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A review on artificial intelligence applications for facades

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ABSTRACT

This review applies a transformer-based topic model to reveal trends and relationships in Artificial Intelligence (AI)-driven facade research, with a focus on architectural, environmental, and structural aspects. AI methods reviewed include Machine Learning (ML), Deep Learning (DL), and Computer Vision (CV). Overall, a significantly growing interest in applying AI methods can be observed across all research areas. However, noticeable differences exist between the three topics. While CV and DL techniques are applied to image data in research on the architectural design of facades, research on environmental aspects of facades often uses numerical data with relatively small datasets and classical ML models. Research on facade structure also tends to use image data but also incorporates numerical performance prediction. A major limitation remains a lack of generalizability, which could be addressed by more comprehensive datasets and novel DL techniques. These include concepts such as Physics-Informed Neural Networks, where domain knowledge is integrated into hybrid data-driven models, and multi-modal diffusion models, which offer generative modeling capabilities to support inverse and forward design tasks. The trends and directions outlined in this review suggest that AI will continue to advance facade research and, in line with other domains, has the potential to achieve a level of maturity suitable for adoption beyond academia and into practice.

Contents

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Acronyms

3D	Three-dimensional
AI	Artificial Intelligence
AR	Augmented Reality
BIM	Building Information Modeling
BIPV	Building-integrated PV
CAD	Computer-Aided Design
CFD	Computational Fluid Dynamics
CMP	Center for Machine Perception
CNN	Convolutional Neural Network
CV	Computer Vision
DL	Deep Learning
DT	Decision Trees
ECP	Ecole Centrale Paris
FCN	Fully Convolutional Networks
FEA	Finite Element Analysis
FNN	Feedforward Neural Network
GA	Genetic Algorithm
GAN	Generative Adversarial Network
GIS	Geographical Information System
GNN	Graph Neural Network
GSV	Google Street View
HOG	Histogram of Oriented Gradients
ICP	Iterative Closest Point
kNN	k-Nearest Neighbors
LLM	Large language model
LR	Logistic Regression
LSTM	Long short-term memory
ML	Machine Learning
MLS	Mobile laser scanning
MLP	Multi-Layer Perceptron
MLR	Multi-Linear Regression
MEx	Multi-expansion loss
NN	Neural Network
NLP	Natural Language Processing
OSM	Open Street Map
PCA	Principal Component Analysis
PCD	Point cloud data
PCM	Phase-change materials
PINN	Physics-Informed Neural Network
PV	Photovoltaic
RANSAC	Random Sample Consensus
RF	Random Forest
RL	Reinforcement Learning
RNN	Recurrent Neural Network
SARSA	State-Action-Reward-State-Action
SfM	Structure from Motion
SIFT	Scale-Invariant Feature Transform
SVM	Support Vector Machines
TF-IDF	Term Frequency–Inverse Document Frequency
TLS	Terrestrial Laser Scanning
UAV	Unmanned Aerial Vehicle
VAE	Variational Autoencoder
VR	Virtual Reality
WoS	Web of Science

1. Introduction

1.1. Background

A building facade serves as an interface between the indoor and outdoor environment and, as such, is crucial for creating comfortable indoor spaces while meeting structural and aesthetic requirements. As they stand in a dialog with their surrounding climatic and cultural context, facades can vary considerably in terms of style, design, purpose, materiality, and technology.

Over the years, methods and techniques used in facade design have changed drastically, reflecting the dynamic link between architecture and technology. Facade design was initially based on manual calculations, craftsmanship, and practical knowledge of materials and structural principles. In the 20th century, the introduction of Computer-Aided Design (CAD) software brought about a transformation for architects, allowing them to create more complex designs with greater accuracy and productivity [1]. Later, the development of Building Information Modeling (BIM) systems enabled a collaborative and multidisciplinary approach that included detailed information on materials, energy performance, and construction processes [2]. More recently, facade design strategies have evolved to incorporate the use of AI and big data, indicating a clear shift towards data-driven approaches.

In general, AI is concerned with imitating human intelligence in computer systems and machines. The task is to create systems that have intellectual abilities such as logical reasoning, meaning discovery, generalization, learning from previous experience, and creativity [3]. Leveraging current AI applications and their emerging methods, building facades are increasingly being designed, maintained, and inspected for various purposes, spanning the domains of building physics, structural engineering, and architectural design.

1.2. Previous reviews

While a comprehensive literature review on AI applications for facades is still lacking, several specialized reviews have been published in recent years, focusing either on specific aspects of facades or specific methods of AI applications in buildings (Table 1). Researchers have focused on tall buildings [4], glass facades [5], net-zero and positive-energy buildings [6], or a specific application of AI techniques such as three-dimensional (3D) reconstruction [7], in-situ thermal transmittance assessment [8], human–cyberphysical systems [9], and automation of architectural design tasks [10]. These reviews also utilized conventional review methods and are limited to a smaller selection of articles, typically reviewing between 40 and 200 articles.

Additionally, research on facades is indirectly covered in literature reviews on AI applications for conceptual design [11] and architectural design [12–14]. These studies offer a comprehensive overview of AI in architectural design processes, but facades are only discussed to a limited extent. Therefore, a more targeted review that specifically addresses AI applications for facades remains necessary and is the focus of this work.

While a substantial body of literature focuses on optimizing facade designs [15,16], these studies are not included in our review. Although optimization techniques such as Genetic Algorithm (GA) are a subset of AI, they primarily aim to find optimal solutions based on predefined objectives. In contrast, this review focuses on AI applications that encompass broader aspects of human intelligence, such as learning, reasoning, and perception, to perform complex tasks beyond optimization, including adaptive control systems, predictive analytics, and computer vision for facade analysis.

1.3. This review

This study examines three aspects of facade design, namely architectural, environmental, and structural design, with a focus on the incorporation of AI applications in various design processes. Although all three aspects of facades are often interrelated, these categorizations are used to structure and organize the discussion. From an architectural perspective, facades are the face of a building exposed to the public space, and they are characterized by their architectural treatment [18]. Materials, color, texture, and the composition of openings (windows and doors) are the components of a facade that reflect the design vision and functional requirements of the building. From an environmental point of view, facades should respond to solar radiation (both heat and light from the sun), allow ventilation, minimize heat loss, and dampen noise [19]. Structurally, an essential requirement for any facade is the ability to effectively support and distribute loads to the primary load-bearing structure to ensure its stability and safety [20]. These three main topics and their subtopics will be presented in an extensive analysis and discussion based on existing research.

This review considers various types of facades that have been the subject of AI applications. Building upon a conventional bibliometric analysis, we used a Natural Language Processing (NLP)-based method, namely transformer-based topic model, and large language model (LLM) to analyze the topics as well as the materials and methods of studies on facades and AI applications (Fig. 1). This approach enabled us to cluster a large corpus of articles, which facilitated and structured further manual analyses. To the best of the authors' knowledge, this review is the first to focus on the application of AI in the design, operation, and maintenance of building facades.

A comprehensive literature search was carried out based on the publications in the Web of Science (WoS) Core Collection [21]. Search terms related to AI and facades were identified (Table 6), and then the articles were retrieved. After the removal of duplicates and manual screening, 323 articles were selected for review. First, a thorough analysis of the existing literature is conducted, focusing on bibliographic information such as keywords, citations, and authors, as well as the methods, data, and tools used in these studies to represent the current scientific landscape. A topic model trained on abstracts is then implemented to highlight the current research areas. Topic modeling includes text embeddings generated with a pre-trained sentence transformer, the result of which is later used for dimensionality reduction and clustering of articles. The identified clusters, i.e. topics, were represented by frequent terms based on Term Frequency-Inverse Document Frequency (TF-IDF) for the clusters. We grouped these topics into the categories described in the next paragraph and discussed them in detail. Further details of the methodology can be found in Appendix A.

This research aims to provide readers with insights into the relationship between research areas, data requirements, and AI applications for facades by addressing the following research questions:

1. What is the current state of research on the use of AI for the design, operation, and maintenance of building facades? (Section 2.1)
2. Which AI methods and data types are used thereby? (Section 2.2)
3. What are the current research topics on AI applications for facades, and what are their limitations and future research directions? (Section 3)
4. What are the trends and relationships between topics, data, and AI applications, and what are potential future directions? (Section 4)

The rest of the paper is organized as follows: Section 2.1 presents the scientific landscape through an analysis of bibliometric data. Section 2.2 introduces the definitions used in the article for AI methods and data that can be used for facade research. Section 3 discusses the

Table 1
Previous literature reviews, in which facades and keywords related to AI (Table 6) have been explicitly mentioned in the abstract, title, or author keywords.

Title	Year	Journal	Ref.
Data-driven prediction and optimization towards net-zero and positive-energy buildings: A systematic review	2023	Building and Environment	[6]
In Situ Thermal Transmittance Assessment of the Building Envelope: Practical Advice and Outlooks for Standard and Innovative Procedures	2023	Energies	[8]
Detailed Three-Dimensional Building Facade Reconstruction: A Review on Applications, Data and Technologies	2022	Remote Sensing	[7]
Long-Standing Themes and Future Prospects for the Inspection and Maintenance of Facade Falling Objects from Tall Buildings	2022	Sensors	[17]
Scientometric mapping of smart building research: Towards a framework of human–cyber–physical system	2021	Automation in Construction	[9]
Artificial intelligence for structural glass engineering applications — overview, case studies and future potentials	2020	Glass Structures & Engineering	[5]
A review of the use of examples for automating architectural design tasks	2018	Computer-Aided Design	[10]

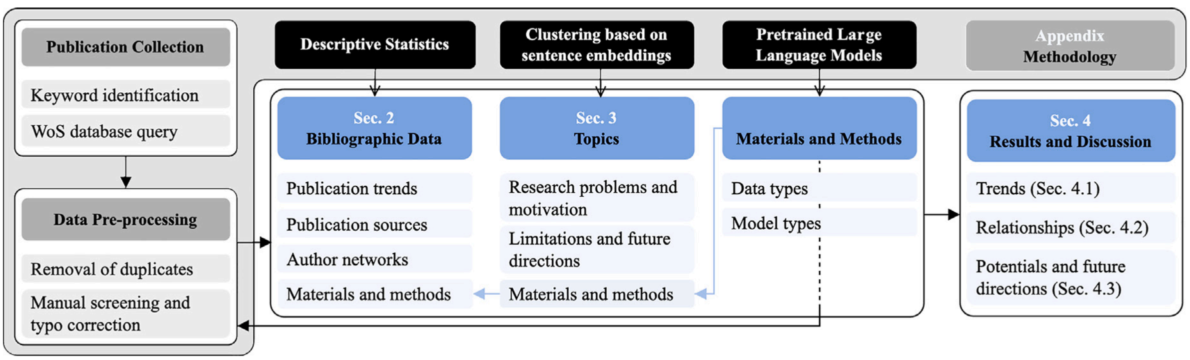

Fig. 1. Overview of the study.

findings in the subtopics of architectural, environmental, and structural design of facades. Section 4 provides insights into the research topics concerning materials and methods used, and discusses potential directions for future research. We conclude our findings in Section 5. A detailed description of the methodology is available in the Appendix A. The list of articles included in this review along with extracted information about topics, data, and models, is provided in the Supplementary Materials. The topic model is also available on Github.[1]

2. Scientific landscape

2.1. Bibliographic data

After removing duplicates, manually screening titles and abstracts, and assessing the use of AI methods within each study, 323 articles were selected for further processing. A more detailed description of the pre-processing steps is available in the Appendix A. Notably, 92% of the articles were published within the last decade, from 2013 to 2023. Fig. 2 shows the trend in the number of articles and unique authors per article over the years. On average, approximately four authors contributed to each article.

In line with growing research interest, journals have increasingly published articles at the intersection of facades and AI (Fig. 3). *Automation in Construction* is the leading journal with a total of 17 articles and has been publishing research on this topic since 2014. Following this, *Building and Environment*, *Energy and Buildings*, and *Journal of Building Engineering* have the next highest number of publications, each ranging between 10 and 14 articles on this subject.

Fig. 4 shows author networks and citations as indicators of seminal works within the broader corpus. Regarding the analysis of structural damage on facades, the authors of the publications [22–24] have the highest number of publications and cumulative citations (marked with 1 in Fig. 4). Another collaborative and highly-cited group of studies, focusing on procedural modeling and building reconstruction, includes the authors of [25–27] (marked with 2 in Fig. 4). Research in a related area, encompassing procedural modeling, architectural style recognition, and facade parsing, has been represented by the authors of [28,29] (marked with 3 in Fig. 4). Towards the periphery, additional highly-cited works include Liu et al. [30], which explores Machine Learning (ML)-based evaluation of urban qualities considering facades,

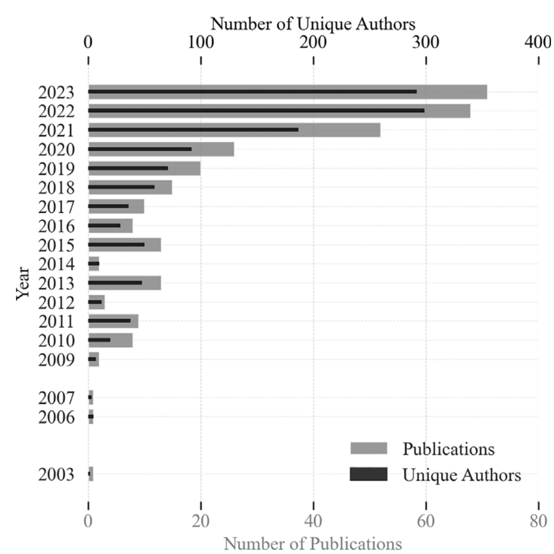

Fig. 2. Publications and unique authors per year.

[1] https://github.com/ycdrn/ai-facades_lit-rev.git.

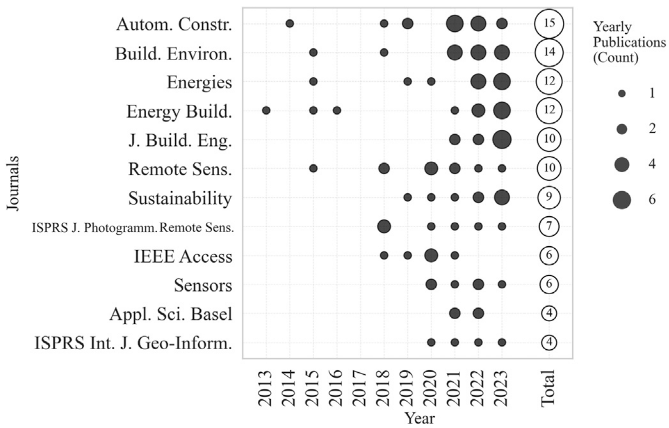

Fig. 3. Publication sources and trends of the published papers.

