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# FROM FIXED-PURPOSE TO ADAPTIVE INTELLIGENCE: PATHWAY TO GENERAL-PURPOSE INTELLIGENCE FOR BUILDINGS

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## Abstract

Buildings own diverse datasets, including geometric, product, logistic, real-time monitoring, regulatory, and occupant feedback data. However, challenges such as data scarcity, insufficient labelling, and the complexity of multimodal data limit conventional AI's ability to provide accurate, scalable and content-aware insights, often confining its application to specific buildings and time. General-Purpose Artificial Intelligence (GPAI) offers the transformative potential to maximise the value of data. Early research explores adaptive AI, meta-knowledge transfer, synthetic data, and foundation models to support generalisation across tasks. This paper examines how these developments position GPAI as a step toward general-purpose intelligence in buildings.

## Introduction

Artificial Intelligence (AI) has been recognised as one of the most transformative innovations of the 21st century (Maslej et al., 2024). It promises to bring revolutionary changes to various industries, estimated to contribute 13 trillion dollars to the global economy by 2030. Benefiting from massive data (e.g., from Internet-of-Things (IoT) devices, crowdsourcing, etc.), AI techniques have improved decision-making, leading to their adoption across sectors such as healthcare, transportation, and construction. In particular, integrating AI into the built environment has demonstrated enormous benefits, such as enhancing energy efficiency and improving operational efficiencies (Himeur et al., 2023).

The successful implementation of AI solutions in buildings depends critically on the availability and quality of data across the entire lifecycle of built assets. Luo et al. (2021) summarise the data types generated and collected during the building lifecycle. These include energy use data, on-site power generation data, indoor and outdoor environmental data, equipment operational data, system control setting/logic, occupant data, design basis data, building and system asset data, utility rates and grid signal data. While building lifecycle data brings smartness to buildings, it is also the root of AI challenges, particularly in achieving interoperability, the prerequisite for AI solutions. The UK's BIM Interoperability Expert Group reported that interoperability issues—driven by the involvement of diverse providers and inconsistent data formats—could account for approximately 2% of design team fees, leading to unnecessary costs of around £200 million annually in the construction industry (BIM Interoperability Expert Group, 2020). Research efforts have increasingly focused on enhancing data interoperability using linked data approaches (Pauwels et al., 2017) and creating the Common Data Environment (CDE) to enable seamless data sharing (Jaskula et al., 2024). Standard data terminologies (e.g., ISO 52000-1), data ontologies and schemas (e.g., IFC, gbXML), as well as data platforms (e.g., BPD, SEED, and OpenEI, as database management tools) are adopted to establish standardised representations. These efforts aim to curate building data effectively, enabling its seamless use throughout the building lifecycle.

While fixing data silos and ensuring seamless integration of cross-domain building data are the prerequisite for AI solutions to thrive in the building sector, further issues such as data scarcity, the lack of sufficient labelled data, and the complexity of handling multimodal data persist and limit the practical implementation of AI in buildings.

- **Data scarcity**: It is estimated that the volume of data collected by smart buildings worldwide reached 37.2 zettabytes in 2020, equivalent to the total storage of more than 185,000 large-scale Google data centres. Despite the massive data generated, the data scarcity issue remains. Much of the data consists of accumulated measurements from the same sensors or sources in newly built buildings. In addition, data silos, which restrict access to diverse data sources, hinder seamless integration and exacerbate data scarcity issues.
- **Insufficient labelled data**: The availability of labelled data is critical for the adoption of AI in buildings, as such applications require training datasets that reflect ground truth in the form of labelled or annotated data to ensure accurate data interpretation. Conventionally, the collection of labelled data from buildings can be an expensive and labour-intensive process. To avoid manual labelling or tagging procedures, efforts have focused on self-labelling through label propagation and weak labelling using data programming, fact extraction or transfer learning (Park and Ko, 2021).

