached, thus supporting pre-emptive interventions, reducing false positives, and enhancing responsiveness during peak activity or environmental stress.

4.5 Sensor Contributions and DT Architecture

Building on the trigger testing and predictive modelling pilots, this section outlines the refined DT simulation model developed to operationalise Smart Heritage in Chinatown Melbourne. The model adopts a modular, layered architecture that supports both technical integration and cultural sensitivity. It incorporates three categories of sensor-derived urban data: pedestrian flow, CO_2 concentration, and ambient sound, which are mapped against both threshold-defined rules and ML predictions to enable dynamic and site-specific heritage activation. The system architecture has been expanded to include six core layers and one cross-cutting heritage layer. As Table 7 shows, these layers progress from real-world sensing to cultural response and post-intervention feedback, and now also include an ML layer that enables probabilistic forecasting of triggers based on temporal and cross-sensor inputs.

Table 7: DT Layers Developed with Cross-cutting Heritage Layer.

Heritage Layer (cross-cutting): Conceptual interpretive lens ensuring cultural legitimacy and symbolic coherence; operates across all layers; embeds cultural logic into sensor interpretation and system behaviour; distinguishes cultural significance in heritage sites.

Layer	Function	Sensor Data Inputs	Smart Heritage / Construction Application
1. Physical Layer	Real-world sensing through heritage streetscape infrastructure	CO_2 sensors, sound sensors, pedestrian counters	Captures environmental and social conditions from Chinatown Melbourne's public realm
2. Virtual Layer	Time-series simulation and visualisation	CSV-formatted datasets integrated via Python scripts	Enables live tracking, historical pattern analysis, and sensor-based modelling
3. Control Logic Layer	Threshold detection and rule-based activation	CO_2 > 452 ppm, Sound > 43 dBA, Pedestrian > 984/hour	Defines when and where Smart Heritage interventions should be triggered
4. ML Layer	Probabilistic prediction of future trigger events using AI models	Rolling averages, time-of-day, sensor cross features	Enhances anticipatory capability, avoids overactivation, supports adaptive decision-making, and works with upcoming/existing constructions in complex urban environments
5. Application Layer	Cultural and spatial intervention mechanisms	Combined sensor triggers (threshold or ML-based)	Activates heritage precinct storytelling, dynamic lighting, zoning overlays, acoustic buffering, and ventilation strategies
6. Feedback Layer	Post-intervention monitoring and design evaluation	Trigger logs, environmental metrics	Supports iterative refinement of design strategies and post-occupancy assessment

The results of this study show that the Heritage Layer mediates between raw sensor outputs and meaningful cultural action by embedding local knowledge, symbolic meaning, and spatial identity into the simulation process. For example, while a 75 dBA sound spike might be interpreted as noise pollution in a commercial district, the same signal during a festival performance may reflect desirable vibrancy within a cultural heritage context. This interpretive nuance is critical for ensuring the cultural legitimacy and contextual appropriateness of any system-activated intervention. The parameter values used in this study, CO_2 > 452 ppm, Sound > 43 dBA, and Pedestrian Flow > 984 people/hour, were selected through a combination of quartile-based statistical analysis and validated predictive modelling. These thresholds serve as proof of concept, demonstrating what is feasible, adaptable, and meaningful for the Chinatown Melbourne context. However, they are not fixed. The framework is designed to be transferable to other urban heritage precincts, where different sensor types (e.g., temperature, humidity, light, air pollutants), cultural narratives, and governance needs may call for alternative indicators or thresholds.

In cities with richer datasets or evolving heritage narratives, this model can be further enhanced through:

- Integration of additional environmental variables (e.g., flood risk, air pollution);
- AI-based clustering for cultural programming opportunities;
- Stakeholder co-design of narrative triggers;
- Proposed construction sites/ period and the scheduling of cultural/heritage events;
- Public engagement interfaces for feedback loops.

