CHAPTER 9

An Ecocentric Assessment Framework for Artificial Intelligence and Computational Design in Architecture

Adil Yirmibeş
Research Assistant, Bursa Uludağ University, Faculty of Architecture, Program of Architecture, Bursa-Türkiye. E-mail: adilyirmibes@uludag.edu.tr
https://orcid.org/0000-0002-4755-6888

ABSTRACT

Artificial intelligence (AI) supports environmental performance prediction and the evaluation of alternatives in architectural design. However, improvements in energy or carbon indicators alone do not demonstrate that non-human life holds independent value in design decisions. This chapter examines AI and related computational design approaches in architecture from an ecocentric perspective through a focused narrative review and conceptual synthesis supported by a structured database search. The 375 raw records retrieved from Scopus and Web of Science were reduced to 256 unique records; following title and abstract screening, a final purposive selection of 19 studies was established. Together with one supplementary publication, the 20 documents were examined under the themes of performance and decision-making, life cycle boundaries, the representation of non-human life, habitat geometry and materials, time and maintenance, and visual generation and ecological validation. The synthesis informs a preliminary ecocentric assessment framework comprising three dimensions: stakeholder scope, integration of environmental and ecological impacts into decision-making, and ecological responsibility. By distinguishing computational success from ecological outcomes, the framework provides an analytical basis for examining who benefits from design decisions, how environmental and ecological requirements influence those decisions, and how responsibility for their outcomes is addressed.

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1. Introduction

The environmental value of artificial intelligence (AI) in architecture depends on the design problem it addresses and how it defines success. A building envelope that reduces energy consumption, a low-carbon material choice, or a form that improves daylighting can deliver environmental benefits. However, these benefits are insufficient to demonstrate that the design treats species, habitats, and ecological processes as beneficiaries worthy of protection in their own right. This distinction between environmental performance and ecocentric orientation provides the starting point for the present study. Architecture is a particularly revealing domain for this inquiry because buildings are long-lived, site-specific interventions that shape habitat conditions and relationships among species. Decisions about siting, envelopes, materials, and maintenance therefore connect computational design choices to ecological consequences that may emerge well beyond the initial design stage (Grobman et al., 2023; Weisser et al., 2023).

In their review of AI in sustainable architectural design, Yao et al. (2025) map 408 studies across design stages, sustainability objectives, and algorithmic applications. Alongside efficiency gains, the review highlights limitations in the transparency of data and methods. Within the related field of life cycle assessment, Yirmibeş and Karasu (2025) identify sustainability, energy, and carbon footprint as prominent themes in architectural research and examine its connections with artificial intelligence. This literature offers opportunities to assess the environmental impacts of design at an earlier stage; however, whose interests are represented requires further examination. A study's use of environmental indicators and its designing for non-human life correspond to different research questions.

Human-centred AI prioritises human oversight and reliable use (Shneiderman, 2020). Existing ethical approaches cannot be said to exclude the environment entirely. The United Nations Educational, Scientific and Cultural Organization (UNESCO, 2022) identifies the flourishing of the environment and ecosystems among the fundamental values of AI ethics. Nevertheless, Rigley et al.'s (2023) review of 146 ethical standards demonstrates the need to question anthropocentrism and the moral standing of non-human entities. The issue is not the presence of human benefit, but the restriction of the assessment scope to it. This inquiry also draws on posthuman and more-than-human approaches to design, which question the privileged position of humans and emphasise relationships among human and non-human actors (Forlano, 2017; Wakkary, 2021). These approaches intersect with multispecies thinking,

which foregrounds coexistence and interdependence among species (Haraway, 2016), but the terms are not interchangeable. In this chapter, biocentrism refers to the recognition of living organisms as valuable in themselves, whereas ecocentrism extends this concern to ecosystems, ecological processes, and abiotic components (Washington et al., 2017). More-than-human design provides a broader relational perspective, while multispecies design focuses on the requirements and interactions of multiple species. These related concepts inform the search strategy, but ecocentrism provides the evaluative orientation: the inclusion of non-human actors or multiple species does not, by itself, establish that ecosystem integrity is considered in design decisions.

This study is designed as a focused narrative review and conceptual synthesis supported by a structured database search. It aims to examine how the environment is represented in architectural AI and related computational design studies, under what conditions non-human life is recognised as a beneficiary of design, and how these representations are incorporated into decision-making processes. The review seeks to develop an assessment framework that brings together stakeholder scope, the integration of environmental and ecological impacts into decision-making, and ecological responsibility.

The central research question is as follows: How can AI and computational design support architectural decisions that account for the requirements of non-human life and ecosystems, and what evidence can be used to assess how these requirements influence decisions? The chapter's principal contribution is an assessment framework that brings stakeholder scope, the integration of environmental and ecological impacts into decision-making, and responsibility for outcomes into a single analysis.