- **Multimodal data**: Time-series data of specific parameters (e.g., temperature, humidity, and carbon dioxide $CO_2$ concentration) dominate the data collected in smart buildings. In addition, data from vision cameras and crowdsourcing platforms, such as X (formerly Twitter), further diversify the data landscape. Collectively, data from buildings and the wider built environment encompass a large variety of modalities (Raj et al., 2023; Alsafery et al., 2023). The integration of multimodal data offers richer and more comprehensive insights into smart buildings, as each modality contributes unique value that cannot be derived from others (Lahat et al., 2015). For example, integrating various sensors, such as PIR (Passive Infra-Red), $CO_2$, and cameras, enables a comprehensive understanding of occupancy patterns, and allows personalised energy-saving recommendations (Dasappa et al., 2024).

Most of the AI solutions developed for buildings focus on solving single tasks, such as predicting the energy consumption of building spaces. This is commonly termed Artificial Narrow Intelligence (ANI). ANI typically relies heavily on large datasets, restricting its applicability to the specific problems for which it was trained. The reliance on extensive data amplifies the three key challenges and further constrains its effectiveness in broad applications within practical building scenarios.

Recently, Artificial General Intelligence (AGI) has gained increasing attention across various domains, including the built environment. AGI refers to a form of AI that possesses the capabilities to comprehend, learn, and execute a wide range of tasks, mirroring human cognitive abilities (Triguero et al., 2024). While AGI remains an aspiration and fiction, advancements in AI technologies are increasingly emulating certain aspects of general-purpose AI (GPAI), which is promising in avoiding the above-mentioned challenges that significantly hinder productivity in the building sector. This paper presents a preliminary review and insights into GPAI adoption in the building sector, providing researchers and practitioners with an understanding of how GPAI's distinctive capabilities and underlying technologies can address the current data-related challenges.

## From fix- to general-purpose intelligence

### Levels of AI

Triguero et al. (2024) elaborate on the transition from fixed-purpose AI (or ANI) to GPAI and ultimately to AGI, as shown in Figure 1. By definition, GPAI is the AI system that can accomplish or be adapted to accomplish a range of distinct tasks, including some for which they were not intentionally and specifically trained, without or with minimum human intervention (Gutierrez et al., 2023).

GPAI is regarded as a more modest and realistic version of AGI, as it does not aim to replicate the full range of human cognitive abilities but rather focuses on the capacity to handle tasks without direct programming for each specific function. While many studies use foundation models and generative AI interchangeably with GPAI, we regard them as only one possible approach to realising GPAI, rather than encompassing its full scope.

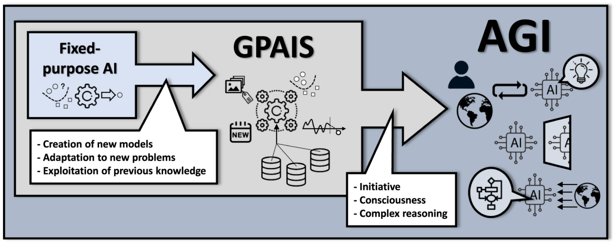


Figure 1: From ANI to AGI (from Triguero et al. (2024)).

Assuming fixed-purpose AI deals with a single task at a time and requires sufficient data to train a model, these techniques designed for a specific purpose generally follow a full cycle comprising the requirement stage (i.e., determining functionalities and interfaces), data-oriented stage (i.e., data collection, cleaning, labelling, feature engineering), model-oriented stage (i.e., model design, training, evaluation), and operational stage (i.e., model deployment and monitoring) (Schlegel and Sattler, 2023). Fixed-purpose AI can be exempt from some stages and reused for other tasks of a similar nature, but only if they are modelled within the same setting. For instance, it is common to apply the same classification technique to different datasets with minor adjustments (e.g., hyper-parameter tuning). However, these tasks are still tackled separately, without explicit knowledge exchange among them.