Overall, this DT simulation framework advances the Smart Heritage agenda by combining real-time sensing, predictive intelligence, and culturally informed control logic. Its modular structure, incorporation of an ML Layer, and grounding in a Heritage Layer enable both technical robustness and cultural resonance. This positions the model as a scalable and transferable framework for adaptive, data-informed urban heritage management across global contexts.

5. DISCUSSION

5.1 Interpreting Sensor Roles in Smart Heritage and Construction Informatics

The findings from the DT simulation highlight the distinct yet complementary roles that different urban sensors can play in both Smart Heritage activation and construction-informed planning, both vital for complex urban heritage sites. As Table 8 presents, each data stream: pedestrian count, CO_2 level, and ambient sound, provides a discrete layer of spatial intelligence that becomes more powerful when integrated within a culturally contextualised framework. These sensors, while operationally embedded in urban infrastructure, transcend their original technical purposes by acting as mediators between cultural narratives and environmental performance. Pedestrian data reflects rhythms of cultural engagement, peak communal gatherings, and temporally dynamic zones of heritage activation. CO_2 levels not only indicate air quality but become proxies for crowd density and ventilation efficacy, linking occupant comfort to the symbolic health of shared spaces. Sound levels, similarly, offer insight into the acoustic identities of streetscapes, supporting distinctions between festive, high-energy areas and quieter reflective zones essential to cultural storytelling. Together, these datasets inform responsive design decisions across multiple scales, from temporary installations and interactive wayfinding to long-term HVAC calibration and façade retrofitting (Geng et al., 2024b, Song and Selim, 2022, Luo et al., 2024). In Smart Heritage contexts, this interdisciplinary synthesis allows for the creation of 'living heritage systems' that are both operationally efficient and culturally expressive.

Table 8: Sensor Contributions to Smart Heritage and Construction Informatics.

Sensor Type	Smart Heritage Role	Construction Planning Implication
Pedestrian Count	Crowd-based storytelling; dynamic precinct zoning	Wayfinding analysis; façade engagement; responsive public realm design
CO_2 Level	Environmental storytelling; cultural atmosphere	HVAC optimisation; airflow and material sustainability strategies
Sound Level	Acoustic identity; quiet vs. active zone mapping	Acoustic façade design; noise buffering; adaptive spatial programming

The inclusion of ML further advances the interpretive capacity of sensors by transforming them from reactive triggers to predictive agents. Rather than responding only to threshold breaches, the system can anticipate them, allowing interventions to be deployed preemptively. This enhances both the functional agility of the DT and its alignment with cultural temporality, for instance, forecasting crowd build-up before a community ritual begins. By embedding learning models that adapt over time, the framework also introduces a dynamic form of heritage governance, where cultural and environmental rhythms evolve in tandem. As Smart Heritage systems evolve, explainable AI becomes essential to ensure transparency, avoid cultural bias, and build trust among heritage custodians and community stakeholders. These insights extend Smart Heritage beyond static documentation or one-time interventions, revealing its potential to act as a live cultural infrastructure. By integrating heritage values with responsive environmental and behavioural feedback loops, sensor data becomes a shared language across cultural, spatial, and technical disciplines. This reconceptualisation of sensors, as both technical instruments and cultural indicators, encourages new modes of stakeholder collaboration between heritage professionals, urban designers, and construction informatics specialists. In doing so, the DT framework becomes not only a tool for monitoring or simulating built environments but also a platform for activating and co-authoring urban memory and future resilience.