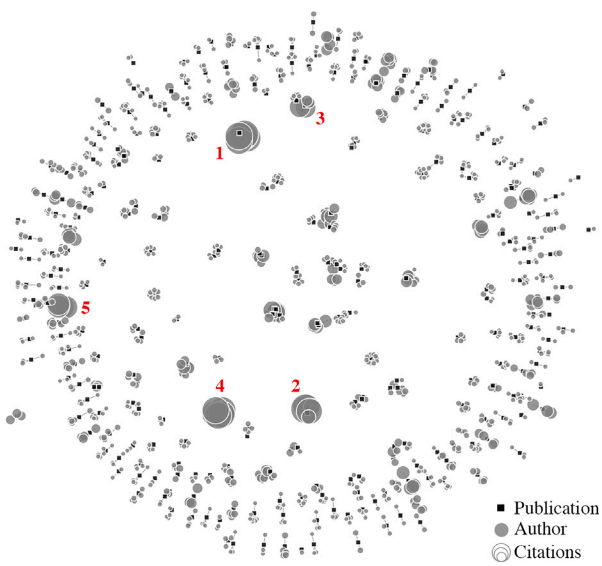

Fig. 4. A visualization of author networks, publications, and citations. Authors with more connections and joint publications are positioned at the center of the figure, while those with fewer collaborations are positioned towards the periphery. An interactive version of the figure is available at https://plotly.com/~aycaduran/3/.

and Kang et al. [31], which focuses on the classification of building instances based on street views (marked with 4 and 5 in Fig. 4).

2.2. Materials and methods

2.2.1. Data

Data is essential for training an AI model, and the effectiveness of AI methods depends critically on the availability and quality of data. The data can be structured or unstructured. Structured data related to facades includes numerical, categorical, time series, and spatial information that can be easily tabulated and stored in databases. Numerical data can include properties of the materials used in a facade, dimensions of facade components, or environmental conditions such as humidity and temperature. Categorical data may include energy ratings, material types, or building use types. Time series data can be, for example, measured environmental data such as temperature and air quality or monitored structural health parameters such as vibration and tilt. Spatial data, also geolocalized data, inherently contains geospatial attributes such as latitude and longitude or elevation. Unstructured data, such as image, video, audio, or text data, on the other hand, refers to information that does not fit into conventional database formats. High-resolution photos or street views are examples of image data. Text data can include architectural specifications, historical documents, and maintenance logs.

For each article reviewed in this study, we identified the data type(s) used in the training of AI models (Fig. 5). Numerical data and image data have been used most frequently since the first studies, while text data is the least frequently observed. With recent advances in NLP, particularly LLMs, this may change in the coming years. The most commonly coupled data types are image and spatial data, such as 3D laser scans and street imagery; image and numerical data, such as infrared thermograms and humidity measurements; and image and categorical data, such as the image and use type of a building (Fig. 5, right).

2.2.2. AI methods

AI techniques include a variety of methods, such as machine learning, deep learning, and computer vision (Fig. 6), which offer potential applications in facade research:

Machine Learning (ML) is a branch of AI that focuses on statistical algorithms that enable computers to learn from data and make predictions or decisions, allowing them to generalize to unseen data. ML algorithms can be categorized into three types based on the learning approach: Supervised, unsupervised, and reinforcement learning, although there is no formal definition or rigid taxonomy to draw clear boundaries [32]. Supervised learning involves learning a function that maps an input to an output based on exemplar input–output pairs. Algorithms such as linear regression are used to predict continuous values, and classification algorithms such as Logistic Regression (LR), are used to predict discrete values. Several other algorithms, such as Support Vector Machines (SVM), Decision Trees (DT), and Neural Network (NN), can be used for both tasks. In unsupervised learning, the algorithm learns patterns from unlabeled data, often aiming to discover hidden structures within it. Clustering algorithms, such as k-means and hierarchical clustering, and association rule learning are commonly used for this purpose. Reinforcement Learning (RL) involves taking suitable action to maximize rewards in a given situation. Various programs and machines utilize RL algorithms, such as Monte Carlo Methods, Q-learning, and State-Action-Reward-State-Action (SARSA), to find the best possible behavior or path in a given context.

Deep learning (DL), a subset of ML, includes NN with multiple layers and representation learning [33]. Among these NNs, Feedforward Neural Network (FNN) forms the foundation, where information flows in one direction from input to output. Convolutional Neural Network (CNN) are characterized by capturing patterns in images by learning spatial hierarchies of features. This is achieved through the use of convolutional layers that apply filters to the raw input data, pooling layers that reduce dimensionality, and fully connected layers that predict output labels based on the extracted features. Sequential models such as Recurrent Neural Network (RNN) and long short-term memory (LSTM) have been developed to recognize patterns in data sequences, such as numerical time series data from sensors or text sequences, by maintaining a memory of previous inputs using their internal state. Recently, generative models such as Variational Autoencoder (VAE) and Generative Adversarial Network (GAN) have gained prominence in the literature due to their ability to produce novel, realistic outputs often used in image synthesis and style transfer. Moreover, attention mechanisms have recently revolutionized Deep Learning (DL) models by allowing them to dynamically focus on relevant parts of the input data to improve their performance in tasks such as sequence processing or recognizing patterns. Deep RL is also used for feedback-based learning from actions and Graph Neural Network (GNN) for data structured in graphs.

Computer vision (CV) is a field of AI that enables computers and systems to derive meaningful information from digital images, videos, and other visual inputs, allowing them to take action or make recommendations. For instance, feature detection and matching methods,

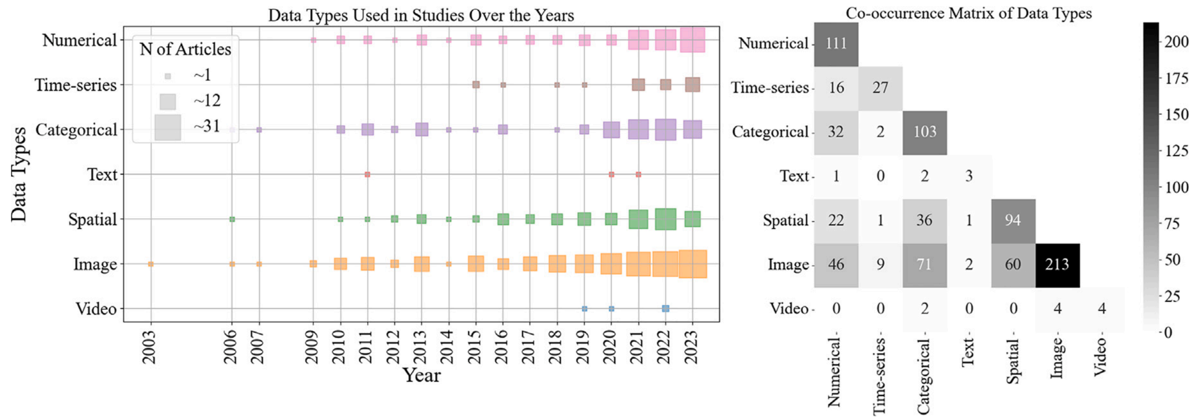

Fig. 5. Data type used in the studies over the years (left) and data type co-occurrence (right).

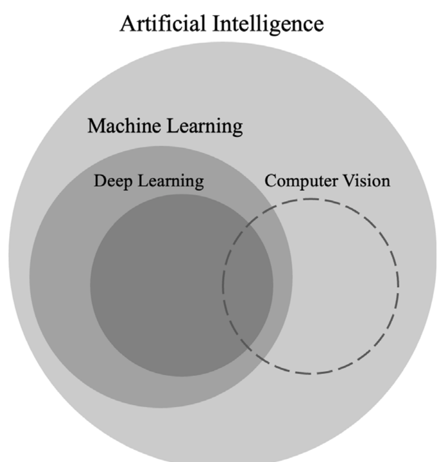

Fig. 6. A diagram of AI methods and their relationships.

such as Scale-Invariant Feature Transform (SIFT) and Speeded-Up Robust Features, help identify specific features in images, such as corners or edges, and find their correspondences across different images. Geometric transformation and alignment methods such as Random Sample Consensus (RANSAC) and Iterative Closest Point (ICP) aim to adjust images to standardize viewpoint or scale, improving the accuracy of other Computer Vision (CV) tasks. Edge and contour detection methods focus on identifying boundaries of objects, facilitating tasks such as shape detection and object tracking. Finally, image segmentation techniques, such as superpixels and active contours, facilitate the classification of objects by grouping similar pixels or detecting object boundaries in complex scenes.

A collection of publications related to AI applications in facade research was searched on WoS bibliographic database [21]. The core concepts described above and more specific methods and models were used as key terms in finding articles along with other search terms related to AI (Table 6 in the Appendix A). Additionally, for each article processed, the core AI concept(s) are captured. As shown in Fig. 6, ML, DL, and CV methods can overlap. In the rest of the paper, although it is difficult to draw boundaries between methods, ML methods that do not involve any DL techniques are referred to as *classical ML*. Similarly, for CV methods, if a CV method does not include any of the ML or DL techniques, it is referred to as *classical CV*.

3. Research topics

This chapter focuses on three main topics: (1) architectural, (2) environmental, and (3) structural design of facades. Each topic is described briefly. Subsections provide examples to illustrate the applications and significance of AI in this field. The common methods, tools, and data are also presented for each subtopic. Finally, the limitations of each topic and future research directions are briefly discussed. An expanded list of articles and datasets are provided in the Supplementary Materials.

3.1. *Architectural design*

The first main topic identified is the architectural design of building facades, focusing primarily on the design and visual aspects of a building envelope. This includes the selection of materials, colors, and textures, which not only contribute to the visual appeal of the building but also reflect its spatial organization and the context in which it is located. Architectural design also encompasses the geometric arrangement of windows, doors, and other openings, as well as the integration of decorative elements. Processes such as site analysis, sketching, drafting, and creating realistic visualizations and models are part of the facade design development.

Of the 323 articles, 162 articles are mainly concerned with the architectural design of facades. More specifically, AI is used for (1) the detection and segmentation of facades and facade components, (2) the identification of architectural style and characteristics of facades, (3) the identification of facade function, materials, and age, (4) the generative design and completion of building facades, and (5) the creation of 3D models (Fig. 7). A summary of the main findings on this topic can be found in Table 2.

3.1.1. *Identification of facades and facade components*

The semantic segmentation and detection of building facades and facade components is one of the largest subtopics in the topic of architectural design (Fig. 7, marked within the dashed lines). Most commonly, windows [41,42] or various other architectural elements [43,44] as well as the complete facade geometry in urban landscapes [28,45] are segmented or detected using images and 3D point cloud data (PCD). Motivations for segmenting facades include improving 3D reconstruction workflows for cultural heritage documentation and feature extraction [41,44,46,47], improving the creation of more realistic architectural 3D models [26,36], effective augmented reality integration [48–50], and benchmarking the accuracy of segmentation and parsing models using open datasets [51–53]. Besides benchmarking studies, segmentation models are used for feature extraction from facades as a preliminary step to improve modeling and design workflows.

Two major data types, image and spatial, are used in the segmentation models. The majority of studies employed open datasets such as the Center for Machine Perception (CMP) Facades Database [54], Ecole Centrale Paris (ECP) Facades Database [55], eTRIMS [56], Graz50 [57], ArtDeco [58], FacadeWHU [59], and Mapillary Vistas [60] for images

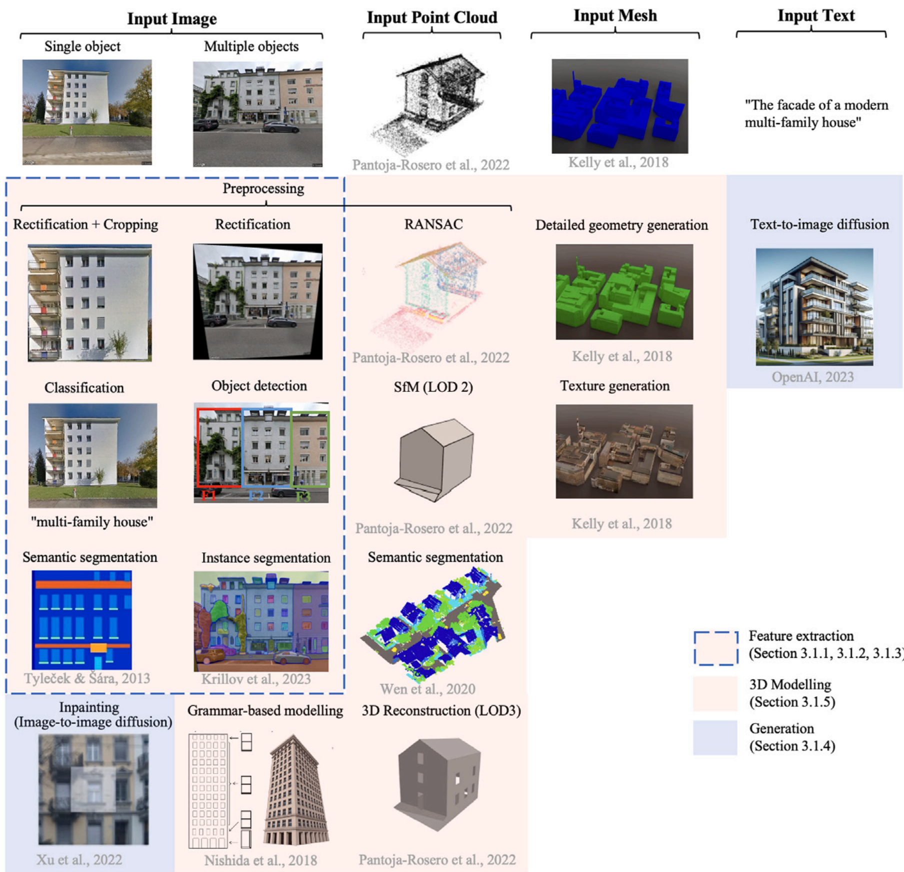

Fig. 7. Common AI tasks related to architectural design of facades for different input data types.
Sources: Nishida et al. [26], Xu et al. [34], Pantoja-Rosero et al. [35], Kelly et al. [36], Wen et al. [37], Tyleček and Šára [38], OpenAI [39] and Kirillov et al. [40].

Table 2
Summary of AI research related to the architectural design of facades.

Objectives and tasks	– Extract facades in urban scenes or components of facades such as windows, doors, etc. – Extract qualitative features such as architectural style and geometric features. – Extract quantitative features such as building function, facade materials and building age. – Generate partial or complete facade images. – Improve the level of detail and workflows for the creation of 3D models. – Benchmarking new methods for image segmentation or object recognition.
Advantages	– Reduce dependency on expert knowledge. – Automation of labor-intensive tasks. – Improve 3D modeling, cultural heritage documentation, AR/VR applications. – Help to understand and automate the documentation of architectural diversity. – Automate computationally intensive tasks such as generating realistic images.
Challenges	– Limited generalization and applicability beyond the training dataset. – Dependence on data quality and quantity. – Complexity and diversity of facade architectures. – Dependence on technologies such as LiDAR, stereo imaging, or UAV-derived datasets. – High computational requirements due to complex networks and large datasets. – Methodological limitations of AI models.
Future directions	– Enhancing data and model scalability and robustness. – Improving model efficiency and real-time applications. – Broadening applicability to diverse architectural styles. – Integration of AI techniques into BIM and parametric modeling.

and Paris-CARLA-3D [61], Dublin3D [62] and RueMonge2014 [63] for 3D point clouds. Some researchers also created their own datasets [41, 42,50]. While most studies have trained AI models on images without occlusion, the segmentation of occluded images has also been tackled [64,65].