Transitioning to GPAI and AGI involves handling multiple related tasks simultaneously, where knowledge transfer between them enhances model generalisation. While AGI outperforms GPAI by exhibiting human-like intelligence through complex reasoning, causality understanding, curiosity for exploring new tasks, and self-awareness, this paper does not focus on these distinctions. Instead, this paper investigates the pathways involved in advancing towards general-purpose intelligence for the building sector using data generated throughout its extended lifespan.

Aligned with the extended lifecycle and dynamic nature of buildings, the '*open-world hypothesis*' adopted in this paper assumes that AI operates in ever-changing environments, requiring it to handle unforeseen scenarios. Under the hypothesis, at time $t$, GPAI is expected to address novel tasks for which it was not intentionally and specifically trained; at time $t+\Delta t$, new tasks may arise due to unknown or unforeseen changes in the scenario, which AI trained on data from time $t$ may struggle to manage without adaptation.

### Pathways to achieve general-purpose intelligence

Under the open-world hypothesis, the general-purpose intelligence for buildings requires competence in domains beyond its intentional and specific training (orange line in Figure 2), and responding effectively to tasks under unseen scenarios arising in the near future by leveraging the limited data generated between now and then (green line in Figure 2).

To achieve these capabilities with minimum human intervention, two distinct philosophies are commonly adopted, namely AI-powered AI and the foundation model. AI-powered AI enables the delivery of multiple related tasks by incorporating an additional layer of abstraction, where AI techniques automate and refine the creation and improvement of underlying AI models. On the one hand, AI at the abstraction level can simply select appropriate models and tune corresponding hyper-parameters or even design components and architectures of underlying AI models, making AI adaptive across diverse tasks at any time, $t$ or $t + \Delta t$. For example, AutoML frameworks like TPOT, AutoWeka, H2O, and FLAML have proven to be efficient in automating data preprocessing, feature engineering, model selection, and hyper-parameter optimisation for predicting building energy loads (Zhang et al., 2023). Despite the advanced capability of AI to design AI, it is still a data-intensive approach. On the other hand, as the open-world hypothesis highlighted, AI tasks need to evolve with the environment, often manifesting as shifts in the underlying data distribution. AI at the abstraction layer can leverage meta-knowledge from preceding tasks to adapt underlying models for unseen tasks and expand the range of open-world scenarios they can handle. This is particularly critical at time $t + \Delta t$, when only limited data may be available for characterising potential future-proof scenarios. Through utilising prior knowledge and experience from related tasks, AI can achieve few-shot or zero-shot learning, allowing AI models to generalise effectively with minimal or even no data. Applying supervised learning may appear counter-intuitive when training data for given tasks is minimal. The gap in the knowledge of AI models due to a lack of sufficient training data can be bridged by either borrowing task-specific knowledge (e.g., model architecture & parameters) or generating synthetic data that helps in creating new knowledge (Kadam and Vaidya, 2020). For example, Tang et al. (2023) propose a privacy-preserving knowledge-sharing framework based on federated learning to improve the prediction performance of buildings with limited data. The framework creates one single public prediction model for buildings with similar energy data distributions, clustered together to enable effective knowledge sharing. Fan et al. (2022) develop a deep generative modelling-based data augmentation strategy, which uses the conditional variational autoencoder to generate synthetic yet meaningful data. This approach enriches data representativeness and enhances short-term building energy predictions.

The foundation model approach, as an alternative, relies on a vast amount of unlabelled data to achieve the AI model generalisation. The foundation models can be adapted (e.g., fine-tuned) to various downstream tasks, but only by pre-training on broad data at scale (Fei et al., 2022). For example, Mulayim et al. (2024) utilise Time-Series Foundation Models (TSFMs) to learn general patterns in time-series data and perform time-series analysis and prediction on unseen datasets. These models demonstrate their potential in predictive building analytics by forecasting electricity usage and indoor air temperature with comparable accuracy to conventional statistics models.