5.2 Reframing the DT as Cultural Infrastructure

Rather than treating the DT as a neutral technical artefact, this study reconceptualises it as a form of cultural infrastructure, a dynamic platform that integrates environmental intelligence with heritage-specific values throughout the lifecycle of the built environment. The proposed six-layer DT architecture, comprising the Physical, Virtual, Control Logic, ML, Application, and Feedback layers, ensures real-time responsiveness and system adaptability. However, it is the addition of a Heritage Layer, conceptual rather than architectural, that distinguishes this model for Smart Heritage applications. Acting as a transversal layer, the Heritage Layer intersects each stage of the system to embed cultural logic into the data interpretation and decision-making process. Importantly, this approach moves beyond abstract digitisation to engage directly with the architectural and urban form of heritage precincts. Sensor data is not only interpreted for functional metrics but also situated within the spatial and symbolic register of the built environment. For example, a pedestrian spike during a Lunar New Year parade in the case study Chinatown Melbourne is recognised not merely as crowd density, but as a moment of heightened cultural expression shaped by the spatial choreography of laneways, thresholds, and public squares. Similarly, acoustic data near historic façades or temple courtyards is analysed not only in decibels but also in terms of how architectural materiality and morphology amplify or soften cultural resonance. Unlike prior Smart City or heritage digitisation initiatives that focus primarily on archival modelling or structural monitoring, our framework integrates a predictive ML layer with an interpretive Heritage Layer to support anticipatory, culturally contextualised responses. Previous DT studies in construction informatics typically prioritise energy performance or structural analysis; in contrast, this study emphasises environmental storytelling, crowd-responsive design, and cultural rhythm alignment. This dual-layer approach distinguishes our work as both technically adaptive and culturally embedded.

This repositioning transforms the DT from a reactive monitoring tool into a context and spatial-aware system that understands how architectural elements, such as arcades, shopfronts, rooflines, or surface textures, mediate cultural behaviours. It could enable planners, designers, and heritage professionals to distinguish between functionally busy periods and symbolically significant moments, supporting interventions that are both materially grounded and culturally attuned. These may include responsive lighting schemes that accentuate façade ornamentation during festivals, zoning overlays that protect quiet courtyards from commercial encroachment, or real-time storytelling prompts aligned with spatial landmarks. By aligning urban morphology and spatial performance with cultural heritage and community memory, the model fosters hybrid heritage practices that integrate environmental management, architectural identity, and place-based storytelling. The layered logic of the DT also permits multi-scalar adaptation, allowing triggers to scale from street-level microclimates and edge conditions to precinct-wide strategies for mobility, zoning, or amenity distribution. In doing so, it reimagines Smart Heritage not just as a technological overlay, but as an architectural and urban intelligence system capable of sustaining the spatial legibility, experiential richness, and cultural continuity of historic environments.

5.3 Practical Implications

While the DT model developed for Chinatown Melbourne is tailored to a specific urban and cultural context, the underlying principles align with emerging directions in Smart Heritage. Globally, cities are beginning to explore sensor-enabled heritage districts, often focusing on digitisation overlays or structural monitoring (Agapiou et al., 2015). However, few of these initiatives have integrated environmental responsiveness with cultural programming to the degree proposed in this study (Geng et al., 2023a). The combination of CO_2, sound, and pedestrian data within a rule-based simulation framework presents a novel contribution, bridging Smart City objectives with heritage curation and post-occupancy design feedback. This approach offers a transferable methodology for culturally significant urban precincts transforming, where safeguarding identity must be balanced with complex urban contexts, involving commercial adaptation, proposed constructions and climate resilience. The model's strength lies in its capacity to quantify behavioural and environmental thresholds while preserving the symbolic and performative character of place. In doing so, it provides a replicable logic for urban managers seeking to align real-time data with long-term cultural stewardship.

From a stakeholder perspective, the implications are equally significant. By relying on open-access datasets and low-barrier tools, the framework enables local governments, heritage practitioners, and community groups to collaboratively prototype Smart Heritage responses. This decentralises technical control and promotes a participatory governance model where activation strategies are co-defined, tested, and iteratively refined by diverse actors (Geng et al., 2024b). Transparency is enhanced as sensor thresholds become shared indicators of cultural rhythm and environmental stress, interpretable across institutional and community domains. Crucially, the model treats sensor data not merely as technical inputs but as cultural artefacts, vehicles for encoding memory, meaning, and everyday use. This redefinition empowers cultural stakeholders, not just engineers or planners, to shape how smart city systems perceive and respond to heritage. The use of ML opens new opportunities for cities to build DTs that continuously learn from sensor data and adjust activation logic according to shifting community behaviours, environmental change, and event cycles. This ability to adapt over time supports sustainable heritage practices and ensures that interventions remain culturally attuned and operationally relevant. In doing so, Smart Heritage is reframed not only as a technological innovation but as a civic infrastructure for negotiating spatial identity, sustainability, and public storytelling in real time.