The methods investigated include a variety of DL architectures and algorithms, ranging from established frameworks such as PSPNet, Yolo, and Mask R-CNN to more recent network architectures such as Solov2 and EACNet. In addition, some studies investigated RL methods [66], the integration of DL with traditional CV techniques through Structure from Motion (SfM) approach [67] and multi-task networks [50]. Recent studies have also employed spatial and channel-based attention modules [42,50,65], cross-view feature aggregation [65], and autoencoder–transformer combinations [68]. The use of Bayesian methods [29,64] and knowledge graphs for explainable AI [46] were also explored, aligning with research trends in the broader literature.

3.1.2. Identification of architectural style and formal organization

Several studies aimed to identify the architectural style and characteristics of facades (Fig. 7, marked within the dashed lines). Key tasks include identifying guidelines that imply a formal organization of the facade [50,69], analyzing symmetry [70], and classifying facade style [28,46,71–73]. The primary motivations of these studies are to improve and automate the understanding and documentation of architectural diversity and heritage. Specific motivations include reducing dependence on fieldwork and facilitating the identification of architectural styles with less labor [71,72], improving explainability in applications related to cultural heritage [46], improving the experience of urban and cultural heritage through augmented reality and semantic enrichment of 3D models [70,73], support in procedural generation of urban environments [28] and better representation of street scene perception [69]. Some studies also combine architectural style classification models with semantic segmentation models [46,50].

The data type used is primarily images in the articles in this subtopic, with most datasets created by the authors themselves. These include a dataset with annotated images of monument facades [72], a dataset with annotations of floor level lines [50], a dataset comprising over 50,000 street views from Amsterdam and Stockholm [71], and several other self-generated datasets consisting of labeled facade images based on architectural style [28,73,74]. Some studies used the publicly available Architectural Style Dataset [75], AHE Dataset [76], and MonumaAI [72]. Unlabeled images were also used for unsupervised CV tasks [69].

Various methods and architectures have been used, ranging from traditional ML and CV algorithms to DL models. Early approaches include SVM with radial basis function kernels [73] and formal grammar rules to classify building symmetries [70]. Other ML and CV techniques, such as isomap and Hough transform, were applied to analyze the visual structures of streetscapes, while a combination of Gabor filters, SVM, and Naive-Bayes nearest neighbor classifiers were used in multi-level classification methods [28,69]. Later DL implementations include recursive context routing in combination with 1D and 2D CNNs for semantic segmentation [50] and the integration of CNNs with knowledge graphs, as in the use of Faster R-CNN and ExplaNet [46]. Recent articles included adaptations such as CA-MSResNet, which leverages group and dilated convolutions to capture detailed architectural features [74], indicating a shift towards more context-aware and spatially attentive AI models.

3.1.3. Identification of facade function, materials and age

The identification of non-geometric quantitative information such as function, materials, and age of buildings is important for various applications. Motivations for classifying building function include improving data that is not available with traditional remote sensing [31,77], improving 3D city models with semantic data to support smart cities and virtual and augmented reality applications [49], overcoming the inefficiencies and high costs associated with the manual classification of dwellings in urban land registers and improving the decision-making of authorities and companies [78–80] and reducing the reliance on expert knowledge for classification of building function in historic buildings [81]. Materials are classified with the motivation of supporting repair, reuse, and recycling efforts [82] as well as understanding the albedo of an urban context for solar panel installations [83], while age information is predicted due to its relevance to architectural history, energy demand, property valuation, and urban planning [71].

The majority of the studies in this subtopic use Google Street View (GSV) images [31,49,71,77,79,80,82–84] to train the learning models. In addition, other open data sources, such as Open Street Map (OSM) and Common Crawl, were also used [31,84]. A few studies exclusively used their own image datasets [81] or in addition to the open image sources [80].

Early studies used SVM in combination with classical CV methods such as GIST, Histogram of Oriented Gradients (HOG), and SIFT-Fisher vectors to classify street views into different types of use [77]. CNNs such as AlexNet, VGG16, and ResNet variants are used in tasks such as spatial sampling optimization and building classification, often complemented by advanced techniques such as spatially adaptive sampling [31] and transfer learning [71]. Hybrid models that combine CNNs with traditional classifiers such as SVMs or DT are also observed to improve classification accuracy by integrating different feature extraction methods [78,79]. More recent studies have adopted newer architectures such as Vision Transformers and EfficientNets [80,82] and integrated object-contextual representations and attention mechanisms [81,83].

3.1.4. Generation of facades

The generation of new, novel facades and the completion (also known as inpainting) of existing facade parts are the tasks of generative AI and can be most closely associated with creative design process (Fig. 7, marked in blue). Completion studies usually focus on the removal of obstacles from facade images [85,86] or from 3D point cloud data [87] to improve 3D reconstruction or the usability of the data for various other purposes such as scene reconstruction, environmental impact assessment, and urban mapping, or to improve existing image completion methods by training and testing their proposed methods on facade images [34,88–90]. Most of the generation studies aim to generate images of historical facades [91–93] for historical urban redevelopment while preserving traditional architectural styles. In addition, the existing generative workflows for generating realistic contemporary facade images [94] and the generation of multiple facades of the same building [95] were addressed as research problems.

Commonly used datasets include street-level imagery [85,86] from sources such as GSV and custom image collections from specific urban areas or historical districts [92–94]. Urban scene datasets such as Cityscapes [96], CMP Facades [54], NYU datasets [97], and eTRIMS [56] are also frequently used to test image generation and inpainting algorithms [34,88–91]. In addition, laser-scanned point clouds of buildings [87], images from the Solar Decathlon competition [95], and scanned images of historical facades from a book [91] show the variety of the data sources used.

The reviewed studies utilize primarily GAN and various sophisticated image-processing frameworks. Many of the studies use well-established GAN models such as pix2pix, CycleGAN, and StyleGAN2 [92, 93,95]. Other architectures, such as the Cascade Refinement Network and the Inception-ResNet, have been integrated into GANs to further refine the generative processes by improving the resolution and quality of the synthesized images [88]. The introduction of hybrid models that include elements for the computation of perceptual losses or the use of novel losses such as the multi-expansion loss (MEx) aim to optimize the training process and the output quality of these networks [34,90]. Several studies have proposed modifications and extensions to these models to address specific challenges. For example, the integration of U-Net and attention mechanisms with GANs is often mentioned to improve image completion and inpainting by increasing semantic accuracy and detail preservation [34,89,95].

In addition to scientific work, state-of-the-art diffusion and attention models can create visualizations of brand-new facades or edit existing facades in a matter of seconds. Mostly, these techniques aim to eliminate computationally intensive ray tracing models for realistic visualization, overcome the dependency on a skilled illustrator or animator, enhance the creative design process, and even encourage co-creation. These techniques are mainly based on text-to-image or image-to-image diffusion models, i.e. they take text or image inputs and generate images as outputs. Since these models are trained with large amounts of data and randomness plays a role, dozens, if not hundreds, of new designs can be created from the same text input. In addition to multipurpose text-to-image generation tools such as DALL-E [39], Midjourney [98], and Stable Diffusion [99], several other web-based tools offer specialized features for facade design [100,101]. However, most of these tools are limited by their control mechanisms and generative capacity. For example, a prompt may not produce the desired results if the prompt contains a feature that is underrepresented in the training data [102].

3.1.5. Creation of 3D models

Studies focusing on 3D modeling of facades form the second largest sub-topic within the main topic of architectural aspects of facades, with 41 articles (Fig. 7, marked in orange). The studies mainly deal with 3D model generation using grammar-based approaches [26,27,36], 3D reconstruction from PCD [103–105] or 2D images [106–108], or a combination of both [37,109], and 3D reconstruction coupled with semantic segmentation or recognition of a complete facade in an urban environment [110,111], openings on the facade [112,113], scaffolding [114], and various other facade components [67,115–117] and materials [107]. A key motivation for these studies is to automate and improve the detailing and accuracy of 3D models to support planning and documentation through the use of AI techniques.

The primary data types employed include aerial and terrestrial images, high-density laser scans and point clouds, and, increasingly, data from Unmanned Aerial Vehicle (UAV) and mobile laser scanning (MLS) systems. In most studies, self-generated datasets based on high-density Terrestrial Laser Scanning (TLS) data or MLS data [103,105], UAV-derived imagery [106,109,112], and street-level imagery of specific sites [36,111] are used. Open datasets such as ISPRS benchmarks [118], EuroSDR [119], Paris-Rue-Madame [120], XIAMEN-buildings [121], PARIS-CARLA-buildings [61], IQmulus & TerraMobilita Contest dataset [122], and the Semantic3D.Net [123] datasets are mostly used for benchmarking and to support additional tasks such as segmentation and detection of facade components.

CV techniques are pivotal for image and spatial data analysis. CV algorithms for the detection of edges and contours, such as Canny Edge Detector [124], and Line Segment Detector [125], methods for feature extraction and matching, such as Fast Point Feature Histograms [105], Signature of Histograms of Orientations [114], SIFT [106] and RANSAC [86,105,107,113,125], methods for image segmentation and classification, such as Hough Transform [113,115,117,124], Active Contours [124], Implicit Shape Model [86] and Mean Shift Segmentation [27], photogrammetric techniques such as SfM [107,112,114,117] and Multi-View-Stereo [107,117] and finally image registration and transformation techniques such as ICP [103,105,111] and Relative Total Variation [125] are used alone or in combination with ML techniques. Some studies have adopted ML approaches, such as DT [26], Random Forest (RF) [26,114], boosted DT [111], and SVM [26,107] to classify facade components, Bayesian Networks [109] to estimate uncertainty related to predicting facade components, and K-Means Clustering [26] to group similar facade elements without prior labeling. DL approaches have increasingly become central to advancing the field, particularly through the use of CNNs and GANs. CNN architectures including, VGG-16, FC-DenseNet, and Mask R-CNN [108], U-Net [112,116], DeepLabV3+ [67], and Faster R-CNN [113] have been used for semantic segmentation for detailed and accurate modeling of building facades. GANs, such as FrankenGAN [36] and Pix2Pix [47], have been applied to enrich the textural and geometric details in the models. Most recently, 3D U-net with SAF-C3 [116] and RanLA-Net [115,116] are employed to process and segment the 3D PCD directly.

3.1.6. Achievements, limitations and future work

Studies have shown that AI has opened up several novel possibilities in the architectural design of facades that were not possible before, such as the automatic extraction of information from facade images, efficient 3D reconstruction with minimal effort, and the generation of novel facade images without manual effort. More specifically, the semantic segmentation of regular facades, i.e. rectangular facades as well as facade components, can be performed using DL techniques with a continuously increasing accuracy over the years. Most recent studies report a pixel accuracy of about 97% when segmenting rectangular windows on ECP and CMP datasets [43,44,126]. Different facade elements can be recognized with up to ≈86% mean intersection over union (IoU) score [43]. Using current CNN architectures with attention mechanisms, the facade styles can be classified with an accuracy of more than 90% in the AHE_Dataset [72,127]. We also observe that the recent studies report satisfactory accuracy for material classification tasks, although the lack of benchmark datasets makes it difficult to compare model performances [82,83]. Segmentation and classification models are widely used on 3D PCD and images to create 3D models with semantically consistent geometric details and textures of facades [26,36]. Recent developments in generative AI techniques have also enabled new research possibilities. Although currently under-researched, completion of facades is possible with an average Peak Signal-to-Noise Ratio (PSNR) of ≈32 dB and Structural Similarity Index (SSIM) of 95%, respectively, on the CMP facades dataset [128].

A common limitation is a heavy reliance on specific, detailed, annotated datasets, which often lack comprehensiveness and fail to represent diverse architectural styles, cladding materials, or geometric compositions of facades. This dependency is compounded by issues like temporal inconsistencies and geographical biases, particularly evident in sources like GSV images. More robust datasets are needed. Except for a few studies, the handling of dynamic, occluded, or complex scenes is often inadequate, resulting in difficulties with background separation, texture recovery, and accurate image reconstruction under varied urban conditions. Future work aims to adopt more sophisticated models to solve these data quality variances and representation biases. Model types can also have some limitations. For instance, GANs often produce facade images that lack diversity, while gradient-based edge detection algorithms like the Sobel operator can be affected by noise and may result in thick or double edges, as well as missing some fine or weak edges. Future work aims to refine existing models and explore new methods, such as diffusion models and transformers. Furthermore, the high computational demands required for processing complex models, such as RL architectures and large-scale 3D reconstructions, limit their practical deployment, especially in real-time applications. Besides the benchmarking studies, future research aims to integrate the AI models into BIM models, Augmented Reality (AR) and Virtual Reality (VR) applications, as well as design and planning workflows. The summary of the research on architectural design can be found in Table 2.

3.2. Environmental design

The second focal topic centers on the environmental design of facades, mainly concerning the environmental sustainability of building envelopes. The application of AI in this area is motivated by objectives such as reducing computing times of physics-based simulators with surrogate models, characterizing envelope and material properties with non-intrusive techniques, and enabling human-centric controls of

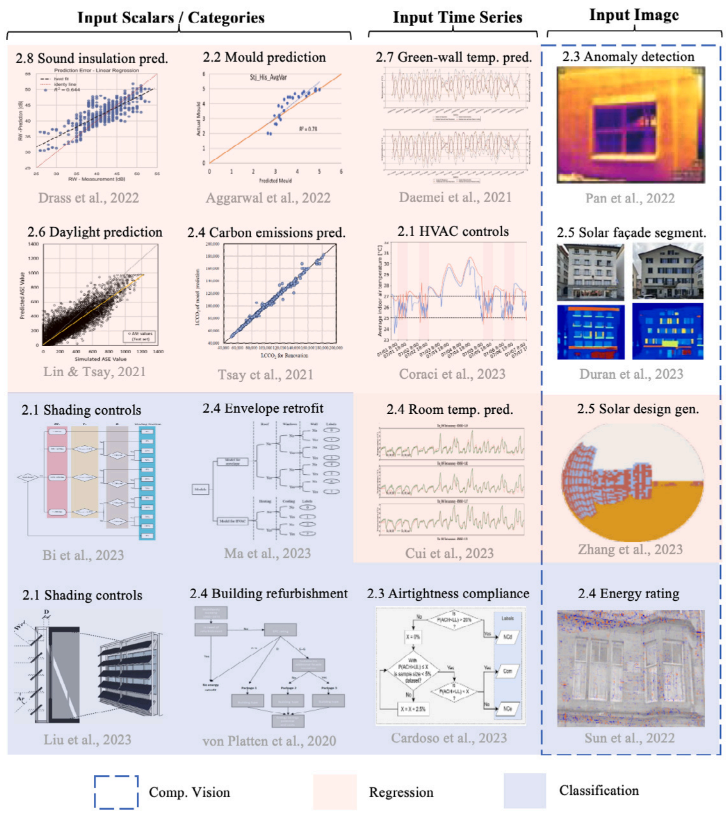

Fig. 8. Common AI tasks related to environmental facade research for different input data types.
Sources: Drass et al. [129], Aggarwal et al. [130], Daemei et al. [131], Pan et al. [132], Lin and Tsay [133], Tsay et al. [134], Coraci et al. [135], Duran et al. [102], Bi et al. [136], Ma et al. [137], Cui et al. [138], Zhang et al. [139], Liu et al. [140], Von Platten et al. [141], Cardoso et al. [142] and Sun et al. [71].

Table 3
Summary of AI research related to environmental design, operation and maintenance of facades.