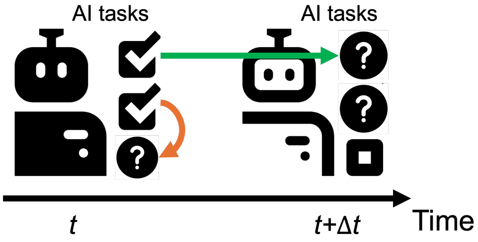


*Figure 2: Capabilities of general-purpose intelligence under the open-world hypothesis.*

## General intelligence for building data

### Building lifecycle data for building smartness

Driven by big data, affordable high-performance computing resources, and advanced algorithms, AI has been applied to building research at various phases of the lifecycle for the past decades. Hong et al. (2020) present an overview of AI and machine learning applications across the building life cycle, including Design, Construction, Operation & Maintenance (O&M), and Retrofit. Table 1 summarises the types of data required for typical smart building applications across different phases of the building lifecycle. Based on the nature of data used at different phases of the building lifecycle, the data can be categorised into the following classes, as shown in Figure 3:

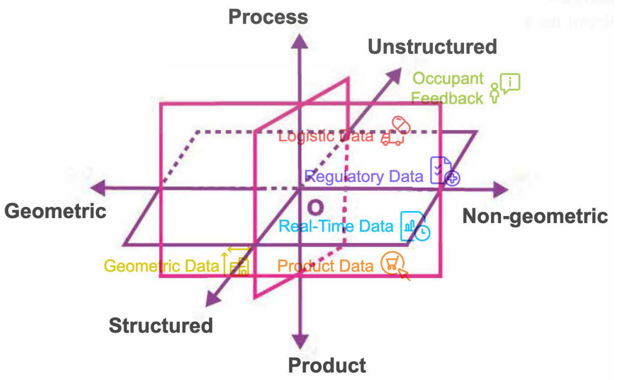


*Figure 3: Categories of data used within various phases of buildings.*

- **Geometric data (G):** Spatial and structural information about a building, such as floor plans, CAD drawings, Building Information Models (BIMs), point clouds, and photogrammetry.
- **Product data (P):** Contextual information related

*Table 1: Data required for smart building applications across various phases*

| Phase | Application | Data Types |
|---|---|---|
| Design | Design generation and emulation | Geometric data, environmental conditions, material properties |
| | Design evaluation | Standards and codes, compliance metrics, material properties |
| Construct | Cost analysis | Material databases, quantity take-offs from geometric data |
| | Construction management and documentation | Geometric data (e.g., construction drawings), project schedules (e.g., construction sequences), material and resource data (e.g., material quantities, equipment schedules) |
| | Defect detection | Visual data (e.g., drone images), point cloud data, inspection records |
| | Construction waste management | Visual data, material properties (e.g., types, quantities, recyclability), logistical data (e.g., transport schedules) |
| O&M | Fault detection and diagnostics | IoT sensor data, equipment fault logs, maintenance records |
| | Energy efficiency improvement | Smart meter data, environmental data, HVAC operation logs |
| | Post-occupancy evaluation | Occupant feedback, IoT sensor data (e.g., temperature, CO2 levels), energy performance data |
| Retrofit | Evaluate energy conservation measures | Smart meter data, utility cost information |

to materials, components, and facilities used in buildings. This also includes lifecycle assessment data, quantifying the environmental impacts from material extraction through construction, operation, and demolition.

- **Logistic data (L):** Data associated with the movement, allocation, and management of resources, including labour, equipment, and products. This also includes fault logs, and maintenance and repair logs generated during the operation of buildings.
- **Real-time monitoring data (RT):** Sequential data dynamically collected during the construction and operation phases using IoT sensors and smart meters (Alsafery et al., 2023). This also includes environmental data such as solar radiation, wind patterns, and ambient temperature.
- **Regulatory and compliance data (R):** Standards and codes that govern building design, construction, and operations.
- **Occupant feedback data (O):** Unstructured data generated by occupants, such as survey responses, social media inputs, and natural language feedback.

