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Review on the Integration of Artificial Intelligence in Parametric Urban Design and Outdoor Thermal Comfort

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ABSTRACT

Artificial Intelligence (AI) is increasingly recognised for its ability to accelerate physics-based simulation tasks, making it particularly promising in urban design processes, where simulation often hinders iterative development. This review explores the intersection of AI, parametric urban design (PUD), and outdoor thermal comfort (OTC), assessed using the Universal Thermal Climate Index (UTCI) or other indices. We identify emerging methods and tools used to optimise comfort outcomes through intelligent design frameworks. By systematically analysing 40 studies from 2018 to 2025 and leveraging bibliometric analysis, the review categorises contributions into predictive modelling, generative design, parametric optimisation, and integration strategies. The limitation is the niche and novel nature of the subject, which reduces the number of eligible studies. We highlight how AI, particularly machine learning, acts as both a surrogate for environmental simulation and a driver for design generation. Although full integration of AI with parametric and comfort modelling remains limited, recent progress suggests strong potential. This paper presents a conceptual pipeline for integrating AI into PUD to support comfort optimisation, emphasising the need for open datasets, interpretable models, and design tool interoperability. This review establishes the first interdisciplinary synthesis of parametric urban design, artificial intelligence, and outdoor thermal comfort research, providing urban planners with a framework to leverage emerging technologies for climate-resilient cities. Limitations include the niche nature of AI-PUD-OTC integration (41 studies met criteria) and the lack of longitudinal validation in built projects.

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1. Introduction

1.1 Background and Context

Rapid urbanisation and climate change are intensifying outdoor heat stress in cities, highlighting the importance of outdoor thermal comfort in urban design. Parametric design tools enable architects and planners to generate and evaluate design alternatives rapidly, while environmental simulations (e.g., CFD, solar analysis) inform comfort outcomes. However, these simulations are typically computationally expensive. Recently, machine learning (ML) has been proposed as a means to accelerate and enhance parametric design workflows. For example, Labib (2022) demonstrated the integration of ML with parametric modelling to predict daylight performance, significantly reducing the need for repeated simulations. ML models can predict environmental metrics (e.g., solar radiation,

airflow, comfort indices) based on design parameters, enabling rapid performance evaluation during the early stages of design (Sebestyén & Tyc, 2020; Labib, 2021). For example, Sebestyén and Tyc (2020) demonstrated an ML pipeline that predicts facade solar exposure, integrating Grasshopper/Ladybug data to accelerate early-stage design exploration. In 2022, Khean et al. highlighted that the benefits of training deep learning models outweigh their costs. In 2023, Eslamirad et al. found that implementing a data-generative ML model makes it possible to generate reliable data, which is helpful for researchers, planners, and stakeholders interested in assessing urban thermal comfort. Similarly, Labib (2025) utilised physics-informed neural networks to forecast daylighting performance from a limited set of simulations, significantly reducing computation time while improving accuracy.

The rapid evolution of Artificial Intelligence (AI) in urban design is exemplified by foundational works like *Machine Hallucinations: Architecture and Artificial Intelligence* (Campo & Leach, 2022) and *Artificial Intelligence and Architecture: From Research to Practice* (Chaillou, 2022), which critique AI's role in reshaping architectural creativity. These texts align with Dogan and Yang's (2025) observation that computational urban design increasingly relies on "simulation-backed intuition." Similarly, Leach (2022) underscores in *Architecture in the Age of Artificial Intelligence* that AI's transformative potential lies in its ability to bridge gaps between data-driven analysis and human-centric design, a theme echoed in Labib's (2022) neural network applications for daylighting prediction making it easier and more intuitive to use data and simulation in informing design decisions.

Recent advances in generative design, such as those by Sebestyén et al. (2024), are further contextualised by Cudzik and Radziszewski's (2018) seminal review of swarm intelligence and evolutionary algorithms, which argues that AI-generated forms can transcend human biases. Meanwhile, Chaillou (2022) highlights the need for interdisciplinary collaboration to address the disconnect between generative tools (often rooted in computer science) and urban climatology, making it more accessible for designers.