6. CONCLUSION

This study offers a practical demonstration of how Smart Heritage can be materially advanced through the use of publicly available urban datasets within a DT framework tailored for urban heritage with dual consideration of construction informatics. By integrating pedestrian, CO_2, and sound data from Chinatown Melbourne, the research develops a multi-sensor simulation capable of triggering context-sensitive heritage interventions. The DT is structured across six layers, including a novel Heritage Layer, which links real-time environmental inputs with cultural significance and spatial logic. This model not only enhances heritage curation but also contributes to post-construction intelligence, supporting informed decision-making in precinct design, retrofitting, and spatial programming. Its key innovation lies in translating open-access data into actionable cultural and operational insights, positioning Smart Heritage as an embedded operational layer in the built environment lifecycle. In doing so, it broadens the scope of construction informatics to include cultural responsiveness and the sustainability of urban identity. As cities face increasing challenges from digitisation, densification, and diversification, Smart Heritage, augmented by DT systems, emerges as a compelling pathway towards more responsive, inclusive, and enduring cultural environments. With a transferable methodology framework and a DT model, this study lays a foundation for future models that fully integrate behavioural, environmental, and cultural metrics into the design, management, and evolution of heritage precincts. By incorporating ML for predictive trigger detection, the framework moves beyond reactive monitoring to enable anticipatory heritage responses, paving the way for continuously learning systems that evolve with both environmental data and cultural rhythms. While the framework shows strong practical potential, several limitations remain. Its scalability depends on the availability and coverage of urban sensor data, which may vary by city. ML outputs may also reflect biases in training data, especially in culturally diverse contexts. Finally, using public space sensor data raises privacy concerns that require thoughtful governance in real-world applications. Future research should investigate how communities and heritage managers can co-train models, refining activation logic through cultural feedback and participatory sensing.

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REFERENCES

Agapiou, A., Lysandrou, V., Alexakis, D. D., Themistocleous, K., Cuca, B., Argyriou, A., Sarris, A. and Hadjimitsis, D. G. (2015), "Cultural heritage management and monitoring using remote sensing data and GIS: The case study of Paphos area, Cyprus", Computers, Environment and Urban Systems, Vol. 54, pp. 230-239.

Aheleroff, S., Xu, X., Zhong, R. Y. and Lu, Y. (2021), "Digital Twin as a Service (DTaaS) in Industry 4.0: An Architecture Reference Model", Advanced Engineering Informatics, Vol. 47.

Al-Ali, A. R., Gupta, R., Zaman Batool, T., Landolsi, T., Aloul, F. and Al Nabulsi, A. (2020), "Digital Twin Conceptual Model within the Context of Internet of Things", Future Internet, Vol. 12 No. 10.

Alkhafaji, A., Fallahkhair, S. and Haig, E. (2020), "A theoretical framework for designing smart and ubiquitous learning environments for outdoor cultural heritage", Journal of Cultural Heritage, Vol. 46, pp. 244-258.

Allam, Z. and Newman, P. (2018), "Redefining the Smart City: Culture, Metabolism and Governance", Smart Cities, Vol. 1 No. 1, pp. 4-25.

Altaweel, M., Khelifi, A. and Shana'ah, M. M. (2023), "Monitoring Looting at Cultural Heritage Sites: Applying Deep Learning on Optical Unmanned Aerial Vehicles Data as a Solution", Social Science Computer Review, Vol. 42 No. 2, pp. 480-495.

Amato, A., Andreoli, M. and Rovai, M. (2021), "Adaptive Reuse of a Historic Building by Introducing New Functions: A Scenario Evaluation Based on Participatory MCA Applied to a Former Carthusian Monastery in Tuscany, Italy", Sustainability, Vol. 13 No. 4.