Most digital data generated across multiple phases of a building's lifecycle is machine-readable and structured, except certain geometric data and most occupant feedback data. Geometric data in digital formats, such as CAD files (e.g., DWG, DXF), BIM models (e.g., IFC), and point clouds (e.g., LAS), is structured. However, raw photogrammetry data is overwhelmingly unstructured and requires preprocessing to extract geometric information. Meanwhile, legacy drawing data on paper sheets can be digitised through scanning but often lacks metadata or vector information, rendering it unstructured. Geometric data and product data are centred around specific building components, such as boilers and pumps. Geometric data captures the spatial characteristics and dimensions of these products, while product data records their attributes, including details like manufacturer specifications and warranty information. Together, they provide a comprehensive view of both the physical and operational aspects of building products. Buildings undergo various processes, such as assembly during construction and the provision of Heating, Ventilation, and Air Conditioning (HVAC) services during operation. Logistic data captures these workflow-centric processes, documenting how individual products interact and function together as an integrated system. This data provides insights into resource management, system performance, and operational workflows across the building lifecycle. Real-time monitoring data captures the performance of both products and processes. For example, vibration sensors on pumps monitor anomalous vibrations, indicating potential mechanical issues, while room temperature sensors assess the quality of heating and cooling services, reflecting the operational performance of the HVAC system. These data provide dynamic insights to ensure efficient and reliable building functionality. Regulatory and compliance data might fall between structured and unstructured, creating a semi-structured gradient. Although regulatory and compliance codes are typically written in natural language, the texts are often highly formalised and structured in layout. They define rules, conditions, and thresholds for products and processes, making them critical for ensuring compliance and operational safety. Figure 4 articulates the accumulation of the product and process information throughout the building lifecycle.

### General-purpose intelligence for geometric data

Geometric data plays a unique role throughout the entire lifespan of a building. For instance, during the design phase, it can be used for building performance simulations and spatial planning; in the construction phase, it aids in tracking the gradual progress and changes of the project; during operation and maintenance, geometric data can support space management and

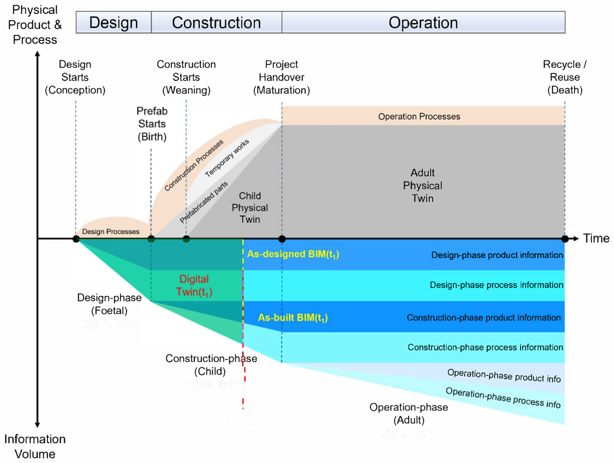


*Figure 4: Product and process information within the lifecycle of buildings (adapted from Drobnyi et al. (2023)).*

maintenance management; ultimately in renovation and demolition, it facilitates material recycling and deconstruction planning, ensuring resource efficiency and sustainability. Specifically, geometric data provides detailed spatial and structural information about buildings and their components, including dimensions, shapes, and relationships between elements. It defines the physical layout and configuration of spaces, as well as building products such as boilers and pumps in HVAC systems.