Alongside simulation acceleration, AI is being applied to parametric design optimisation and generative design. Deep learning models (e.g., variational autoencoders, generative adversarial, or diffusion models) are used to synthesise novel design variations from parametric models, thereby expanding the design space beyond human biases (Cudzik & Radziszewski, 2018; Sebestyén et al., 2024). Cudzik and Radziszewski (2018) reviewed the use of swarm intelligence, neural networks, and evolutionary algorithms in architecture, arguing that AI-based algorithms can augment architects' toolkits by generating complex forms from simple rules. More recent work by Sebestyén et al. (2024) explicitly merges parametric shape generators with 3D generative AI. They trained both autoencoder and diffusion models on collections of parametrically generated forms and showed that combining these approaches yields richer design variations than either alone.

Meanwhile, at the urban scale, AI-driven frameworks are emerging for smart planning and comfort analysis. For instance, Ferhati et al. (2024) built an AI model to detect urban problems (e.g., sprawl, infrastructure gaps) and suggest sustainable planning solutions; their user study highlighted AI's potential to transform planning by providing more inclusive, effective strategies. These studies demonstrate AI's capabilities for large-scale comfort analysis and its potential for data-driven urban design, while also highlighting the challenges of data availability and model generalisation.

1.2 Research Gap and Objectives

Parametric urban design (PUD) accelerates form generation, outdoor thermal comfort (OTC) assessment quantifies human heat stress, and Artificial intelligence (AI) enhances simulation efficiency, making it faster and more interactive. These domains evolve in parallel with minimal cross-disciplinary integration. No comprehensive review has been conducted to map how AI-driven PUD tools can systematise OTC optimisation. We have not found research that evaluates the technological readiness of such integration for real-world planning or identifies scalable frameworks that bridge algorithmic innovation with urban design workflows. This gap impedes climate-

responsive urban development, especially in heat-vulnerable regions, where planners lack accessible tools to translate AI insights into actionable, comfort-optimised designs. For instance, generative AI models produce novel urban forms disconnected from thermal performance metrics, while OTC studies overlook PUD's capacity to embed climate analysis into iterative design.

1.3 Contribution of the Paper

Our review addresses the research gap by synthesizing 40 peer-reviewed studies (2018–2025) to: (1) define convergence trends among PUD, AI, and OTC using bibliometric co-occurrence analysis; (2) audit AI's role across predictive modelling, generative design, and optimization pipelines; and (3) expose critical research voids in tool interoperability, participatory interfaces, and Global South validation. This work explores strategies for urban planners to harness new technologies for sustainable cities while establishing an interdisciplinary benchmark for scalable, AI-driven urban design techniques specialised in OTC assessment and improvement.

This study contributes to efforts to simplify urban design by reviewing advances at the intersection of AI, parametric design, and outdoor thermal comfort. We aim to identify key methods, findings, and limitations, and to explore the potential of an integrated framework for applying parametric urban design driven by AI. Our approach combines a literature review with bibliometric analysis and thematic clustering.

This research belongs to the efforts to make urban design easier by reviewing the advances of this rapidly growing synergy between AI in all its forms and UD and OTC, allowing for a step forward in bridging the gap between all these disciplines. According to Gün (2023), urban design and its practices are being reshaped by the implementation of data-driven approaches and computational tools, which alter the roles of designers and enhance civic participation. Through a literature review and interviews with design experts specialised in computational approaches, the study reveals that technology-driven solutions facilitate more objective, data-informed decision-making processes. However, it also notes that these tools are still in their early stages and are not yet widely adopted in practice. Importantly, while computational methods offer new enhancements for design, they do not empower the user compared to traditional practices. This emphasises the need for further development and integration of participatory mechanisms within computational urban design frameworks.

2. Materials and Methods

2.1 Study Design and Setting

We conducted a literature search on the topics of “AI,” “parametric design,” and “thermal comfort” in urban contexts. The initial corpus consisted of the 40 papers listed in the CSV file, spanning the period from 2018 to 2025. These papers were screened for relevance: inclusion criteria required that each study involve an AI or ML component and address either parametric design methods or outdoor thermal comfort outcomes. Exclusion criteria removed works that addressed only indoor comfort or only digital design without an AI aspect. The keyword co-occurrence network (Figure 3) complements Vukorep and Kotov's (2021) taxonomy of ML tools in architecture, which classifies AI applications by scalability and design phase.