Objectives and tasks	– Identifying facade features (window-wall-ratio, building age, building type, etc.) descriptive of environmental performance (heat loss, daylight utilization, acoustic performance, etc.). – Recommending facade design solutions or retrofitting interventions. – Generating optimal control policies for adaptive facades. – Lowering the usage barrier of complex and slow building performance analytics, e.g., Computational Fluid Dynamics (CFD). – Generating reliable prediction models using multimodal, sparse, and/or noisy data.
Advantages	– Enabling non-intrusive techniques (e.g., based on images instead of wall probing). – Lowering the barrier to using advanced analytics (e.g., CFD) by surrogate models. – Human-in-the-loop design methodologies and human-centric adaptive controls. – Inferring from noisy, sparse and multimodal data.
Challenges	– Existing models do not generalize well. – Small datasets for training. – High effort in creating individual training datasets. – Datasets often not shared publicly slowing down development. – Simulation-based datasets often not validated. – Expertise required in training and tuning advanced AI techniques.
Future directions	– Applying advanced DL algorithms instead of classical ML models. – Integrating domain knowledge into ML, e.g. with PINN. – Using multimodal datasets (visual, numerical, time-series, 3D). – Combining simulation data with measurements for training.

adaptive facades. Fig. 8 provides a graphical overview of common tasks and data types. Achievements, challenges, and future directions of AI research for the topic of environmental facade design are summarized in Table 3.

The 103 papers reviewed are grouped into the following sub-topics: (1) adaptive facades and controls, (2) envelope characterization, (3) compliance checking and diagnostics, (4) building energy and emissions, (5) solar energy, (6) daylight utilization, (7) airflow, ventilation and microclimate, (8) sound and acoustics.

3.2.1. *Adaptive facades and controls*

Adaptive facades are systems with dynamic elements, such as sunscreens or apertures, which can be operated either manually or automatically. Most articles in this area focus on controlling these adaptive facade systems. Whereas, some studies also apply AI to support the design process through analytics, such as the prediction of daylight utilization and building energy loads [143].

AI techniques in controls are employed to determe time-resolved optimal states of dynamic elements in order to improve thermal and visual comfort or reduce energy consumption. Several studies utilize environmental sensors for temperature, irradiation, and illuminance to inform control algorithms [144,145]. In some cases, controls focus on the building energy system rather than the facade system, where envelope properties and shading states, alongside occupancy and meteorological conditions, are defined as key inputs for control decisions [135]. Liu et al. [140] demonstrated AI-driven controls for an energy-generating facade, where tilt angle schedules of dynamic shades with attached Photovoltaic (PV) are determined to optimize for both solar energy generation as well as daylight utilization. Other studies explore more specialized topics such as the controls of ventilated facades with Phase-change materials (PCM) [146], optimizing heat flux in thermally activated walls [147], determining the states of electrochromic glazing [148], and load forecasting and flexibility provision in microgrids at the district scale [149].

Data for AI models is sourced from simulations [135], sensor readings [150], or a combination of both [144]. Given that occupant behavior is a crucial factor in adaptive facades, surveys are also utilized for data acquisition [145,148,151]. The primary data type is numerical, such as sensor data or performance metrics, often in the form of time-resolved loads or schedules. Only a few studies incorporate categorical variables, such as discrete states for tilt angles, which are typically ordinal. For instance, Kobayashi et al. [152] applies a binary classifier using k-Nearest Neighbors (kNN) to optimize the operational schedule of electrochromic glazing states. The use of visual data is observed in very few studies, as exemplified by Wang et al. [151] where hand gestures are detected via cameras and translated into occupant thermal comfort perception.

Regarding the AI techniques, RL is most commonly used, with fewer examples relying on supervised regression and classification models. A typical application of regression is provided by Papinutto et al. [145], where gradient boosting DT was trained as a surrogate model for daylight prediction. In this approach, AI is not used directly for control actions but rather for generating signals to inform shading controls. Among the studies utilizing RL, some apply deep RL algorithms, such as Q-Learning [153] and Q-iteration coupled with auto-encoders [154], whereas others employ classical RL, such as SARSA [146]. An interesting line of research involves combining black-box RL controllers with explicit methods, such as model predictive control [149]. Overall, controls and RL for adaptive facades constitute an extensive and rapidly developing field, with focused reviews providing further insights [155].

3.2.2. Envelope characterization

The articles reviewed focus on the physical characterization of both novel constructions and existing or historic buildings. A key motivation for applying AI, particularly for existing buildings, is the potential for non-intrusive assessment techniques. Additionally, AI facilitates the characterization of an unknown material system with minimal experimental data. Several studies use AI models to predict mold growth, moisture content, or hygrothermal effects within envelopes [130,156–158], thermal resistance of enclosed airspaces [159] and opaque walls [160], air temperatures within ventilated facades [161], or PCM performance [162]. AI techniques are also applied for novel constructions, including models for describing heat flux in thermally activated envelopes with hydronic loops [147] and for predicting indoor air temperatures when special facade coatings are applied [163].

Data is sourced from simulations [147,157], measurement databases such as ASHRAE [159], or experimental campaigns [158,161,163]. Some studies also combine measurements with simulation data [160,162,164]. The primary data type is numerical, such as temperature or moisture readings, and sometimes time series data. For instance, Baasch et al. [160] uses sub-hourly metered data to determine whole-building heat loss coefficients with RNN and CNN. Visual data is used less frequently; examples include Khan et al. [164], where thermal cameras are employed to assess the thermal resistance of envelopes and moisture within the walls.

Most commonly, AI techniques for regression tasks are utilized. These include XGBoost and Multi-Layer Perceptron (MLP) [147]; sequential models such as Time Delay NN [165]; RNN such as LSTM [161]; and even CNN variants suited for sequential data, such as WaveNet [157] are utilized. A recent study also combines LSTM with transformers [163].

3.2.3. Compliance checking and diagnostics

Compliance checking and diagnostics is another subtopic, with a focus on assessing whether buildings meet regulatory standards or identifying fabric properties related to energy efficiency, ventilation, and moisture. The use of AI techniques is motivated by their potential to simplify measurement campaigns by requiring fewer samples and shorter time frames, to enable non-intrusive techniques [8].

CV and visual data are the most prominent in this subtopic. For instance, Yi et al. [166] use GSV images of facades to classify building types by age and use, to aid decision-making in optimal energy retrofitting interventions. Using CapsNet, a CNN based on ResNet and pre-trained on ImageNet, Pan et al. [132] analyze thermal images to detect heat bridges and ventilation anomalies. Similarly, Arjoune et al. [167] apply various CNN architectures for the anomaly detection and segmentation of infrared facade images. Previous studies that rely on thermal images tend towards classical CV [168]. An older example with a similar research objective is provided by Ribarić et al. [169], where traditional image processing techniques, feature extraction methods, and a knowledge-based system that uses fuzzy logic are combined for inference and decision-making. Another research direction combines thermal images with HDR photos or photogrammetry [168,169], for instance, to create 3D models from infrared images and photogrammetry [170]. While most of the studies collect infrared images manually, some studies mount thermal cameras on vehicles [171] or on UAV [167].

Non-visual techniques are primarily used for regression and classification of numerical data. For example, Agaian and Balasubramanian [172] focus on the prediction of wall temperatures of unknown constructions using Multi-Linear Regression (MLR) and FNN, while Cardoso et al. [142] use various regression and classification models, such as SVM, DT, RF, and XGBoost, to predict air change rates for airtightness compliance checking of the Energy Performance of Buildings Directive (EPBD) norms. Gumbarević et al. [173] present an example of time series prediction, where a custom LSTM was used to speed up in-situ measurement campaigns that typically require weeks of data sampling.

3.2.4. Building energy and emissions

Motivations for applying AI techniques in studies focusing on building energy and emissions include integrating occupancy and other uncertainties into performance assessment, developing fast surrogate models as replacements for simulation programs, and identifying facade features that can reduce energy consumption or carbon emissions. Most of the reviewed research falls into the category of surrogate models trained on simulation data, using whole-building simulation programs such as EnergyPlus [143], software for transient heat and moisture transport through walls such as WUFI [174], or software for life cycle emissions such as Tally, SimaPro [175]. A main driver is to facilitate iterative design processes, for instance, by integrating surrogate models directly into optimization routines [176].

Simulation outputs are more frequently used as training data, particularly when the analysis is at the building scale. Measurement data are utilized for more specific tasks, such as estimating the impact of envelope coatings on indoor temperature [163]. In addition, surveys and municipal databases, such as energy ratings, are used to combine socio-economic observations with technical features [177] and, in some cases, with simulation or visual data [178,179]. However, the primary data type in this topic is numerical, which is reflected in the popularity of supervised regression models, including DL architectures such as

FNN and Bayesian Networks, and classical ML models such as DT, RF, MLR, or SVM. Some studies utilize time series data to predict indoor air temperature or heat transmission [163,180], disaggregate total loads for non-intrusive load monitoring [181], or develop a time-resolved energy demand model [138]. In these studies, more advanced DL architectures such as RNN and transformers are also employed, in addition to classical architectures such as FNN and RF.

When features and predictions cannot be easily described numerically, such as building use type, climate region, retrofitting interventions, or energy ratings, a classification task is performed [141,178,182]. Certain ML techniques, such as RF, Linear Genetic Programming, and SHAP values, are also suitable for sensitivity analysis to provide insights into the significance of design features for the performance metric to be predicted [138,175]. More recently, CV techniques have been adopted for building energy estimation, using GSV images and CNN to classify the energy ratings of buildings [182] or to determine whether a building is suitable for retrofitting [141,179]. An unconventional approach is presented by Zhao et al. [183], where energy and daylight performance for different facade design variants are pre-simulated, and screenshots of the facades are stored in a look-up table. Using CV techniques, hand-drawn designs are matched with the most visually similar design in the database and the known performance.

3.2.5. Solar energy

AI techniques have also risen in popularity in solar energy [184], despite well-established existing physics-based principles [185]. The benefits of using AI include faster performance evaluation to facilitate iterative design processes, deriving secondary performance metrics such as energy demand and daylight utilization from solar radiation, or enabling predictions with incomplete information when 3D models, construction details or vegetation data are missing.

The majority of identified articles focus on either total annual [166,186–189] or higher resolution time-resolved [139,190–192] values. Predictions are often inferred from geometric and spatial information, such as urban morphology, sky view factors, tilt and orientation, LiDAR data and photogrammetry, and digital elevation models, as well as meteorological data [187,188,191,192]. Complex spatial data is commonly transformed into simpler metrics. Local measurements, such as power output at a 5-min resolution, are only utilized for Building-integrated PV (BIPV) electricity prediction [192]. A few studies use AI to directly infer optimal solar facade designs, such as identifying design parameters for tandem Perovskite–Silicone solar cells [193], formulating PV suitability design guidelines [186], or determining optimal PV panel tilt angles [140].

Due to the prevalence of feature engineering in this topic, many studies rely on classical regression and classification models while achieving high prediction accuracy. Models used include MLR [187], DT, Gaussian processes, SVM, and LR [188], XGBoost and RF [191], Radial Basis Functions [193], and, for short-term PV output time series, FNN, DT and Quadratic SVM [192].

More recent studies utilize CV techniques and CNN-based architectures to predict surface solar irradiation in 3D [189], forecast BIPV power based on photogrammetry [190], and segment facade images from GSV to identify suitable surfaces for BIPV deployment using Pix2pix [102]. Additionally, Zhang et al. [139] utilize segmented fisheye images of urban environments to predict annual hourly time series on roofs and facades, by utilizing beta-VAE and ID-GAN, as well as DoppelGANger based on LSTM. In CNN-based studies dealing with visual inputs, the training data itself can stem from either simulation programs [139,187,189], measurements [166,190,191], a combination of both [140,193], or from urban cadasters and other databases such as GSV [102,186,188,192].

3.2.6. Daylight utilization

Similar to the topic of solar energy, the estimation of daylight in indoor spaces is a well-established field with validated simulation programs such as Radiance and standardized measurement procedures. Nevertheless, AI techniques can be beneficial in this domain, for example, as surrogate models to replace computationally expensive raytracing software [194], or to infer daylight performance from metadata such as facade images [195]. AI is also used for daylight-driven facade controls, such as for the actuation of blinds, dimmable light sources, or electrochromic glazing [145,148,195].

Approximately half of the reviewed studies rely on raytracing-based simulation data for their models [176,194], whereas the remainder rely on images, measurements, and surveys, sometimes in combination with simulation data [144,145,148,166,183,195,196]. Chen [196] addresses the challenge of bridging discrepancies between building simulation and actual measurements. In this study, both data sources are used to train an FNN for predicting indoor illuminance, achieving higher prediction fidelity compared to simulations alone. Another example of mixed data sources is provided by Papinutto et al. [145], where survey data and raytracing simulations are used to predict illuminance and glare, as well as the corresponding human response to visual comfort.

Classical regression models, such as MLR, FNN, and Gradient Boosting are commonly used in surrogate models [145,176]. Studies on controls frequently employ RL architectures [148] and CV techniques [195]. Some studies integrate daylight surrogate models into GA-based optimization workflows [194]. These studies have some overlap with the topic of building energy, presumably due to the significant impact of daylight on building energy consumption. Consequently, Nault et al. [176] develop surrogate models to predict both daylight utilization and energy demand coupled within an optimization workflow. The Urban-SOLve tool by Nault et al. [176] uses approximate solar irradiation simulations on building surfaces as inputs to an MLR model to predict daylight performance and energy demand, thus serving as an example of physics-informed AI.

3.2.7. Airflow, ventilation, and microclimate

The environmental performance of facades is largely influenced by their convective interaction with the outdoor environment. Simulation programs, such as CFD, and standardized physical experiments, such as the Blower Door Test, are available to evaluate ventilation performance. In this area, AI techniques can speed up computationally intensive simulations or make inferences from metadata, e.g., images, urban context, or facade construction elements.

Only four papers have been identified on this topic using the data-driven literature review methodology, one of which is a review paper. Daemei et al. [131] trained an MLP to predict temperature and relative humidity reduction inside buildings with green facades. The model is trained on urban microclimate simulations with EnviMet, supplemented by a 4-day measurement campaign. Shahrestani et al. [197] is another urban microclimate study, where Pix2Pix has been trained on outputs from EnviMet simulations to predict urban thermal comfort on generic urban layouts with vegetation. Their work shows the impact of facade materials and other urban design parameters on urban comfort, and the utilization of a surrogate model is motivated by allowing a fast assessment of urban design variants. With a custom CNN, Rampini et al. [198] utilize actual facade images to recognize surface materiality and color, from which the contribution of the facade to the urban heat island is inferred. A thematically slightly different study is presented by Taptiklis et al. [199], which explores how different house and facade characteristics impact the presence of visible mold and musty odor. An MLR regression model is developed for New Zealand based on three surveys conducted in 2005, 2010, and 2015, involving 1,616 timber-frame homes.

3.2.8. Sound and acoustics

The acoustic performance of facades is particularly important in noisy urban environments, where sound protection from ground and aerial traffic or busy public squares is essential. In this area, AI is used to predict technical variables, such as noise penetration and occupants' behavioral responses to noise disturbances. The use of AI techniques is motivated by the need to avoid extensive experimental data collection or computationally expensive simulations.