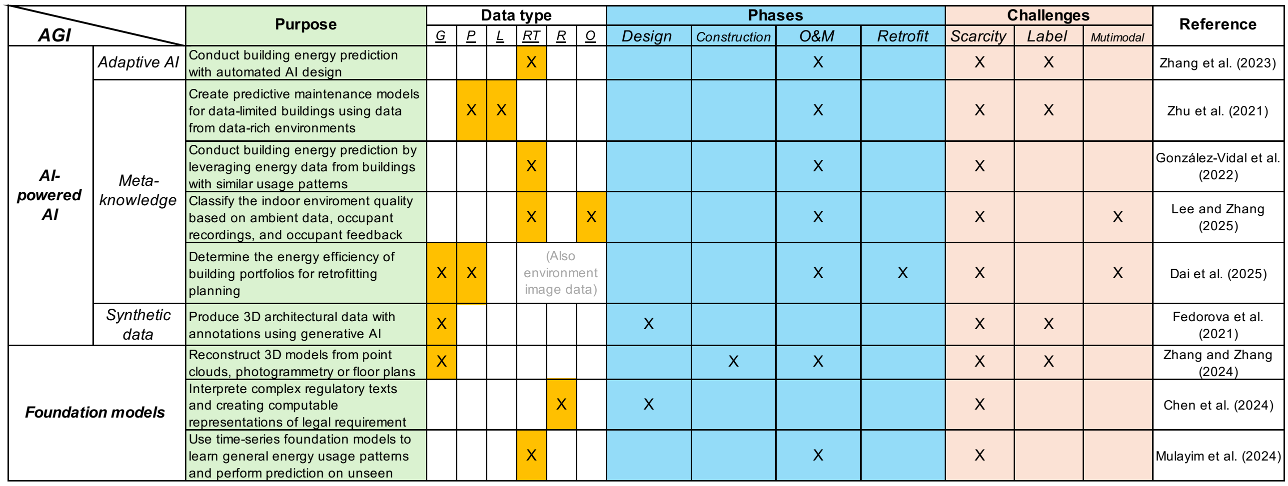
Geometric data enables the creation and updating of 3D models of buildings, also termed BIM or digital twins in some studies. This section focuses exclusively on GPAI for geometric data, while the integration of 3D models with other data for building analyses, such as energy simulation, will be discussed in the multimodal data section. In the design phase, these 3D models act as blueprints, representing the intended construction. Generative AI is explored as a tool for automating the generation of 3D models, enabling more efficient and innovative design workflows. Aalaei et al. (2023) develop a graph-structured conditional Generative Adversarial Network (cGAN) to automate the generation of architectural layouts. Using the RPLAN dataset, which contains 80,000 architectural floor plans of residential units, the cGAN can generate space layouts for residential buildings based on user-defined constraints (e.g., building border or entry position), demonstrating a degree of generalisation. To address the insufficient building design data for training, Fedorova et al. (2021) propose a synthetic data generation pipeline capable of producing 3D architectural data with associated annotations. This framework facilitates various deep learning tasks by providing customisable datasets for building design. Generative AI-based building design overcomes the challenges of low design efficiency and insufficient data reuse, and enjoys the optimised quality with fewer searches (Liao et al., 2024).

In the construction and operation phases, 3D models serve as digital representations of buildings' as-constructed, as-built, or as-is status. However, a significant proportion of existing buildings lack such 3D models. To address this gap, GPAI is increasingly employed to reconstruct building 3D models from point clouds, photogrammetry and even floor plans in raster format. Mehranfar et al. (2024) integrate decision tree classifiers and knowledge-based algorithms to process point cloud data, generating semantic digital models of buildings. A feature-based decision tree classifier extracts building elements, and a knowledge-based algorithm is utilised for 3D space parsing. Zhang and Zhang (2024) develop a novel Multi-object Few-shot Segment Anything Model (GMFS-SAM), enabling the segmentation of multiple rooms and doors in a 2D raster floor plan using only five reference samples. By integrating the vision foundation model SAM and few-shot learning, the approach reduces the need for extensive training and enhances SAM's capability to segment multiple target objects within a single image simultaneously. The GPAI demonstrates the ability to generate accurate digital representations of existing buildings from a wide range of data inputs. Similarly, GPAI can drive the dynamic updating of 3D models based on newly acquired data, ensuring that the digital representations remain consistent with real-world conditions throughout the building's lifecycle (Wang et al., 2024).