Anderson, K. (1990), "'Chinatown Re-oriented': A Critical Analysis of Recent Redevelopment Schemes in a Melbourne and Sydney Enclave", Australian Geographical Studies, Vol. 18 No. 2, pp. 137-154.

Angelidou, M. and Stylianidis, E. (2020), "Cultural Heritage in Smart City Environments: The Update", ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Vol. V-2-2020, pp. 957-964.

Anokwa, Y., Hartung, C., Brunette, W., Borriello, G. and Lerer, A. (2009), "Open Source Data Collection in the Developing World", Computer, Vol. 42 No. 10, pp. 97-99.

Barrientos, F., Martin, J., De Luca, C., Tondelli, S., Gómez-García-Bermejo, J. and Casanova, E. Z. (2021), "Computational methods and rural cultural & natural heritage: A review", Journal of Cultural Heritage, Vol. 49, pp. 250-259.

Batchelor, D., Schnabel, M. A. and Dudding, M. (2021), "Smart heritage: Defining the discourse", Heritage, Vol. 4 No. 2, pp. 1005-1015.

Borda, A. and Bowen, J. P. (2017), "Smart Cities and Cultural Heritage – A Review of Developments and Future Opportunities.", Electronic Visualisation and the Arts (EVA 2017), pp. 9-18.

Brusaporci, S. and Maiezza, P. (2021), "Smart Architectural and Urban Heritage: An Aplied Reflection", Heritage, Vol. 4 No. 3, pp. 2044-2053.

Capece, S., Chivăran, C., Giugliano, G., Laudante, E., Nappi, M. L. and Buono, M. (2024), "Advanced systems and technologies for the enhancement of user experience in cultural spaces: an overview", Heritage Science, Vol. 12 No. 1.

Casazza, M. and Barone, F. (2024), "Cultural heritage structures and infrastructures vibration monitoring: vibration sensors metrological characteristics identification through finite elements modelling and simulation", Acta IMEKO, Vol. 13 No. 2, pp. 1-9.

Casillo, M., Colace, F., Gupta, B. B., Lorusso, A., Marongiu, F. and Santaniello, D. (2022), "A Deep Learning Approach to Protecting Cultural Heritage Buildings Through IoT-Based Systems", 2022 IEEE International Conference on Smart Computing (SMARTCOMP), pp. 252-256.

Chakraborty, A., Wilson, B., Sarraf, S. and Jana, A. (2015), "Open data for informal settlements: Toward a user's guide for urban managers and planners", Journal of Urban Management, Vol. 4 No. 2, pp. 74-91.

Chau, H.-w., Dupre, K. and Xu, B. (2016), "Melbourne Chinatown as an iconic enclave.", in Bosman, C. and Dedekorkut-Howes, A. (Eds.) The 13th Australasian Urban History Planning History Conference 2016, pp. 39-51.

Chianese, A. and Piccialli, F. (2014), "Designing a smart museum: When cultural heritage joins IoT", Proceedings - 2014 8th International Conference on Next Generation Mobile Applications, Services and Technologies, NGMAST 2014, pp. 300-306.

Cook, K. and Hill, G. (2019), "Digital Heritage as Collaborative Process", Studies in Digital Heritage, Vol. 3 No. 1, pp. 83-99.

Deng, M., Menassa, C. C. and Kamat, V. R. (2021), "From BIM to digital twins: a systematic review of the evolution of intelligent building representations in the AEC-FM industry", Journal of Information Technology in Construction, Vol. 26, pp. 58-83.

Dore, C. and Murphy, M. (2017), "Current State of the Art Historic Building Information Modelling", The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Vol. XLII-2/W5, pp. 185-192.

Elwood, S. (2008), "Volunteered geographic information: future research directions motivated by critical, participatory, and feminist GIS", GeoJournal, Vol. 72 No. 3-4, pp. 173-183.

Fan, Z. and Loo, B. P. Y. (2021), "Street life and pedestrian activities in smart cities: opportunities and challenges for computational urban science", Computational Urban Science, Vol. 1 No. 1.