Only five studies have been identified on this topic, and all of them use classical ML regression approaches. In Jones et al. [200], second order Polynomial Regression is used to predict the wind-induced noise risk from perforated facade panels on high-rise buildings. Drass et al. [129] predict the sound insulation performance of different glazing types, using LR, RF, and DT, trained on experimentally determined sound insulation values for different industrial glazings. Ögren et al. [201] use LR trained on vibration measurements and questionnaires of occupants to predict annoyance levels from sound and vibration originating from nearby railways. Kluizenaar et al. [202] present a similar approach for road noise by training a LR model on survey data from a large population (N = 18,000) and utilizing the Dutch SRM2 norm, a Geographical Information System (GIS)-based noise calculation procedure. Argiento et al. [203] focus on the reproducibility of experiments and compare identically conducted sound insulation level experiments in different laboratories. Using Bayesian Models and Principal Component Analysis (PCA), the authors could establish relations between the individual experiments and filter for variations, thus addressing inconsistencies and repeatability in experimental research. In stark contrast to the other environmental topics reviewed, nearly all the studies on sound and acoustics rely on measurements and survey data, with only one study also using simulation data from a CFD solver [200].

3.2.9. Achievements, limitations and future work

AI and ML have led to several significant achievements in the environmental design of facades. A major breakthrough is the wide utilization of surrogate models that can provide near real-time performance feedback, offering an alternative to slow and tedious simulations. These surrogate models are especially popular in building energy analysis, solar and daylight assessment, and airflow prediction, thus facilitating collaborative performance-driven design processes. For the characterization of physical properties of constructions and material systems, as well as diagnostics and compliance checking, AI has introduced a new set of non-intrusive techniques based on CV and time series forecasting. Traditionally, intrusive techniques, such as wall probing, or long-term measurement campaigns, were required for such tasks. A key topic for sustainable facade design is circularity and life-cycle assessment, which was underrepresented in our review, with only a few studies addressing it [82,134,175]. However, AI, particularly through CV techniques, holds the potential for advancing this domain by enabling automatic material recognition and identifying the recycling potential of building components. In the topic of adaptive facades, RL have contributed significantly to the popularization of human-centric controls, where individual preferences regarding thermal and visual comfort can be effectively integrated into dynamic facade systems. Finally, another significant achievement is in AI-driven generative design of facades using algorithms such as VAE and GAN for open-ended, forward, and inverse performance-driven design [139].

A major limitation consistently reported across all topics is the lack of generalizability in AI models. Often, models are trained for well-defined conditions, such as specific climates or building types, and are likely to fail when applied to conditions outside the training data. Specific to RL controls is the challenge of transferability, which refers to the ability of a trained model, such as facade controllers, to be applied to unseen facade systems. Furthermore, RL controls carry a risk of long training times when deployed, as they may require extensive time to converge to well-performing control policies.

When simulation data is used exclusively for the training of surrogate models, a common limitation is the lack of validation with real buildings or facades. Therefore, some studies use a mix of simulation data and real measurements. Another challenge arising from this approach is that databases tend to be relatively small and limited since the measurements are tedious to conduct or require computationally expensive simulations, such as CFD. As a result, many studies employ simpler ML models instead of DL models, such as autoencoders or transformers, which require significantly larger datasets.

When real data is used for training, model performance heavily relies on data quality. Common sources of error and noise include damaged or poorly installed sensors, as well as human bias and behavioral randomness in occupant studies. Additionally, limitations may arise from the inherent capabilities of the chosen AI algorithm, such as the inability of a CNN architecture to handle long-range dependencies. Some studies also report low prediction accuracy, which authors generally aim to improve through hyper-parameter tuning, newer learning models, or improved datasets.

3.3. Structural design

The third facade topic focuses on structural performance, durability, and safety. With 58 articles identified, this topic represents the smallest subset of articles in this review. In this context, AI is employed to enhance the accuracy and precision of structural inspections, such as detecting facade structural defects. Automation of these labor-intensive tasks is a key motivation for using AI in detection processes, which also helps mitigate the potential risks associated with human inspection. Additionally, AI facilitates the development of predictive maintenance strategies, allowing for cost reductions in building repairs. The application of AI also supports real-time processing and monitoring, enabling rapid response and intervention to maintain the safety of facade structures.

Articles in this section are categorized based on the different facade-related tasks for which AI is employed (Fig. 9): (1) detection and classification of defects, (2) structural health monitoring, (3) detection and prediction of environmental agents, (4) structural component detection, (5) structural dynamics and load analysis. A summary of key insights is provided in Table 4.

3.3.1. Defect detection

The largest group of papers employs advanced AI and imaging technologies to detect, classify, and analyze defects in building facades, from cracks to broader deterioration like erosion, spalling, and discoloration, which compromise facade integrity. Detailed assessment of facade cracks with limited manual input [205,216–224] and comprehensive classification of defect types for automated reporting [213–215,225–230] are the main objectives. AI enhances the efficiency and precision of crack detection in challenging environments like high-rise buildings, streamlining labor-intensive processes [205,217,218], and reduces error-prone and hazardous manual detection of defects and contaminants under different environmental conditions [213,214,225]. Autonomous systems using DL-powered robotic imaging devices reduce human involvement in inspections, enabling real-time detection of cracks in glass facades and immediate response to defects [220].

Image data serves as the primary input for training AI models to detect and segment facade defects and damages. Most studies use annotated images with explicit labels for supervised learning models. Some studies show that models can begin with minimal data and progressively enhance performance by incorporating larger amounts of unlabeled data, for example using uncertainty filters in semi-supervised learning [216] or informativeness-guided active learning strategies [224]. Many studies develop their own datasets or augment existing ones for specific research needs by incorporating data from established datasets [217] and generating synthetic data [221]. UAVs, such as drones with high-resolution cameras, capture images of facades from

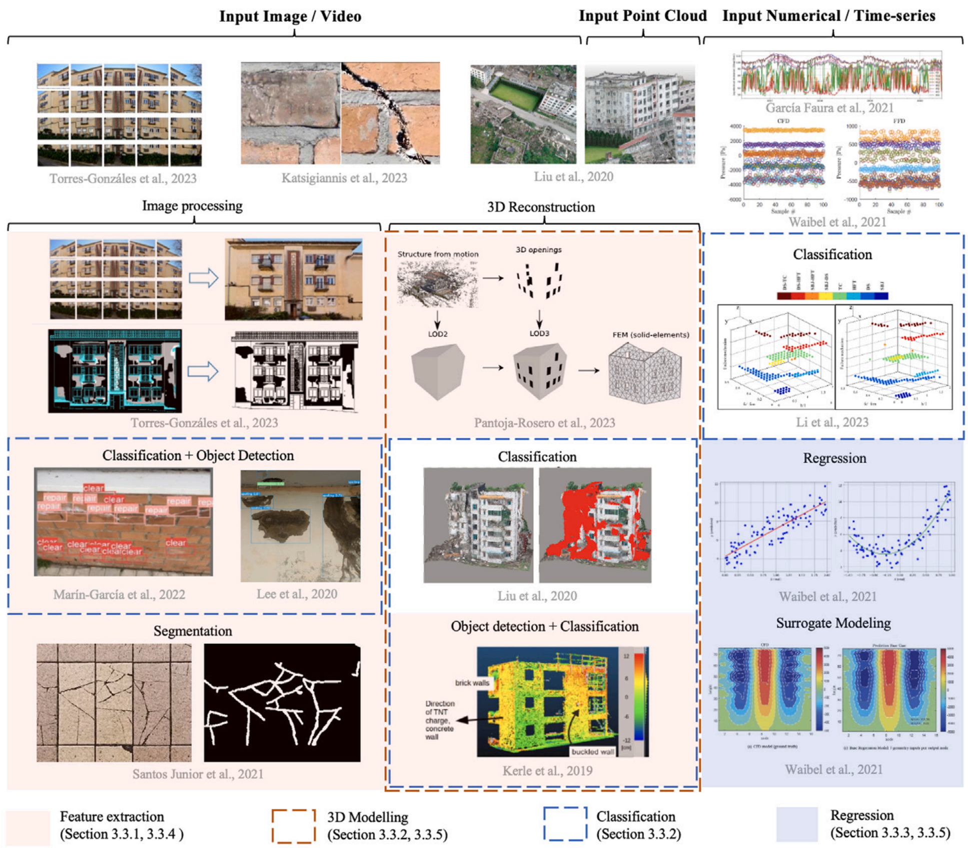

Fig. 9. Common AI tasks related to facade structural research for different input data types.
Sources: Torres-Gonzáles et al. [204], Katsigiannis et al. [205], Liu et al. [206], García Faura et al. [207], Jiang et al. [208], Pantoja-Rosero et al. [209], Li et al. [210], Waibel et al. [211], Tran and Hoang [212], Marín-García et al. [213], Lee et al. [214], Junior et al. [215] and Kerle et al. [23].

Table 4
Summary of AI research related to the structural design and maintenance of facades.

Objectives and tasks	– Classify facade defects such as cracks and erosion. – Automate structural health assessments for maintenance and disaster response. – Detect structural components for risk assessment and 3D modeling. – Predict environmental aging effects and maintenance needs. – Model facade structural responses and wind loads.
Advantages	– Automates inspections and anomaly detection. – Minimizes risk to inspectors by using AI and UAVs. – Lowers costs of traditional structural simulations. – Supports predictive maintenance and risk evaluation.
Challenges	– Relies heavily on data quality and representativeness. – Faces generalization challenges across diverse environments. – Incurs high computational costs for DL training and real-time use. – Affected by environmental variables like lighting and weather. – Requires validation with real-world data.
Future directions	– Enhance diversity and quality of data. – Integrate multiple data types to refine detection capabilities. – Boost model robustness and efficiency for real-time applications. – Conduct real-world testing and validation of models.

different angles, leveraging improved accessibility [217]. To complement image data, Draganić et al. [231] uses tachymetry to obtain spatial measurements of control points on the facade for accurate geometric precision. Additionally, Chen et al. [232] enhance high-resolution images with GIS and location-based information from UAVs, facilitating systematic storage, retrieval, detection, assessment, and documentation of facade defects.

The studies predominantly use DL techniques for segmentation, feature extraction, and classification tasks. CV algorithms are used to enhance image datasets using filtering techniques [215] or to preprocess images using feature extraction techniques, such as SIFT [224] and HOG [220], before applying DL models. A few studies exclusively use CV techniques, like color space analysis and thresholding, for detection and classification to identify facade defects [204]. Classical ML techniques are integrated with DL architectures for tasks like classification and regression [216,224,227].

CNNs are commonly used for classifying and detecting facade defects [216,219]. Multiple studies fine-tuned VGG-16 model for detection tasks [205,222,229]. In Guo et al. [229], meta-learning is also utilized to dynamically adjust the CNN for optimized learning from underrepresented data classes. Rozsas et al. [221] employ a Siamese CNN to compare synthetic crack patterns in masonry facades with images annotated by structural engineers. CNN models often serve as the backbone for more complex tasks, such as pixel-level crack and defect segmentation using architectures such as U-Net [215,217], DeepLabv3 [218] and Mask R-CNN [223,230]. For real-time detection of contaminants and defects, architectures like YOLOv3, v5, and v7 are used for their speed and efficiency [213,225,226]. For accurate and effective defect detection in complex backgrounds, a few studies employ Faster R-CNN [214,227] while others implement Retina-net to balance speed and accuracy in detecting small objects [224].

3.3.2. Structural health

A second group of papers utilizes AI for automated assessment of building facade integrity and health over time. These studies employ various AI techniques to automate and enhance building maintenance and integrity evaluation processes, motivated by the reduction of manual inspection costs and minimization of human errors. In post-disaster scenarios, AI-powered, UAVs-aided automated inspections enable safer, remote evaluations. Additionally, AI is used to manage and process large datasets from modern surveying methods like TLS. For structural health monitoring, AI is applied to a variety of tasks, including semantic segmentation of historic masonry structures from image data [233] and point cloud segmentation and classification for structural damages [234]. Object detection and classification are used to identify different types of structural damages in post-disaster scenarios [22,23,206,235] and texture irregularities [236].

The data types in these studies include high-resolution images from drones and UAVs [22,24,233,235], street-level images, and thermal infrared images from field studies to enhance texture mapping and object detection over time [236]. Multi-temporal and multi-view datasets with images taken before and after seismic events are also used [24]. TLS is employed to derive spatial data using CV techniques for geometric model creation and structural deviation analysis in Masiero and Costantino [234], while SfM techniques derive detailed 3D models from images in Vandenabeele et al. [233]. Combining image data with geometric data from 3D models is explored to enhance the complexity of recognized damage patterns [22,23].

For these tasks, DL techniques are extensively used, particularly CNN architectures combined with image data for segmentation and detection. Popular architectures are classical Fully Convolutional Networks (FCN) [233] but also region-based CNNs (Faster RCNN) with architectures such as ResNet, Inception and their variants as backbone [235]. When working with PCD for segmentation and classification, CV techniques are combined with ML algorithms, such as SVM [234], or Latent Dirichlet Allocation (LDA) topic model and RF classifier [206].

3.3.3. Environmental agents and durability

The studies in this group use AI to detect deterioration of building facades caused by environmental agents and predict their progression. They utilize diverse data types and AI techniques to address issues like moisture detection, algal growth, and overall facade deterioration, which can compromise structural integrity. The tasks are broadly categorized into detection [207,237,238] and prediction [207,212,239–241]. AI mainly improves accuracy in detecting anomalies and variations compared to traditional methods and enables predictive maintenance for forecasting potential damages and planning interventions.

For detection tasks, studies use image data, including annotated visual and microscopic evaluations [238] and infrared thermograms [237]. For unsupervised anomaly detection, non-annotated time-series data documenting the moisture content in wooden structures are used in García Faura et al. [207]. In prediction tasks, a variety of data types are used, from categorical and numerical data describing features and properties of facades, such as material, roughness, porosity, and surface pH [212,239], to spatial data helpful in understanding location-specific variables [241,242] to e-participation data from citizens reporting the status of urban facades [240].

Classical ML, DL, and CV models are employed in the reviewed studies. CV techniques like PCA and Nonnegative Matrix Factorization are used to decompose and reduce the dimensionality of infrared images, highlighting key features related to moisture presence [237]. LR predicts the probability of mold growth based on paint characteristics and environmental exposure in Gobakken et al. [238]. Interestingly, García Faura et al. [207] combine detection and prediction by using classical ML techniques such as isolation forest, local outlier factor, and cluster-based local outlier factor to identify anomalies in moisture content in different wood structures, along with LSTM models to predict future values in time-series data. Different ML techniques (LR, SVM, kNN, and RF) handle various aspects of predictive analysis from structured data and textual feedback in Antonov et al. [240]. Tran and Hoang [239] use a hybrid architecture, Adaptive Neuro-Fuzzy Inference System, combining neural networks with fuzzy logic to predict algal appearance on facade surfaces.

3.3.4. Structural component detection

A small set of studies utilize advanced imaging techniques and ML to enhance facade structural component detection for various applications. Automated classification of building stock based on facade structure aids in assessing seismic risk and post-disaster response [243–245], while detecting facade structures supports 3D reconstruction and procedural modeling for urban design and planning [244,246]. In these studies, AI improves accuracy and precision over manual image processing, reduces the cost of extensive fieldwork and inspections, and allows scalability and applicability to different datasets.

Central to all the studies, facade images are extensively used to detect structural components such as windows, doors, and regular patterns. These images are sourced from various platforms, including UAVs, web-crawled databases [244], and GSV [243,245]. Images are often supplemented with geospatial data from OSM [245] and structural characteristics from public cadaster data [243]. In Jiang et al. [208], numerical data on geometric moments and centroids, derived from geometric calculations on segmented facade images, aids the detection process.