## General-purpose intelligence for non-geometric data

Non-geometric data is highly diverse, encompassing a wide range of information about building products, processes, and their interactions with occupants. This data captures how individual elements combine to form systems, how these systems function within the building as a System of Systems (SoS), and how they deliver services to occupants. General-purpose intelligence for non-geometric data aims to optimise the performance of products, streamline processes, enhance the quality of services provided to occupants, and enable intelligent decision-making throughout the building lifecycle. These applications hold significant potential to improve operational efficiency, sustainability, and occupant satisfaction.

Non-geometric data primarily includes information about products, processes, and occupant behaviour. While process data is dynamic and influenced by evolving occupant behaviours, product data is generally standardised. When applied to building products, GPAI holds great potential for compliance checking and predictive maintenance. Foundation models, particularly Large Language Models (LLMs), can automate building code compliance by efficiently interpreting complex regulatory texts and creating computable representations of legal requirements, leveraging few-shot learning to reduce reliance on large annotated datasets (Chen et al., 2024). Combining LLMs with Retrieval-Augmented Generation enables intelligent compliance-checking systems that integrate domain-specific knowledge to evaluate construction schemes effectively (Li et al.,



| AGI | | Purpose | Data type | | | | | | Phases | | | | Challenges | | | Reference |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | G | P | L | RT | R | O | Design | Construction | O&M | Retrofit | Scarcity | Label | Mutimodal | |
| AI-powered AI | Adaptive AI | Conduct building energy prediction with automated AI design | | | | X | | | | | X | | X | X | | Zhang et al. (2023) |
| | Meta-knowledge | Create predictive maintenance models for data-limited buildings using data from data-rich environments | | X | X | | | | | | X | | X | X | | Zhu et al. (2021) |
| | | Conduct building energy prediction by leveraging energy data from buildings with similar usage patterns | | | | X | | | | | X | | X | | | González-Vidal et al. (2022) |
| | | Classify the indoor enviroment quality based on ambient data, occupant recordings, and occupant feedback | | | | X | | X | | | X | | X | | X | Lee and Zhang (2025) |
| | | Determine the energy efficiency of building portfolios for retrofitting planning | X | X | | (Also environment image data) | | | | | X | X | X | | X | Dai et al. (2025) |
| | Synthetic data | Produce 3D architectural data with annotations using generative AI | X | | | | | | X | | | | X | X | | Fedorova et al. (2021) |
| Foundation models | | Reconstruct 3D models from point clouds, photogrammetry or floor plans | X | | | | | | | X | X | | X | X | | Zhang and Zhang (2024) |
| | | Interprete complex regulatory texts and creating computable representations of legal requirement | | | | | X | | X | | | | X | | | Chen et al. (2024) |
| | | Use time-series foundation models to learn general energy usage patterns and perform prediction on unseen | | | | X | | | | | X | | X | | | Mulayim et al. (2024) |

*Figure 5: Summary of studies pursuing general-purpose intelligence for buildings.*

2024). In building maintenance, preserving critical assets/products is vital for ensuring the building's functionality and serviceability. Transfer learning addresses the scarcity of inspection, repair, and failure data by utilising information from data-rich buildings equipped with advanced monitoring systems. It enhances predictive models for data-limited buildings, improving accuracy and reliability even with insufficient training data (Zhu et al., 2021).

The dynamic nature of processes in buildings poses significant challenges for achieving general-purpose intelligence. For building energy prediction, AutoML enhances efficiency and scalability by automating model selection, hyper-parameter tuning, and feature engineering, streamlining AI adoption for energy forecasting (Zhang et al., 2023). Alternatively, transfer learning improves prediction accuracy by leveraging energy data from other buildings with similar usage patterns, offering a practical solution in scenarios with limited data availability (González-Vidal et al., 2022). Early-stage studies also investigate the potential of time-series foundation models to advance building energy analytics by capturing complex temporal dependencies and patterns (Mulayim et al., 2024).