Fiorucci, M., Khoroshiltseva, M., Pontil, M., Traviglia, A., Del Bue, A. and James, S. (2020), "Machine Learning for Cultural Heritage: A Survey", Pattern Recognition Letters, Vol. 133, pp. 102-108.

García Diego, F. J., Esteban, B. and Merello, P. (2015), "Design of a hybrid (wired/wireless) acquisition data system for monitoring of cultural heritage physical parameters in smart cities", Sensors (Switzerland), Vol. 15 No. 4, pp. 7246-7266.

Geng, S., Chau, H.-w., Jamei, E. and Vrcelj, Z. (2023a), "Understanding place identity in urban scale Smart Heritage using a cross-case analysis method", International Journal of Tourism Cities.

Geng, S., Chau, H.-W., Jamei, E. and Vrcelj, Z. (2023b), "Urban Characteristics, Identities, and Conservation of Chinatown Melbourne", Journal of Architecture and Urbanism, Vol. 47 No. 1, pp. 20-34.

Geng, S., Chau, H.-W., Jamei, E. and Vrcelj, Z. (2024a), "Demystifying the Use of Open-Access Data in Smart Heritage Implementations", Tourism and Hospitality, Vol. 5 No. 4, pp. 1125-1150.

Geng, S., Chau, H.-W., Jamei, E. and Vrcelj, Z. (2024b), "Enablers and challenges of Smart Heritage implementation – the case of Chinatown Melbourne", Smart and Sustainable Built Environment.

Goodchild, M. F. (2007), "Citizens as sensors: the world of volunteered geography", GeoJournal, Vol. 69 No. 4, pp. 211-221.

Goodchild, M. F. (2009), "Geographic information systems and science: today and tomorrow", Procedia Earth and Planetary Science, Vol. 1 No. 1, pp. 1037-1043.

Guen, M. L. (2017), "Urban transformations, ideologies of planning and actors' interplay in a Booming City - Austin, Texas", Urbanities, Vol. 7 No. 2, pp. 22-34.

Hao, J., Zhu, J. and Zhong, R. (2015), "The rise of big data on urban studies and planning practices in China: Review and open research issues", Journal of Urban Management, Vol. 4 No. 2, pp. 92-124.

Jeannot, G. (2019), "Smart city projects in the continuity of the urban socio-technical regime: The French case", Information Polity, Vol. 24 No. 3, pp. 325-343.

Jordan-Palomar, I., Tzortzopoulo, P., García-Valldecabre, J. and Pellicer, E. (2018), "Protocol to Manage Heritage-Building Interventions Using Heritage Building Information Modelling (HBIM)", Sustainability, Vol. 10 No. 908.

Jouan, P. and Hallot, P. (2020), "Digital Twin: Research Framework to Support Preventive Conservation Policies", ISPRS International Journal of Geo-Information, Vol. 9 No. 4.

Khajavi, S. H., Motlagh, N. H., Jaribion, A., Werner, L. C. and Holmstrom, J. (2019), "Digital Twin: Vision, Benefits, Boundaries, and Creation for Buildings", IEEE Access, Vol. 7, pp. 147406-147419.

Klein, L. J., Bermudez, S. A., Schrott, A. G., Tsukada, M., Dionisi-Vici, P., Kargere, L., Marianno, F., Hamann, H. F., Lopez, V. and Leona, M. (2017), "Wireless Sensor Platform for Cultural Heritage Monitoring and Modeling System", Sensors (Basel), Vol. 17 No. 9.

Laohaviraphap, N. and Waroonkun, T. (2024), "Integrating Artificial Intelligence and the Internet of Things in Cultural Heritage Preservation: A Systematic Review of Risk Management and Environmental Monitoring Strategies", Buildings, Vol. 14 No. 12.

Lenzi, S., Sádaba, J. and Lindborg, P. M. (2021), "Soundscape in Times of Change: Case Study of a City Neighbourhood During the COVID-19 Lockdown", Frontiers in Psychology, Vol. 12 No. March.