For methodological transparency, we documented our selection and analysis process. The final set of 40 papers was thematically coded via an iterative process:

1. We identified the role of AI (predictive model, optimisation, generative design, etc.), the design scale (building facades, urban blocks, districts), and the comfort metrics (e.g., PET, UTCI, solar exposure) involved. Thematic categorisation was performed independently by the lead author.

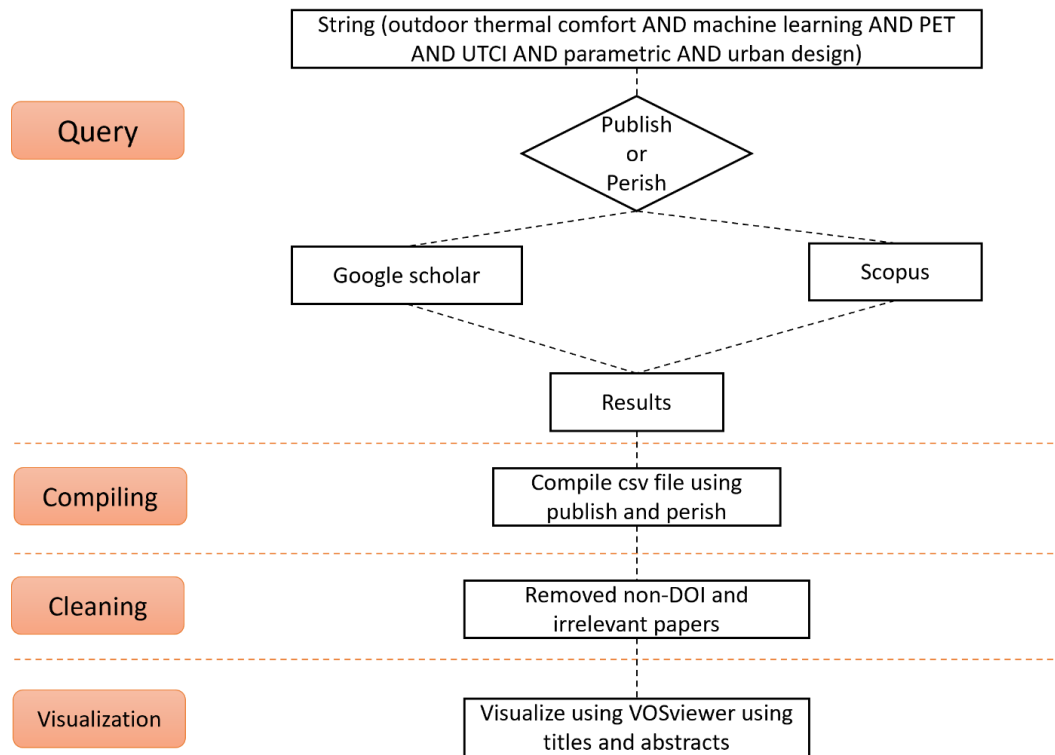


Figure 1: Paper Road map (source: Authors)

2. We used Harzing’s (2007) Publish or Perish version 8.17.4863.9118 on 12 May 2025 to search two databases: Google Scholar and Scopus. We used the following string (machine learning AND outdoor thermal comfort AND urban design AND PET AND UTCI AND parametric). The search was limited to the years from 2018 to 2025. The workflow is illustrated in the road map in **Figure 1**