### General-purpose intelligence for multimodal data

Multimodal data from diverse sources across the building lifecycle is beneficial for achieving general-purpose intelligence. It integrates complementary data types, enabling a comprehensive understanding of tasks and environments. By capturing interdependencies within complex systems and supporting cross-domain learning, multimodal data helps identify transferable patterns and insights, which are vital for addressing interconnected tasks.

For the indoor environment quality (IEQ) classification task, ambient environmental data, nonintrusive occupant recordings (e.g., audio, video, thermal) and subjective occupant feedback (e.g., self-reported comfort and health) are integrated using Transformer models with a multimodal fusion layer, translating fused features into final classifications (Lee and Zhang, 2025). By identifying patterns across diverse data modalities, this approach demonstrates how multimodal AI can advance general-purpose intelligence through transferable knowledge from indoor environments, even when some data is missing.

Similarly, multimodal AI has been applied to determine the energy efficiency of building portfolios by combining images (capturing environmental factors like green spaces and surrounding structure density) with textual data (detailing building characteristics and material properties). Using a modality-aware attention fusion network to prioritise relevant features enables transferable insights for urban development and retrofitting planning, even when data is incomplete (Dai et al., 2025).

## Discussion

While AI is widely explored in the building sector, efforts toward general-purpose intelligence remain limited and emergent. A key obstacle to the success of GPAI is poor interoperability resulting in data silos, and weak incentives for data sharing, both of which make data inaccessible. GPAI depends on interoperable datasets, without which its potential cannot be realised. Although GPAI is believed to address data scarcity, it does so by drawing on data or knowledge from different buildings and time periods, rather than relying on information from specific buildings and times.

Figure 5 summarises the relevant studies, illustrating approaches to achieving general-purpose intelligence in buildings across various phases of the building. In short, for geometric data, GPAI tends to generate 3D models using generative AI or transform point clouds and other data formats into 3D models through vision foundation models. In contrast, non-geometric data presents a more complex challenge due to its diverse nature. Feasible approaches for real-time monitoring data include using adaptive AI to dynamically adjust configurations akin to expert-guided trials, transferring meta-knowledge from homogenous cases to reduce reliance on extensive training data, and leveraging time-series foundation models that embed knowledge from vast datasets. For textual data in natural language, such as building codes, LLMs serve as powerful tools for interpreting complex text and generating computable representations, such as knowledge graphs.

## Conclusion

AI applications in buildings face challenges such as data scarcity, limited labelled data, and the complexity of processing multimodal information, often restricting their use to narrow, building-specific scenarios with short-term validity. Early studies have explored strategies of adaptive AI, meta-knowledge transfer, synthetic data generation, and foundation models to achieve general-purpose intelligence for buildings and ensure robust performance over various tasks. Future research should prioritise tackling the challenges in the following directions to advance general-purpose intelligence for buildings:

- **Multi-task learning**: develop methods to leverage insights from related tasks and improve generalisation. Tackle negative transfer due to task heterogeneity, through task affinity analysis and hierarchical learning.
- **Meta-knowledge transfer**: develop AI to learn from prior or similar tasks (e.g., through synthetic data) and adapt to dynamic, unseen scenarios with minimal data. Maintain transfer effectiveness under changing conditions and mismatched data distributions across buildings.
- **Scalable foundation models**: develop and train domain-specific foundation models that can be fine-tuned effectively with minimal data from the target building. Address data scarcity and domain adaptation challenges through federated learning for decentralised data use, parameter-efficient fine-tuning (e.g., LoRA, adapters), and self-supervised pre-training to leverage unlabelled data.
- **Cross-domain learning**: investigate methods that harness complementary modalities for knowledge transfer from data-rich to data-poor domains, to enhance AI's generalisation and problem-solving across new tasks. Address representation alignment challenges using normalising flows and graph-based methods to map diverse feature spaces into a shared latent space.

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