DL techniques are used in the studies for classification and identification tasks, with transfer learning facilitating the application of pretrained models. The DenseNet201 and VGG-16 architectures are used to classify building structural types [243] and building floors [245], leveraging transfer learning to reduce training time. Zhang et al. [244] use a deep CNN to learn complex features from UAV images, incorporating a novel “prior knowledge attention branch” to prioritize crucial image parts for identifying structural types. CV techniques are also used to detect structural regularity; for example, SIFT detects points of interest in images [246], adaptive threshold segmentation handles unevenly illuminated images [208], and geometric moments and centroid calculations are used for pixel-wise segmentation [208].

3.3.5. Structural dynamics and load analysis

The last group of reviewed studies closely aligns with common structural analysis themes for building facades. Some articles employ AI techniques for predictive modeling of structural behavior [210] and wind pressure conditions [211,247]. Other studies automate traditional engineering tasks using AI, such as generating finite models from images [248] and identifying wind damage-prone facade areas [249]. AI also improves monitoring tasks, enhancing wind pressure data resolution [247] and enabling collapse warning systems at construction sites [250]. Implementing AI in these studies increases computational efficiency for structural assessments traditionally based on Finite Element Analysis (FEA) and CFD simulations and scales facade structural analysis from buildings to district and urban levels.

The majority of studies in this category use numerical and time-series data for training models, generated through FEA and CFD simulations to obtain wind pressures on facades [211], blast wave response [251], and masonry wall load responses [210]. Some studies also utilize real-world data from facade sensors [247] and meteorological wind speed data [250]. Additionally, image data from drones or standard cameras is used for segmentation tasks [249] and 3D reconstruction [248].

A variety of AI models tackle different structural analysis tasks, combining traditional ML techniques with new DL models. For regression tasks, models like kNN, DT, and SVM are used in Waibel et al. [211] for surrogate modeling based on Fast Fluid Dynamic simulations. Back Propagation MLP is employed in Li et al. [210] to predict the shear capacity of masonry piers using data from numerical simulations of various load conditions. DL techniques enhance experimental data resolution in Wu et al. [247] with a Super-Resolution CNN, incorporating physical constraints like pressure gradients into the loss function to ensure physical accuracy of the super-resolved outputs. CNNs are used for image segmentation to accurately describe facade elements in Pantoja-Rosero et al. [248], with SfM techniques transforming image data into 3D models. Additionally, Gu et al. [249] use PIX2PIX for image-to-image translation tasks, processing segmented facade images and mapping window layouts. The collapse warning system in Wei [250] employs LSTM neural networks to forecast future wind velocities based on historical data, enabling real-time or near-real-time wind speed predictions.

3.3.6. Achievements, limitations and future work

The reviewed studies report notable achievements in AI applications for facade structure-related tasks, particularly in model accuracy. Many studies report accuracies from over 90% up to 100% accuracy for various tasks ranging from crack detection [205,219,222] to algal appearance prediction [239]. Increased model accuracy was reported by using multi-temporal data approaches and integration of CNN with 3D PCD features in structural damage detection [22,24]. Satisfactory accuracy in structural behavior prediction was reported in Li et al. [210], encouraging practical engineering application, and strong generalization to unseen data in crack detection was reported in Rozsas et al. [221]

Studies have demonstrated that AI can reduce computational costs compared to traditional methods, such as manual defect detection and model construction [248], and even some existing AI models. YOLO architectures have become particularly popular variants and have been used in many studies for tasks involving real-time object detection [213,226]. Reduced and simplified training processes were highlighted in studies using transfer learning [205,243,245]. Super-Resolution CNN offer an efficient alternative to CFD simulations by reconstructing high-resolution pressure distributions from sparse measurements [247]

Furthermore, innovative approaches to deal with limited, imbalanced, or partially labeled datasets have been presented in various studies. These methods are based on semi-supervised learning strategies using an uncertainty filter [216], informativeness-guided active learning approaches [224], a few-shot learning methods [228] and meta-learning for refined training [229]. Another interesting direction is the integration of real-world data with synthetic data for training and testing. By combining, for example, GSV images and project-specific data, the robustness and generalizability of the models can be increased [222,243,245]. Moreover, training and testing on real-world data demonstrate the great potential for practical application [205,219,242].

A key limitation across the studies is the dependency on data quality and quantity, which affects model generalizability and accuracy. Obtaining high-quality, noise-free image data is a limitation reported in many studies [243,245] and models often show sensitivity to the environmental conditions of image datasets [208,220,225,244,245]. The precision of monitoring tasks is also affected by the accuracy and resolution of data capture techniques [206,234,236]. Reliance on large, high-quality labeled datasets impacts the effort needed for manual annotation [216,223,224] and data management in large datasets [23,232,248]. Training AI models on high-resolution images for accurate damage assessments also entails significant computational costs [222]. Considerable computational power is needed, especially to support real-time processing tasks [219]. Furthermore, ensuring that datasets are representative of diverse loading conditions, facade shapes, styles, and material systems is crucial for robust model generalization but is also challenging [205,208,210,211,243,247]. Models relying on synthetic data from controlled experiments [207,212] or from CFD and structural analyses [211,240,251] may not capture real-world complexities and dynamics, restricting the models' practical applicability and generalization potential.

Future directions identified in the reviewed studies emphasize enhancing data diversity and quality by advanced data augmentation techniques and generating synthetic data to improve model effectiveness [215,216,221]. Meta-learning strategies and few-shot learning, as demonstrated in Cui et al. [228], Guo et al. [229], show great potential to reduce reliance on extensive datasets. Multimodal datasets, incorporating images, thermal imaging, environmental data, and depth sensor data are an interesting future direction discussed in many studies to augment model capabilities [22,24,215,225,229,230,234,236,240]. Expanding training datasets to include a broader variety of facade materials, typologies, and environmental conditions is also emphasized [205,210–212,218,220,221,238,239,241,247–249,251]. Studies that currently depend on synthetic or controlled data plan to bridge the gap to practical applications by integrating and validating their models with real-world data [207,212,221]. Finally, future research aims to advance DL architectures to improve model efficiency and robustness [219,223,226,229], also enhancing real-time processing capabilities [22,23,219,224].

4. Discussion

The detailed analysis of the topics lays a foundation for further discussion of the trends, relationships between topics, data, and model types, as well as a summary of key insights gained from the review. The discussion aims to serve as a guide for future research in AI applications for building facades.

4.1. Trends

Research on the architectural design of facades dates back to 2003 in the corpus, representing the largest topic examined, with nearly three times as many articles as those on structural design (162 articles vs. 58, Fig. 10). A total of 103 articles were reviewed on the environmental aspect of facades. In terms of data, models, and tasks, we found several similarities between the topics of architecture and structure, while research on environmental aspects stands out.

As shown in Fig. 10, image data has consistently dominated research on the architectural design of facades, as images can capture complex

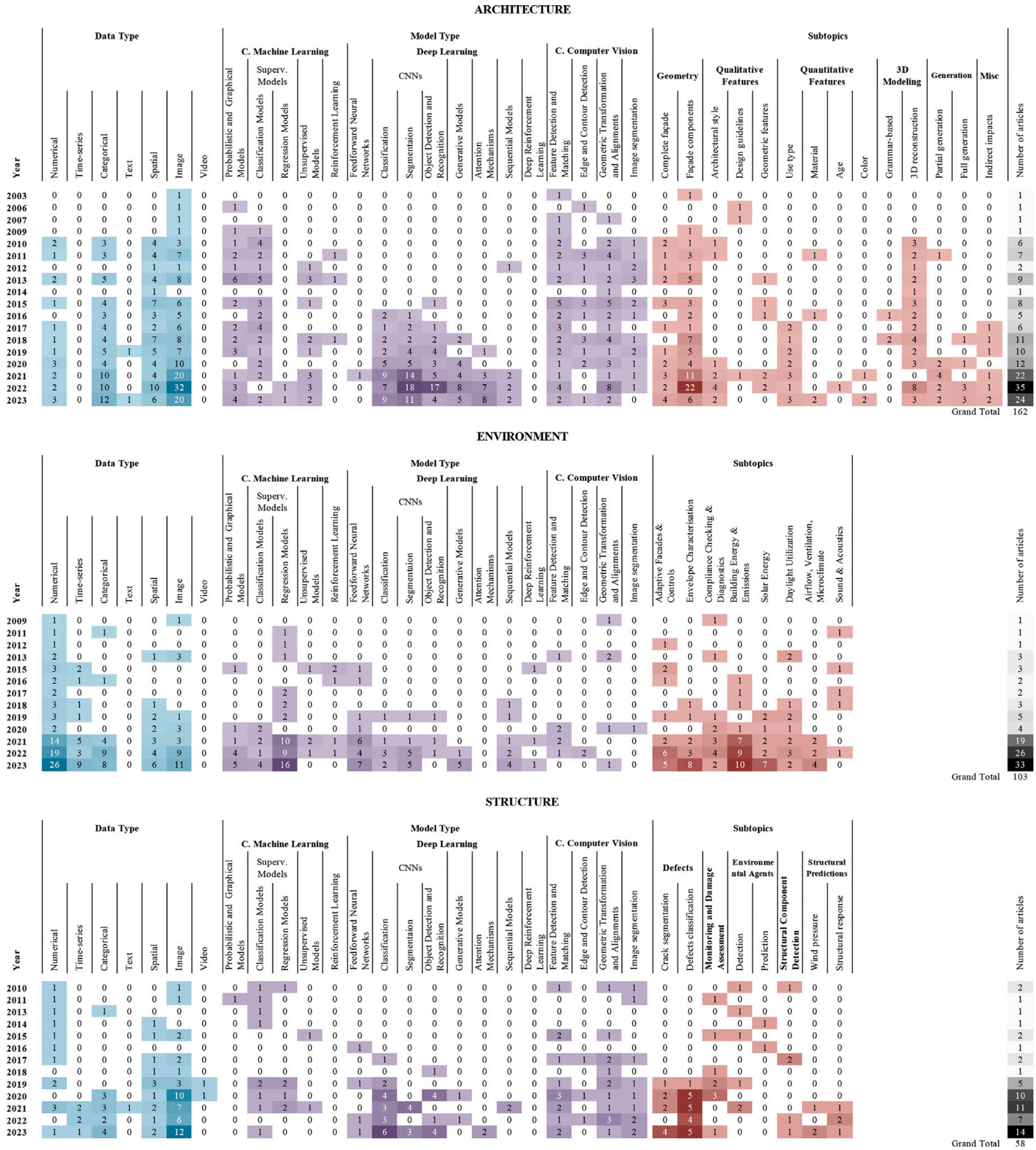

Fig. 10. Trends of data and model type in relation to different topics of facade research.

visual features. Structural research has also seen a significant increase in the use of image data, especially since 2015. The use of image data has also increased significantly since 2020, likely due to advances in imaging technology, such as UAV and TLS, and DL architecture. In addition to image data, spatial data is also frequently used in architectural research, to capture both visual and spatial relationships. Some (geo-)spatial data sets, such as 3D point clouds, however, often require special equipment and expertise for data acquisition. In contrast, image datasets can be more easily created through crowdsourcing or obtained from open data sources (see the list of open datasets in Supplementary Materials).

In structural tasks, instead, the use of spatial data has shown a clear upward trend, especially when supplementing image data with physical layouts or geographical information. Recent years have seen a clear trend towards diversifying data types, e.g., multimodal data sets including time series, images, and numerical values. This trend is likely linked to the growing focus on monitoring and predictive analysis tasks. Similarly, environmental research is moving away from solely utilizing numerical data towards multimodal datasets that incorporate a combination of categorical, image, spatial, or time series data.

In line with trends in datasets, classical CV and DL models trained on image data are most commonly used for the architectural and structural design of facades. Until 2014, studies mainly used classical CV and ML methods. Since 2015, studies using DL models have significantly increased, closely aligned with the increasing use of image data. In environmental research, however, most studies rely on classical ML techniques for regression tasks up until 2019. From 2020 onward, there has been a significant increase in the application of CNNs across all topics, particularly for tasks involving image and video data, driven by advances in computing power and the increasing availability of large