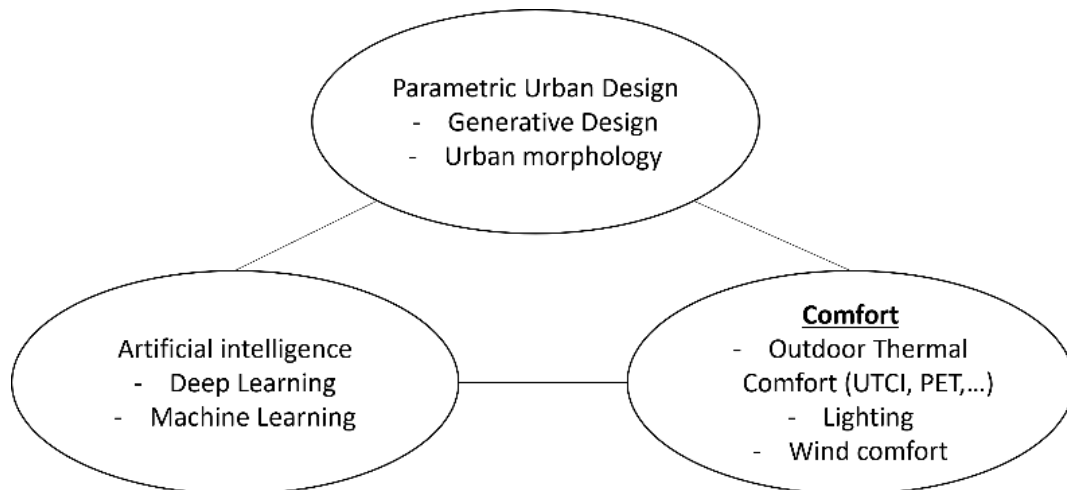


Figure 2. Keywords of the query string and their acceptable derivatives (Source: Authors)

3. The goal of this review is to explore all technologies related to Artificial Intelligence, Urban Design, and Outdoor thermal Comfort. To achieve an acceptable level of relevance and avoid getting a sample that is too small, we eliminated results that did not have two of the three most important pillars, mentioned above, including all subcategories or closely related keywords, as illustrated in Figure 2. With this method, we can ensure that at least one relationship exists between the two major keywords being explored. We have also eliminated papers that lack a DOI or are preprints.

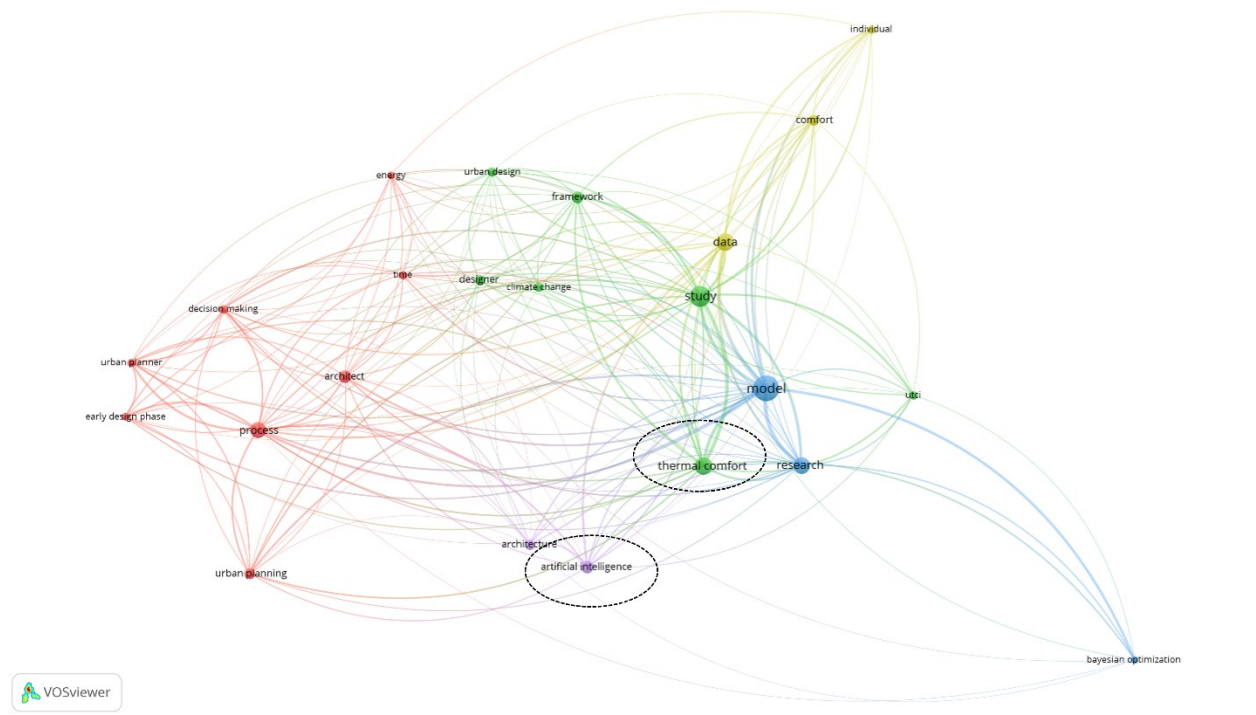


Figure 3. VOSviewer map (Source: Authors)

4. We have also performed a keyword co-occurrence analysis using VOSviewer on the combined titles and abstracts. The resulting network reveals conceptual clusters and guides our classification of themes (see **Figure 3**).