Liu, L., Coops, N. C., Aven, N. W. and Pang, Y. (2017), "Mapping urban tree species using integrated airborne hyperspectral and LiDAR remote sensing data", Remote Sensing of Environment, Vol. 200, pp. 170-182.

Liu, M., Fang, S., Dong, H. and Xu, C. (2021), "Review of digital twin about concepts, technologies, and industrial applications", Journal of Manufacturing Systems, Vol. 58, pp. 346-361.

Lu, Q., Xie, X., Parlikad, A. K. and Schooling, J. M. (2020), "Digital twin-enabled anomaly detection for built asset monitoring in operation and maintenance", Automation in Construction, Vol. 118.

Luo, F., Isa, M. I. and Roosli, R. (2024), "Research status and development direction of smart heritage: a bibliometric review (1994-2024)", Journal of Asian Architecture and Building Engineering, pp. 1-24.

Lydon, G. P., Caranovic, S., Hischier, I. and Schlueter, A. (2019), "Coupled simulation of thermally active building systems to support a digital twin", Energy and Buildings, Vol. 202.

Matrone, F., Grilli, E., Martini, M., Paolanti, M., Pierdicca, R. and Remondino, F. (2020), "Comparing Machine and Deep Learning Methods for Large 3D Heritage Semantic Segmentation", ISPRS International Journal of Geo-Information, Vol. 9 No. 9.

Mitro, N., Krommyda, M. and Amditis, A. (2022), "Smart Tags: IoT Sensors for Monitoring the Micro-Climate of Cultural Heritage Monuments", Applied Sciences (Switzerland), Vol. 12 No. 5.

Piccialli, F. and Chianese, A. (2018), "Editorial for FGCS special issue: The Internet of Cultural Things: Towards a Smart Cultural heritage", Future Generation Computer Systems, Vol. 81, pp. 514-515.

Rasheed, A., San, O. and Kvamsdal, T. (2020), "Digital Twin: Values, Challenges and Enablers From a Modeling Perspective", IEEE Access, Vol. 8, pp. 21980-22012.

Song, H. and Selim, G. (2022), "Smart Heritage for Urban Sustainability: A Review of Current Definitions and Future Developments", Journal of Contemporary Urban Affairs, Vol. 6 No. 2, pp. 175-192.

Song, H., Selim, G. and Gao, Y. (2023), "Smart Heritage Practice and Its Characteristics Based on Architectural Heritage Conservation—A Case Study of the Management Platform of the Shanghai Federation of Literary and Art Circles China", Sustainability, Vol. 15 No. 24, pp. 16559-16559.

Talari, S., Shafie-Khah, M., Siano, P., Loia, V., Tommasetti, A. and Catalão, J. P. S. (2017), "A review of smart cities based on the internet of things concept", Energies, Vol. 10 No. 4.

Udeaja, C., Trillo, C., Awuah, K. G. B., Makore, B. C. N., Patel, D. A., Mansuri, L. E. and Jha, K. N. (2020), "Urban heritage conservation and rapid urbanization: Insights from Surat, India", Sustainability (Switzerland), Vol. 12 No. 6.

Xie, X., Lu, Q., Rodenas-Herraiz, D., Parlikad, A. K. and Schooling, J. M. (2020), "Visualised inspection system for monitoring environmental anomalies during daily operation and maintenance", Engineering, Construction and Architectural Management, Vol. 27 No. 8, pp. 1835-1852.

APPENDIX

GLOSSARY

AECO	Architecture, engineering, construc
AI	Artificial intelligence
BIM	Building information modelling
CNN	Convolutional neural networks
CSV	Comma-separated values
DT	Digital twin
GIS	Geographic information system
GPS	Global positioning system
H-BIM	Heritage-building information modelling
HVAC	Heating, ventilation and air-conditioning
IoT	Internet of things
MAE	Mean Absolute Error
ML	Machine learning
POE	Post-occupancy evaluation
SoundAvg	Sound average
UAV	Unmanned aerial vehicle
UWB	Ultra-wideband
VGI	Volunteered geographic informaiton
VOC	Volatile organic compounds
MAE	Mean Absolute Error