			Data Type							Model Type: C. Machine Learning	Superv. Models				Deep Learning	CNNs							C. Computer Vision				
Topics	Subtopics		Numerical	Time-series	Categorical	Text	Spatial	Image	Video	Probabilistic and Graphical Models	Classification Models	Regression Models	Unsupervised Models	Reinforcement Learning	Feedforward Neural Networks	Classification	Segmentation	Object Detection and Recognition	Generative Models	Attention Mechanisms	Sequential Models	Deep Reinforcement Learning	Feature Detection and Matching	Edge and Contour Detection	Geometric Transform. and Alignments	Image segmentation	Number of articles
ARCHITECTURE	Geometry	Complete façade	0.18	0.00	0.64	0.00	0.55	0.77	0.00	0.32	0.36	0.00	0.23	0.00	0.00	0.18	0.45	0.14	0.00	0.00	0.00	0.00	0.14	0.18	0.41	0.23	22
		Façade components	0.07	0.00	0.33	0.00	0.41	0.85	0.00	0.21	0.14	0.00	0.11	0.04	0.01	0.17	0.47	0.38	0.08	0.10	0.04	0.00	0.19	0.08	0.25	0.10	73
	Qualitative Features	Architectural style	0.09	0.00	1.00	0.00	0.18	0.91	0.00	0.09	0.27	0.00	0.09	0.00	0.00	0.64	0.09	0.27	0.00	0.27	0.09	0.00	0.09	0.00	0.18	0.00	11
		Design guidelines	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.33	0.00	0.00	0.00	0.00	0.00	0.00	0.33	0.33	0.00	0.33	0.00	0.00	0.33	0.33	0.33	0.00	3
		Geometric features	0.00	0.00	0.43	0.00	0.43	1.00	0.00	0.00	0.14	0.00	0.14	0.00	0.00	0.29	0.43	0.00	0.14	0.00	0.00	0.00	0.14	0.00	0.00	0.00	7
	Quantitative Features	Use type	0.00	0.00	0.86	0.07	0.07	1.00	0.00	0.14	0.29	0.00	0.14	0.00	0.00	0.50	0.36	0.21	0.00	0.14	0.00	0.00	0.29	0.00	0.00	0.07	14
		Material	0.25	0.00	1.00	0.00	0.50	1.00	0.00	0.00	0.25	0.00	0.00	0.00	0.00	0.25	0.25	0.00	0.00	0.50	0.25	0.00	0.25	0.25	0.50	0.00	4
		Age	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1
		Color	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.33	0.00	0.00	0.67	0.00	0.00	0.67	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.33	0.00	3
	3D Modeling	Grammar-based	0.00	0.00	0.09	0.09	0.18	1.00	0.00	0.33	0.00	0.00	0.33	0.00	0.00	0.67	0.67	0.33	0.33	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3
		3D reconstruction	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.17	0.25	0.00	0.06	0.00	0.00	0.08	0.33	0.17	0.03	0.00	0.00	0.00	0.33	0.28	0.61	0.14	36
	Generation	Partial generation	0.00	0.00	0.33	0.00	0.33	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.18	0.45	0.00	0.73	0.27	0.18	0.00	0.09	0.00	0.18	0.09	11
		Full generation	0.20	0.00	0.29	0.00	0.89	0.63	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.13	0.13	0.13	1.00	0.13	0.00	0.00	0.00	0.00	0.00	0.00	8
	Misc	Indirect impacts	0.57	0.00	0.86	0.00	0.43	0.57	0.00	0.14	0.43	0.29	0.14	0.00	0.00	0.43	0.00	0.00	0.00	0.00	0.00	0.00	0.14	0.00	0.00	0.00	7
ENVIRONMENT	Adaptive Facades & Controls		0.94	0.44	0.11	0.00	0.06	0.11	0.00	0.06	0.17	0.28	0.06	0.28	0.22	0.00	0.06	0.00	0.00	0.00	0.00	0.17	0.00	0.00	0.00	0.00	18
	Envelope Characterisation		0.80	0.27	0.13	0.00	0.07	0.20	0.00	0.07	0.00	0.67	0.00	0.00	0.27	0.27	0.00	0.00	0.00	0.00	0.40	0.00	0.00	0.00	0.00	0.00	15
	Compliance Checking & Diagnostics		0.36	0.14	0.07	0.00	0.21	0.71	0.00	0.07	0.21	0.14	0.07	0.00	0.00	0.00	0.21	0.21	0.00	0.00	0.07	0.00	0.29	0.07	0.21	0.07	14
	Building Energy & Emissions		0.90	0.13	0.57	0.00	0.07	0.13	0.00	0.23	0.10	0.53	0.03	0.00	0.23	0.07	0.03	0.00	0.00	0.00	0.07	0.00	0.03	0.03	0.00	0.00	30
	Solar Energy		0.71	0.36	0.00	0.00	0.50	0.36	0.00	0.00	0.07	0.50	0.00	0.00	0.36	0.07	0.14	0.00	0.14	0.00	0.07	0.00	0.00	0.00	0.07	0.00	14
	Daylight Utilization		1.00	0.08	0.08	0.00	0.54	0.31	0.00	0.08	0.00	0.46	0.00	0.00	0.31	0.00	0.08	0.00	0.00	0.00	0.00	0.08	0.15	0.08	0.08	0.00	13
	Airflow, Ventilation, Microclimate		0.38	0.00	0.13	0.00	0.38	0.63	0.00	0.00	0.00	0.13	0.00	0.00	0.13	0.00	0.63	0.00	0.50	0.00	0.00	0.00	0.00	0.00	0.00	0.00	8
	Sound & Acoustics		1.00	0.00	0.40	0.00	0.00	0.00	0.00	0.20	0.00	0.80	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	5
STRUCTURE	Defects	Crack segmentation	0.00	0.00	0.33	0.00	0.00	1.00	0.22	0.00	0.11	0.00	0.00	0.00	0.00	0.56	0.33	0.00	0.11	0.00	0.00	0.00	0.22	0.11	0.00	0.11	9
		Defects classification	0.05	0.00	0.30	0.00	0.15	1.00	0.00	0.00	0.10	0.00	0.00	0.00	0.00	0.35	0.15	0.35	0.00	0.05	0.00	0.00	0.30	0.05	0.15	0.05	20
	Monitoring and Damage Assessment		0.11	0.00	0.11	0.00	0.67	0.89	0.00	0.11	0.22	0.22	0.00	0.00	0.00	0.33	0.11	0.22	0.00	0.00	0.00	0.00	0.22	0.00	0.56	0.44	9
	Environmental Agents	Detection	0.83	0.17	0.33	0.17	0.17	0.17	0.00	0.00	0.50	0.33	0.33	0.00	0.17	0.00	0.00	0.00	0.00	0.00	0.17	0.00	0.17	0.00	0.00	0.00	6
		Prediction	1.00	0.00	0.00	0.00	0.50	0.00	0.00	0.00	0.50	0.00	0.00	0.00	0.50	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2
	Structural Component Detection		0.20	0.00	0.20	0.00	0.20	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.40	0.00	0.20	0.00	0.20	0.00	0.00	0.40	0.20	0.60	0.40	5
	Structural Predictions	Wind pressure	0.67	0.33	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.33	0.00	0.00	0.33	0.33	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3
		Structural response	0.25	0.75	0.00	0.00	0.25	0.50	0.00	0.00	0.00	0.25	0.00	0.00	0.25	0.25	0.00	0.00	0.25	0.00	0.25	0.00	0.00	0.00	0.50	0.50	4

Fig. 11. The probability of co-occurrence of subtopics with respect to data and model types.

image datasets. While the majority of studies on the environmental design of facades still use classical ML, DL architectures, such as FNN and CNN, are also gaining popularity.

In recent years, CNNs for segmentation and object recognition have gained significant attention in the architectural and structural design of facades. Currently, the trend is shifting towards generative models, which support various design tasks and co-creation in design processes. Additionally, models that incorporate attention mechanisms allow for a deeper understanding of contextual information within images. However, unlike studies focusing on the architectural design of facades, the application of generative models and newer approaches, such as GAN and attention mechanisms, remains limited in the structural and environmental design of facades, with only a few studies [102,139,197,224].

These trends can partly be explained by differences in data sources and their availability across different research topics. Research on the environmental and structural aspects of facades suffer from limited data availability and fewer benchmark datasets compared to architectural research, which benefit from public databases, such as CMP Facade Database [54], MonuMAI [72] or AHE_Dataset [76] (Table 5). Generally, most studies on the structural and environmental aspects of facades create their own datasets, e.g., oblique facade images or synthetic experimental data, rather than relying on publicly available data, with data volume, variety, and quality often cited as limitations. Only a few studies have utilized publicly available data sources, such as GSV or OSM. In contrast, research on the architectural aspects of facades uses both self-generated and crowdsourced or publicly available datasets.

4.2. Relationship between topics, models, and data

Different subtopics within architectural, environmental, and structural design are associated with diverse types of data and modeling techniques (Fig. 11). Most subtopics within architectural design rely on image data, whereas multi-modal approaches are also emerging. Research on extracting visual features and 3D modeling frequently utilizes spatial data, either in addition to image data or independently. Specifically, research on 3D reconstruction predominantly uses 3D PCD, while images were used complementary to PCD in 61% of research in this area. Studies investigating the indirect effects of facades, such as window view quality and urban quality, often rely on survey data from which categorical and numerical data can be derived. In terms of learning models, CNNs are widely used for various tasks, including but not limited to classifying building age or color, architectural style, use type, or grammar-based modeling. More recent generative DL architectures, however, are primarily used to generate facade images. Specialized CNNs for segmentation tasks are more frequently utilized, as segmentation often serves as a preliminary step to improve various other tasks, such as grammar-based modeling, image completion, and the extraction of qualitative and quantitative facade features. In recent research on feature extraction and generative tasks, attention mechanisms have begun to be integrated into CNN models trained with image data.

In research related to the environmental aspects of facades, most studies rely on numerical data, although the type of data used generally depends on the subtopic. Exceptions include topics such as envelope characterization, compliance checking and diagnostics, and airflow, ventilation, and microclimate, where the proportion of studies using numerical data ranges from 40% to 74%. Image data is most commonly used in compliance checking and diagnostics due to the application of thermal imaging and HDR cameras. Occasionally, categorical data is also used, particularly in the building energy domain, as many features in this domain are often categorical, such as building use type, construction types, and climate regions. Training data often comes from computationally intensive simulation programs, such as ray tracing simulators or CFD programs, which is one of the main

Table 5
Dataset characteristics. Articles may feature datasets in several categories, which may lead to a total exceeding 100% in "Data Sharing" and "Data Origin", respectively. A list of open datasets is provided in the Supplementary Materials.

Topic	Data sharing			Data origin	
	Open (Existing)	Open (Self-Created)	Closed	Real world	Synthetic
Architecture (N = 162)	36%	12%	61%	99%	6%
Environment (N = 103)	13%	2%	85%	60%	55%
Structure (N = 58)	9%	3%	88%	93%	12%

reasons for the prevalence of small data sets. In addition, experimental data are often tailored to studies and are not widely shared or published (Table 5). Text data is not yet utilized in environmental design; however, the increasing popularity of LLMs may influence future research. The subtopics and their associated data types largely determine the AI models used. For instance, RNN architectures are commonly trained with time series data for envelope characterization to predict time-resolved wall temperatures. CNN architectures and CV techniques dominate in compliance checking and diagnostics, where images are the primary data type. RL architectures are found relevant for studies on adaptive facades and controls. As noted above, classical ML models for regression tasks are predominant in many other topics, especially due to the availability of numerical data and relatively small datasets (N<1000).

Across structural design subtopics, different data types are selected to fulfill specific tasks. Image data predominates for visual inspection tasks such as facade defect detection and crack segmentation, whereas video data is used for real-time detection tasks. Numerical and spatial data are primarily used in predictive modeling and structural response evaluations to understand the behavior of the structure under varying loads and conditions. Time series data is used in monitoring applications to track changes in building facades over time, such as the degradation of facade materials, the impact of environmental factors, or post-disaster damage. Classical ML models are often utilized for classification tasks, such as identifying the effects of different environmental agents on facades, and for regression tasks to predict environmental and load-induced degradation. Some studies use sequential NNs with time series data for these purposes. CV techniques in combination with DL are widely used to automate and refine traditional inspection methods. In particular, CNNs are popular for image-centric tasks across multiple subtopics, primarily for classification as well as for segmentation and object detection in facade defect and structural health monitoring. In addition, GANs are used in research to improve the quality of datasets, like deblurring UAV-captured images or for image-to-image translation. Classical CV models also play an important role, both as a preprocessing tool to improve image data quality for CNN models and as a primary analysis tool in the detection and segmentation of structural defects and the creation of 3D models using SfM techniques.

4.3. Insights and potential directions

4.3.1. Data quality and sharing

A major limitation, particularly in environmental and structural facade research, is the quality and quantity of available data. A larger share of open datasets is available in architectural facade research, whereas other topics more frequently rely on the creation of custom data sets (Table 5). Furthermore, in environmental design, AI models are strikingly more often trained on synthetic data compared to models in structural or architectural design. This trend is particularly noticeable in applications on the whole-building scale, where data is often generated through CFD, raytracing or dynamic thermal simulations. In these domains, obtaining large quantities of real-world data presents inherent challenges.

A key development for both simulation and experimental data would be the shared use of datasets, as the data is often created from scratch with significant effort. An important step in this direction is the Building Data Genome project, which provides a large dataset of metered data from real buildings accessible to building energy researchers [252]. Larger datasets would also enable the adoption of more complex AI architectures, including generative models. Another challenge is the need for high-quality annotated data, such as for detecting facade defects or architectural objects, which is costly and labor-intensive to produce. Factors such as environmental conditions or expertise of the labeler can further impact data reliability. Future developments should focus on the adoption of meta-learning strategies that allow models to quickly adapt to new labels, such as new defect types, with minimal data. Implementing informativeness criteria for active learning could also help prioritize annotation of unlabeled data.

The increasing diversification of data types observed in recent studies suggests that multimodal models could leverage the strengths of different data types. Multimodality, such as the combination of text and image data as proposed in the CLIP model [253], or integrating spatial recognition capabilities of CNNs with the temporal analysis strength of LSTMs as demonstrated by Elmaz et al. [254], will likely receive increasing attention in future research.

4.3.2. Addressing generalizability

The challenge of generalizability is consistently reported across all topics of facade design, operation and maintenance. When large and more varied databases are difficult to obtain, this challenge is often addressed through careful feature engineering. By transforming raw data into derived metrics with high information content relevant to the target output, even simple ML models can achieve accurate predictions. For example, some studies translate complex spatial data, such as 3D models, spatial solar potentials on surfaces, or images, into numerical features to be used as inputs for classical ML-based regression and classification models [186,192]. However, these models are often highly specialized and face difficulties when scaled for diverse contexts or real-world applications due to overfitting or narrow applicability.

Recent AI advancements offer alternative solutions to improve generalizability beyond reliance on extensive feature engineering. Transfer learning, for instance, has proven effective in facade research by enabling models trained on large datasets from related domains to adapt to more specialized tasks like facade age and style prediction with minimal retraining [71]. This approach allows models to leverage patterns learned in one context to perform well in another, reducing the dependence on large, specialized datasets. Additionally, Physics-Informed Neural Network (PINN) represent another method to enhance generalizability, especially when domain knowledge can be incorporated into black-box AI techniques, thus informing models with physical principles [255]. As a result, AI models become less bound to specific training datasets and are instead informed by equations governing real-world phenomena. Although targeted reviews on the application of PINN already exist in fields like fluid dynamics [256] and heat transfer [257], evidence of this trend in facade research is limited. Overall, these varied strategies, feature engineering, transfer learning, meta-learning, and physics-informed approaches, can expand the toolkit for addressing generalizability in facade AI research.

4.3.3. Novel architectures for facade generation

Existing research on facades primarily focuses on architectural aspects, particularly feature extraction or 3D modeling of existing buildings, with the aim of reducing reliance on expert knowledge and automating labor-intensive tasks. Beyond these tasks, a new trend has emerged towards co-design using generative models, especially using LLMs. Advances in open text-to-image and image-to-image diffusion models can democratize the design process by reducing the need for powerful hardware for realistic renderings or 3D modeling, enabling co-creation with AI in the design of new facades. However, this also raises concerns about monopolization, as well as issues regarding the ownership of generated data.

In contrast, studies concerning the environmental and structural aspects of facades use regression models based on classical ML techniques, whereas DL and CV techniques are emerging, mainly for control, diagnostic, and assessment tasks. Few studies focus specifically on generative design [102,139]. A promising future direction for performance-driven design tasks involves integrating advanced generative models such as diffusion models, VAE, and GAN. Originating from heuristic optimization methods such as GA, these novel approaches can capture complex relationships even in ill-posed and wicked problems. A relevant example from another domain is provided in Bucher et al. [258], where Conditional VAE was applied to translate structural performance requirements into bridge design solutions. This illustrates a case of *inverse design*, where instead of evaluating the performance of a given design proposal, typical of *forward design*, the generative model suggests potential solutions based on specific performance criteria, such as maximal load-bearing capacity. Another promising model architecture is GNNs, which can be well-suited to facade design and performance simulation, as many problems in this area can be effectively represented as complex spatial relationships. An example of this approach can be found in Cao et al. [259], where GNN is applied to the spatial layout of buildings to predict energy efficiency, demonstrating how spatial configurations can significantly influence building performance.

Overall, although successful application of AI techniques on facade research have been reported, there remains a noticeable delay between the introduction of new AI techniques and their adoption in the field. Recently popularized approaches, such as transformers and generative models, are still rare in facade research. While still in its early stages, the work by Zhao et al. [183] exemplifies an early realization of such a model. Some domains, such as biomedicine, even drive the development of new DL architectures, such as U-Net [260]. We believe that facade design, with its unique challenges, has the potential to similarly inspire specialized AI techniques.

5. Conclusion

This review applies a method based on sentence transformers to explore trends and relationships in AI-driven facade research, focusing on (1) architectural, (2) environmental, and (3) structural aspect of facade design, maintenance, and operation. Insights into the existing literature are provided by linking research topics to data and models across 323 articles. Overall, a growing interest in the application of AI techniques is observed.