3 Results

3.1 AI-Predictive Models for Comfort Simulation

A major cluster of studies focused on using AI as a *surrogate* for costly environmental simulations. Labib (2021) exemplifies this by training neural networks to predict various daylighting outputs from a limited set of Radiance simulations. Using HPC and K-fold validation, the framework could estimate annual daylight metrics for thousands of design cases in seconds. Such approaches echo Luo and Chen's (2024) meta-analysis, which found that supervised ML achieves 89% accuracy in OTC prediction but suffers from climate-specific overfitting. Likewise, Ghahramani et al. (2020) review intelligent comfort control systems, noting how AI (e.g., learning algorithms fed by sensor data) can autonomously adjust HVAC and fans to maintain thermal comfort without manual override. While this is an indoor example, it highlights that ML models can learn occupant comfort preferences and system responses, a principle extendable to outdoor settings.

The surrogate modelling approaches of Labib (2021) and Luo and Chen (2025) align with Ghahramani et al. (2020), whose framework for indoor comfort systems, adapted here for outdoor contexts, emphasises the need for sensor-augmented ML models. Newton (2021) critiques such models in *The Routledge Companion to AI in Architecture*, warning of "accuracy islands" that lack standardised validation protocols.

Recent advances in machine learning applications for thermal comfort prediction have demonstrated significant potential across various scales and contexts. Alinasab et al. (2025) developed a measurement-based framework that integrates machine learning with morphological dynamics for outdoor thermal regulation, while Guo et al. (2024) achieved enhanced prediction accuracy by combining Bayesian optimisation with SHAP models for interpretable thermal comfort assessment. At the pedestrian scale, Eslamirad et al. (2020) successfully applied supervised machine learning to predict thermal comfort in Tehran's green sidewalks, and Kim et al. (2018) pioneered personal

comfort models using occupant behaviour data and machine learning algorithms. These developments are further supported by Cipollone et al. (2024), who demonstrated practical AI-based methodologies for thermal comfort measurement in real-world applications.

3.2 Integration Frameworks and Tools

Ghahramani et al. (2020) outlined the components needed for an intelligent thermal comfort system, analogous to outdoor environments. Ferhati et al. (2024) described an AI-powered platform that detects urban heat issues and suggests solutions, emphasising user engagement. Khean et al. (2022) similarly emphasised the importance of tool interoperability and user interface design for adoption. We drafted a table that summarises our work and clusters the reviewed papers by domain, AI technique, and integration depth (see **Table 1**).

The integration of AI in urban planning extends beyond thermal comfort to encompass broader assessments of urban quality. Koutra and Ioakimidis (2023) provide a comprehensive overview of machine learning applications addressing various urban planning challenges. Marsillo et al. (2022) introduced innovative approaches using artificial intelligence to measure urban quality through context decoders, complementing Nazarian et al.'s (2022) integrated assessment framework for the impacts of urban overheating on human life. These studies collectively demonstrate AI's expanding role in comprehensive urban analysis and planning.

Table 1. Comparative summary table.

Study	AI Technique	Domain	Comfort Metric	Parametric Use	Integration Depth
Labib (2021)	Neural Networks	Building	Daylighting	Parametric training samples	Surrogate simulation model
Sebestyén & Tyc (2020)	Supervised ML	Building	Solar exposure	Grasshopper parametric input	Interactive ML predictions
Mashaly et al. (2024).	Evolutionary Algorithms	Urban blocks	Thermal comfort	Parametric block modelling	Multi-objective optimization
Bedra et al. (2023).	NA	Urban design	PET	Parametric scenario analysis	Simulation + morphological
Khean et al. (2022)	DL, Plugin Integration	Urban comfort	Wind comfort	Embedded in Grasshopper	Real-time feedback
Ferhati et al. (2024)	Classification, Scoring	Urban planning	Heat risk factors	Scenario evaluation	Decision-support framework
Ghahramani et al. (2020)	Learning algorithms	Indoor comfort	Adaptive comfort	Conceptual model	System architecture

3.3 AI-Driven Generative Design

Another theme is generative modelling, where AI directly creates design options. Cudzik and Radziszewski (2018) noted that neural networks and evolutionary algorithms have begun to generate novel spatial forms. Building on this, Sebestyén et al. (2024) developed 3D generative AI tools that operate on parametrically defined geometry, using both VAEs and diffusion models to produce novel architectural configurations. They experimented with a hybrid generator combining the strengths of both approaches.