The transformer-based review method posed several challenges that required manual intervention. For instance, queried search terms may exclude relevant articles if terminology differs from the selected keywords. While the topic model effectively distinguished the three main topics and automatically assigned the articles to these categories, some subtopics within these topics were unintuitive or overlapping, requiring expert clarification. This review focuses explicitly on facade research, though extensive literature exists on many related topics covered in this review, where further details can be found. These include research on 3D reconstruction, PINN, inverse design, and others. Nevertheless, this review aims to offer a comprehensive overview of AI applications within facade research.

The reviewed papers highlight significant differences in the application of AI across various topics of facade research. Image data is prevalent in architectural and structural design, leading to the frequent use of CV techniques and DL architectures suited for image processing, with growing interest in incorporating 3D data in addition to 2D. In contrast, environmental design more commonly utilizes classical ML models, likely due to the prominence of numeric data and limited data availability in this topic. Across all topics, however, rapid advancements are anticipated with the introduction of generative models, such as LLM, GAN, VAE, and diffusion models, which are expected to foster collaborative forward and inverse design workflows. To address existing challenges and limitations in AI-driven facade research, we discuss various recommendations, particularly the dissemination of shared open datasets, as limited data and data quality remain major bottlenecks for progress. In conclusion, AI methods are expected to significantly advance facade design, and this review aims to provide a useful starting point for researchers in this field.

CRediT authorship contribution statement

Ayca Duran: Writing – original draft, Visualization, Software, Methodology, Investigation, Data curation, Conceptualization. **Christoph Waibel:** Writing – original draft, Data curation, Conceptualization. **Valeria Piccioni:** Writing – original draft, Data curation, Conceptualization. **Bernd Bickel:** Writing – review & editing, Supervision. **Arno Schlueter:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Methodology

In this review, a traditional literature analysis based on bibliographic data, i.e. keywords, citations, and authors, is first conducted to provide background information on trends and collaborations. A topic model is then trained to identify the current research focus. First, (1) a publication query is performed with the identified keywords. After (2) the data preprocessing, (3) a statistical analysis of the bibliographic data is performed, and the relationships between publications and authors are presented. (4) The main topics covered in the literature – architectural, environmental, and structural design – were extracted using a topic modeling method based on transformers. Finally, these articles are further analyzed manually.

Table 6
Search terms.

Categories	Subcategories	Keywords
Architectural	–	Building facade, facade*, building envelope
AI-related	Core concepts	Artificial intelligence, machine learning, deep learning, generative
	Models and algorithms	Support vector machines, decision trees, random forest, k-nearest neighbors, principal component analysis, logistic regression, bayesian networks, autoencoders, long short-term memory, gated recurrent unit, transformer models, variational autoencoders, self-attention mechanism, adversarial networks, generative adversarial networks, reinforcement learning algorithms, evolutionary algorithms, bayesian deep learning, dimensionality reduction, convolutional neural networks
	Learning techniques	Adversarial training, supervised learning, unsupervised learning, semi-supervised learning, transfer learning, reinforcement learning, one-shot learning
	Applications and techniques	Computer vision, image recognition, machine vision, machine translation, topic modeling, sentiment analysis, gpt, transformers, text generation, information retrieval, content extraction, siamese neural networks, feed-forward neural networks, graph neural networks, recurrent neural networks, natural language processing (NLP), object detection, facial recognition, pattern recognition, anomaly detection, feature extraction

A.1. Publication collection

Publications were retrieved from the bibliographic database Web of Science (WoS) [21]. The keywords related to facades and AI applications are identified. The keywords appear either in the abstract, the author's keywords, or in the title of the publications.

Two main categories of keywords, facade in the architectural sense and AI-related, are identified 6. Although facade is a universal term in most studies and can refer to a specific part of a building, AI application is more of an umbrella term that encompasses many sub-areas and methods. Therefore, specific methods that belong to the core concepts of AI and ML are also included (Fig. 6). Using these search terms, we captured the publication information, i.e., title, abstract, author, citations, and publication year, as a comma-separated text file for further analysis.

A.2. Data preprocessing

The query returned 583 articles containing at least one keyword from the two keyword categories mentioned above. The original dataset was pre-processed by removing duplicates, manually checking titles and abstracts, and manually correcting text in these sections. In the abstracts, typos are corrected, such as from "pre-diction" to "prediction" or from "fa?cade" or "fa ade" to "facade", and information about the copyright and DOI number of the manuscript was removed. Mathematical expressions are simplified when observed (e.g. from I_{w} to Iw).

During the manual screening, some articles were identified resulting from some search terms that may have multiple meanings not related to building facades or AI applications, i.e., often "generative" and "facade". For example, studies investigating the generative potential of spaces or facades of fields are removed from the dataset. In addition, in some studies in which a novel method is developed, the application to the building envelope is only indicated as a future research area. These studies were also removed from the dataset as the research focus was not directly related to the facade. Summaries containing only an introductory sentence, such as "street-level imagery and satellite remote sensing can provide information on facades", were also excluded. Lastly, articles on single- and multi-objective optimization have been manually excluded. Studies that focus directly or partially on building facades were included in the dataset.

Although the approach described above allows a large proportion of existing studies to be automatically captured based on the identified keywords, some minor inconsistencies in terminology may have led to a small selection of articles going unnoticed. Therefore, we manually added 8 articles where we detected such discrepancies. The pre-processed dataset consists of a total of 323 articles.

A.3. Topic modeling

A transformer-based topic modeling approach has been selected due to its ability to adapt to the semantic nuances of subject domains, in contrast to traditional probabilistic or algebraic topic modeling approaches such as Latent Dirichlet Allocation (LDA) and Non-negative Matrix Factorization (NMF). [261] The BERTopic [262] library is utilized to identify clusters, i.e. topics, of articles that have similar foci. BERTopic uses transformer-based embeddings to create dense vector representations of text, which are then clustered to identify predominant themes within a corpus of documents. The topic model consists of five main modules (Fig. 12) described below. Further information about the method can be found in [262].

1. **Embeddings**: Embeddings allow the models to understand the context and meaning of the text by transforming words into vectors. The embedding model `bge-large-en-v1.5` [263], one of the best performing open embedding models at the time of modeling the topics for this review, is used to create dense vector representations for the abstracts of each article.
2. **Dimensionality reduction**: The embedding vectors are compressed into a lower-dimensional space while preserving the essential structures to avoid the *curse of dimensionality*. The Uniform Manifold Approximation and Projection (UMAP) approach is used due to its superior preservation of local and global features compared to other well-known methods such as PCA and t-SNE [264].
3. **Clustering**: Topics, i.e. groups of similar studies, are explored by clustering. Hierarchical Density-Based Spatial Clustering of Applications with Noise (HDBSCAN) is applied due to its efficiency in forming clusters based on density and allowing noise to be modeled as outliers, thus preventing unrelated studies from being assigned to a random cluster [262].
4. **Bag of words**: After clustering, the documents within each cluster are combined to form a bag of words.
5. **Topic representations**: Representative words for each topic, in the form of a bag of words, are selected by the class-based Term Frequency–Inverse Document Frequency (c-TF-IDF) scores, as proposed in BERTopic [262]:
$$W_{x,c} = \|tf_{x,c}\| \times \log\left(1 + \frac{A}{f_x}\right)$$
where $tf_{x,c}$ is the frequency of word x in class c, f_x is the frequency of word x across all classes, and A is the average number of words per class.

A.4. Model selection

The modularity of the BERTopic approach facilitates the tuning of various hyperparameters to adapt the model to specific dataset

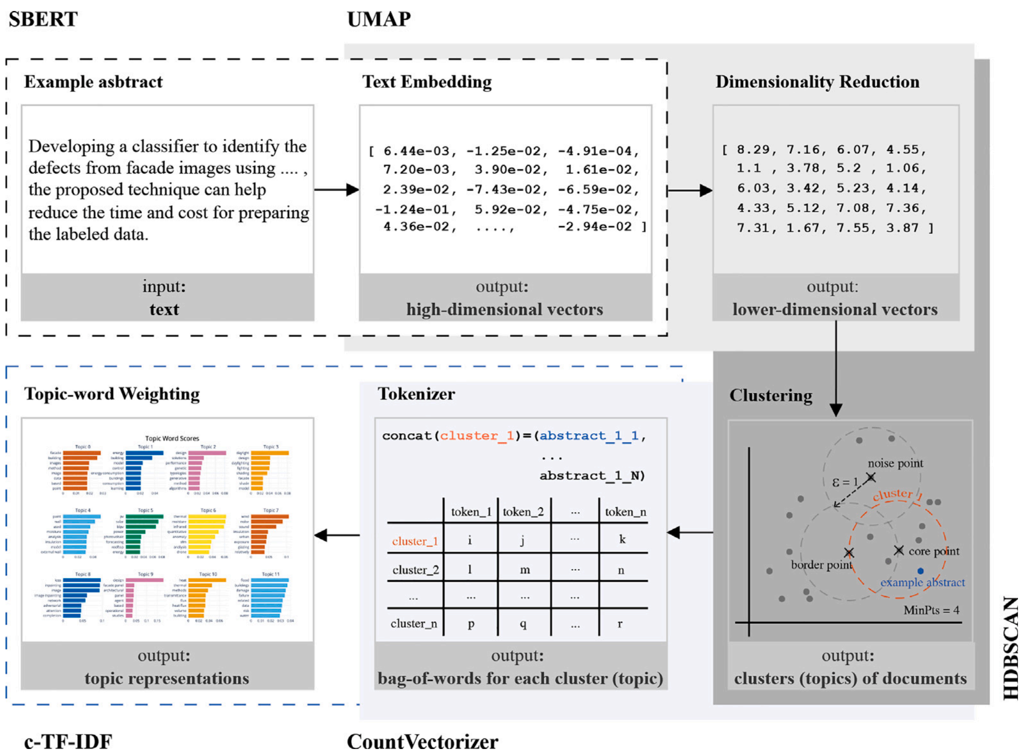

Fig. 12. Topic model used to inform the grouping of reviewed articles.

characteristics. However, since the ground truth does not exist for the unsupervised task we performed, the evaluation of the models is based on selected metrics to evaluate clustering performance as well as the authors' manual evaluation.

The selected topic model utilizes the `bge-large-en-v1.5` to generate embeddings, which are then processed to identify them atic clusters. Parameters for UMAP, HDBSCAN, and CountVectorizer were tuned with the grid search method using the tuned parameters (Table 7).

We recorded two widely used performance evaluation metrics for topic models: coherence and diversity. Coherence is a measure of how meaningful the topics are. High-scoring words in each topic are compared based on their semantic similarity. Higher coherence implies higher similarity between the abstracts belonging to the same topic. Topic diversity measures how different the topics are by inspecting the top words of each topic. A higher diversity score implies more distinct topics. Topic coherence and topic diversity are calculated as follows:

$$C_V = \frac{1}{T}\sum_{t=1}^{T}\frac{1}{n_t-1}\sum_{i=2}^{n_t}\sum_{j=1}^{i-1}\log\left(\frac{D(w_i,w_j)+\epsilon}{D(w_j)}\right)$$

$$Diversity = \frac{\text{Number of Unique Words in Top N across Topics}}{\text{Total Number of Top Words across Topics}}$$

where T is the number of topics, n_t is the number of words in topic t, $D(w_i, w_j)$ is the number of documents containing both words w_i and w_j, and $D(w_j)$ is the number of documents containing word w_j. ϵ is a small number to avoid a log of zero. Although topic diversity and coherence scores objectively evaluate the topic model, visualizations and expert knowledge play a crucial role in evaluating the models.

A.5. Selected topic model

A total of 5880 models were trained. We tried to strike a balance between topic diversity and coherence (Fig. 13). While high values for topic coherence and diversity are favored, some undesirable results are observed near the maximum value of 1. A topic diversity close to 1

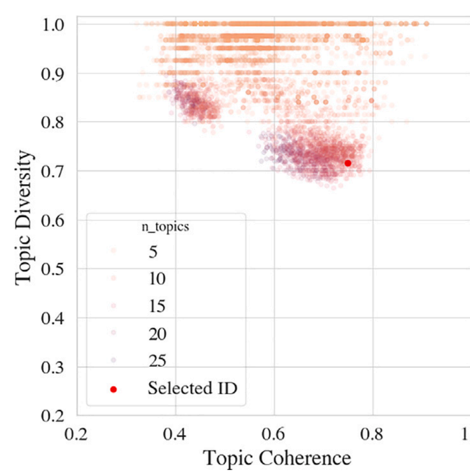

Fig. 13. Selected topic model.

leads to an explosion in the number of topics, so that the topics are all very different from each other and do not overlap, but are separated from each other due to very small details. Topic coherence close to 1 leads to larger blocks of topics that are less numerous but more comprehensive, but not detailed enough. The selected model resulted in a topic coherence of 0.75 and a diversity of 0.72 (Fig. 13), which are found satisfactory. The 2D vector representations of the articles and topics can be found in Fig. 14. The pre-trained model is available at https://github.com/ycdrn/ai-facades_lit-rev.git

Appendix B. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.buildenv.2024.112310.

Table 7
Tuned hyper-parameters, ranges, and definitions.

Module	Parameter	Ranges	Description	Selected value
UMAP	*n_neighbors*	(5 to 20)	Influences the local vs. global structure of the data, affecting topic granularity.	7
	n_components	(5 to 20)	Controls the number of dimensions after reduction, impacting topic detail and noise.	20
	min_dist	(0.0 to 0.1)	Sets the minimum distance between points, crucial for defining cluster tightness and topic specificity.	0.0
HDBSCAN	*min_cluster_size*	5 to 20	Determines the granularity of topics, with smaller sizes allowing for more detailed topics.	6
CountVectorizer	*ngram_range*	{(1, 2), (1, 3), (2, 3), (1, 4)}	Sets the word group size to consider, influencing context capture and thematic richness.	(1,4)

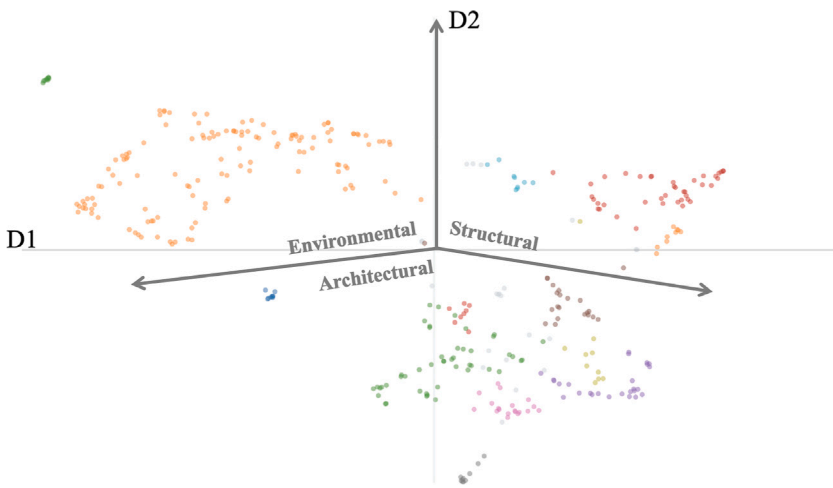

Fig. 14. Topics and articles represented in 2D vector space. The subtopics identified by the topic model are shown in different colors. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Data availability

The data are available in the supplementary materials, and the topic model can be accessed at the following GitHub link: https://github.com/ycdrn/ai-facades_lit-rev.git.

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