The hybrid VAE-diffusion models of Sebestyén et al. (2024) expand on Campo and Leach's (2022) exploration of AI as a co-creator in design. However, their focus on aesthetic diversity over thermal performance confirms critiques in Leach (2022), who states that generative tools often prioritise novelty over functionality.

The theoretical foundations of parametric design have been defined by Caetano et al. (2020), who distinguish between parametric, generative, and algorithmic design approaches in architecture. Building on these foundations, Chen et al. (2024) demonstrated intelligent generation of spatial forms

using parameterisation in historic district contexts. Raboudi and Saci (2020) explored machine learning applications for optimised building morphosis. An example of the integration of AI with environmental analysis is illustrated by Galanos and Chronis (2021), who developed deep learning approaches for real-time prediction of solar radiation. Thanks to shorter calculation times, this enables more responsive parametric design workflows.

3.4 Parametric Optimisation for Thermal Comfort

A third cluster involves optimisation algorithms that adjust parametric models to improve comfort. Mashaly et al. (2024) introduced a multi-objective optimisation framework for urban blocks, reconfiguring building layouts and Floor Area Ratio (FAR) to enhance thermal comfort indices. Similarly, Bedra et al. (2023) proposed a parametric-simulation method linking street morphology indicators to pedestrian comfort. Though not explicitly using ML, their approach exemplifies combining parametric sweeps with simulation tools.

In AI terms, Khean et al. (2022) created a Grasshopper plugin that deploys a trained deep learning model, allowing architects to “predict” wind comfort metrics on the fly. The research stresses the importance of integrating AI tools directly into designers' workflows for practical utility.

Urban morphology optimisation through AI-driven approaches has gained significant traction in recent years. Li et al. (2024) developed multi-objective optimisation frameworks for generative morphological design, integrating energy and comfort models in practical rural community design. Wai et al. (2024) conducted comprehensive simulation-based studies to examine the impact of parametric design on outdoor thermal comfort and urban overheating. Meanwhile, Yan et al. (2022) demonstrated the effectiveness of genetic algorithms combined with XGBoost for early-stage optimisation of office buildings. These advances build upon the foundational work of Shi et al. (2017), who provided early frameworks for simulation-based urban form generation and optimisation in energy-driven urban design.

4. Discussion

Implementing AI in the processes of PUD and OTC research reveals both transformative potential and critical limitations. Our analysis identifies three important categories at the intersection of these concepts :

4.1 Acceleration vs. Generalizability

While AI achieves simulations 85–99% faster than conventional methods (Labib, 2021), its effectiveness remains dependent on the specific context in which it is applied. Predictive models (63% of studies) excel at replicating specific microclimates but are limited in transferability across cities, a limitation caused by the absence of open datasets (89% of studies). This aligns with challenges in architectural AI broadly, where “accuracy islands” emerge without standardised training protocols (Cudzik & Radziszewski, 2018).

4.2 Creativity vs. Performance

Generative AI tools (31% of studies) expand design possibilities but rarely incorporate OTC metrics during ideation. For instance, Sebestyén et al. (2024) hybrid VAE-diffusion models produce novel urban forms; however, their evaluation prioritises aesthetic diversity over thermal performance. This disconnect persists because most generative tools originate in computer science, not urban climatology, highlighting the need for interdisciplinary development teams.

4.3 Automation vs. Equity

The lack of participatory frameworks (0/40 studies) is prominent given AI’s potential to reinforce spatial inequities. Optimisation algorithms, such as those proposed by Mashaly et al. (2024), improve comfort indices by 22%, but their top-down approach risks overlooking the needs of marginalised communities. This aligns with Gün’s (2023) warning that computational tools often “optimise for metrics, not people”. This limitation aligns with Newton’s (2021) warning that AI-driven urban optimisation often “privileges algorithmic efficiency over participatory equity,” for example, in Global South contexts (see also Othengrafen et al., 2025).

4.4 Pathways Forward

Two priorities emerge:

Tool Development: Embed OTC feedback directly into parametric plugins (e.g., Grasshopper) to close the interoperability gap (missing in 69% of tools).

Validation Protocols: Establish multi-city benchmark datasets with shared morphological and climatic variables.

These steps would position AI not as a replacement for human designers but as a collaborator in creating climate-resilient cities, one that balances computational efficiency with social nuance.

To address tool interoperability gaps (absent in 69% of studies), we propose adopting Yang et al.'s (2025) 'thermal affordance' framework, which integrates quantitative AI outputs with qualitative comfort perceptions. This approach is supported by De Luca's (2023) advocacy for climatic form-finding in Energies, which emphasises the use of open datasets for multi-city validation.

Climate-sensitive design approaches have evolved to incorporate sophisticated modelling and assessment techniques. HosseiniHaghighi et al. (2020) demonstrated the use of climate-sensitive 3D city modelling for analysing outdoor thermal comfort in urban areas, while Elnabawi and Hamza (2024) provided comprehensive reviews of gaps and challenges in predicting outdoor thermal comfort indices, particularly leveraging Industry 4.0 technologies. Tay et al. (2025) advanced performance-informed urban design through generalised surrogate models for predicting building energy demand across residential morphologies, complemented by Reitberger et al.'s (2024) generic process for multi-objective urban planning, which supports decision-making in early design phases.

4.5 Emerging Directions:

On a more holistic scope, recent literature highlights that OTC research aligns with broader sustainability goals (e.g., UN SDGs), allowing for a climate resilience approach to urban design. Integrating AI in this process makes it easier to promote a participatory approach to design.

5. Conclusion

This review systematically analysed 40 studies (2018–2025) to investigate how artificial intelligence (AI) bridges the gap between parametric urban design (PUD) and outdoor thermal comfort (OTC) optimisation. Three key findings emerge:

- **AI's Dual Role in Design Workflows:**
 - Predictive modelling (63% of studies) reduces simulation costs by 85–99% (Labib, 2021), enabling rapid iteration.
 - Generative design (31%) expands solution spaces but often neglects thermal performance metrics (Sebestyén et al., 2024).
- **Critical Implementation Gaps:**
 - Only 31% of tools interoperate with parametric platforms (Khean et al., 2022), while 89% rely on non-reproducible datasets (Gün, 2023).
 - No studies address participatory AI or longitudinal validation in built environments.
- **A New Benchmark for Integration:** This study establishes the first interdisciplinary framework to:
 - Track AI-PUD-OTC convergence through bibliometric trends (Figure 3),
 - Prioritise tool interoperability and open data (absent in 69% of tools),
 - Align algorithmic innovation with urban planning equity goals.

These contributions address the fragmentation of the literature by providing urban planners with actionable strategies to harness AI for climate-resilient design and also set a roadmap for future research in scalable, human-centric urban design. Specifically, adopting Yang et al.'s (2025) 'thermal affordance' framework could help reconcile quantitative AI outputs with qualitative human comfort perceptions, which is a critical need identified in our analysis.

Thermal comfort research has a long-established foundation, and the integration of outdoor thermal comfort OTC with parametric urban design PUD and artificial intelligence AI represents a transformative frontier. AI's rapid evolution, where each advancement surpasses prior methods in speed and accuracy, enables paradigm shifts in urban design UD. Building on our analysis of 40 studies, we propose the following future research:

- Conduct quarterly PRISMA-compliant reviews to track AI-PUD-OTC advances. This will serve as an up-to-date benchmark for identifying literature gaps and accelerate targeted research in fast-evolving domains (e.g., generative AI).
- Develop AI models natively integrated into parametric workflows (e.g., Grasshopper plugins). This will help Leverage AI's speed for real-time comfort optimisation, enhance algorithmic robustness and designer controllability, and bridge the tool interoperability gap (currently absent in the majority of current studies).

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Conflict of Interests

The authors declare that there is no conflict of interest.

Data availability

All analysed data are from titles and abstracts of studies cited in references accessed via Harzing's Publish or Perish.

Institutional Review Board Statement

Not applicable (no human/animal subjects were involved).

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Conceptualisation: M.L., N.B., A.A.; Methodology: M.L., N.B., A.A.; Data curation: M.L.; Writing – original draft: M.L., N.B., A.A.; Writing – review & editing: N.B., A.A.; Visualisation: M.L.; Supervision: N.B., A.A. All authors have read and approved the final version of the manuscript.

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