Three questions guide the research: (1) How do AI and computational design incorporate environmental performance information into architectural design decisions? (2) How are nature and non-human requirements represented in AI and computational design studies? (3) What criteria and types of evidence are required for an ecocentric assessment of these relationships? The study does not aim to enumerate all applications in the literature or calculate a pooled effect size. The structured search defines the source pool for conceptual comparison, while purposive selection enables studies addressing different aspects of the research questions to be examined together. Accordingly, the study is not described as a systematic review or meta-analysis.

2. Material and Method

2.1. Databases and Search Strategy

This study is designed as a focused narrative review and conceptual synthesis supported by a structured database search. Searches of Scopus and the Web of Science Core Collection were conducted in September 2026. The search covered English-language articles, reviews, and conference papers published between 2018 and 2026. The final publication stage filter was applied in Scopus; coverage of 2026 extended only to the time of the search.

The search was organised into two conceptual layers. S1 links AI and surrogate modelling terms with architectural design, environmental performance, and design decision-making. Within the second layer, S2A focuses on ecocentric and multispecies approaches, while S2B addresses biodiversity and habitat relationships. Computational and generative design terms in the S2 groups were used to encompass related methods that translate ecological requirements into design decisions. Consequently, not all computational approaches in the selection were classified as learning-based AI applications. The search terms and Boolean relationships are presented in Table 1.

2.2. Record Consolidation and Data Audit

The search yielded 375 raw records, comprising 239 from Scopus and 136 from Web of Science. Deduplication based on DOI, database record identifier, normalised title, and bibliographic information removed 119 duplicate records, resulting in 256 unique records. Of these, 123 appeared only in Scopus, 23 only in Web of Science, and 110 in both databases. Their distribution across search groups is presented in Table 2.

Title, author, year, and abstract fields were available for all records. The 22 records without a DOI were not excluded solely on this basis. Because Web of Science records included early access labels, the Scopus final publication stage filter was not generalised to the combined pool; records whose language or document type could not be established were classified as uncertain.

Within the search results, S1 yielded 193 unique records, whereas S2A yielded 12. This contrast indicates that the search strategy retrieved substantially more publications connecting AI with environmental performance and architectural design than publications explicitly connecting computational design with ecocentric or multispecies concerns. However, the search groups differ in terminology and scope, and their record counts may

Table 1 Search terms and query structure used in the database search (Designed by Author 2026).

Search	Search terms and Boolean relationships
S1	("artificial intelligence" OR "machine learning" OR "deep learning" OR "generative AI" OR "surrogate model*") AND ("architectural design" OR "building design" OR "building design optimization" OR "early-stage design" OR "early design" OR "conceptual design") AND ("energy performance" OR "building energy" OR "energy efficiency" OR "carbon emission*" OR "embodied carbon" OR "thermal comfort" OR daylight* OR "environmental performance") AND ("design optimization" OR "design evaluation" OR "design decision*" OR "design alternative*" OR "parametric optimization" OR "early-stage prediction")
S2A	("artificial intelligence" OR "machine learning" OR "generative AI" OR "generative design" OR "computational design") AND (ecocentr* OR "more-than-human" OR multispecies OR "non-human") AND ("architectural design" OR "building design" OR "urban design" OR "landscape architecture")
S2B	("artificial intelligence" OR "machine learning" OR "generative AI" OR "generative design" OR "computational design") AND (biodivers* OR habitat*) AND ("architectural design" OR "building design" OR "urban design" OR "landscape architecture") AND (design* OR generat* OR optim* OR decision*)

Table 2 Raw and unique record counts by search group (Designed by Author 2026).

Search	Scopus	WoS	Raw records	Unique records
S1	173	115	288	193
S2A	11	6	17	12
S2B	55	15	70	57
Combined pool*	239	136	375	256

* The combined S2 pool comprises 64 records because S2A and S2B share five records. S1 and S2B share one record. Unique record counts across search families cannot be added directly.

also be influenced by database indexing. The imbalance is therefore interpreted as a feature of the retrieved literature rather than an estimate of the relative prevalence of these approaches across the field.

2.3. Title and Abstract Screening

After eight conference volumes that did not constitute individual research publications were set aside, the titles and abstracts of 248 records were assessed. Eligibility required the simultaneous presence of a design context, a computational contribution, an environmental or ecological objective, and a design function (Table 3). Reviews and conceptual studies were retained when they addressed these relationships meaningfully in relation to the research questions.

Screening classified 184 records as eligible candidates, 32 as uncertain, and 40 as out of scope, including the eight volumes initially set aside. Reasons for exclusion were the absence of an environmental objective or methodological connection (14), being an entire conference volume (8), the use of terms outside the relevant context (6), an exclusive focus on operation or control (5), structural optimisation without an environmental objective (3), falling outside the relevant design fields (2), and classification or prediction studies not linked to a design intervention (2). Features that could not be established from the abstract were recorded as uncertain rather than treated as absent.

Table 3 Eligibility criteria used in title and abstract screening (Designed by Author 2026).

Criterion	Inclusion requirement
I1 Design context	A direct relationship with architecture, building design, urban design, or landscape design.
I2 Computational contribution	An explicit role in application or conceptual discussion for AI, learning, or surrogate modelling in S1, and for AI or computational/generative design in S2.
I3 Environmental or ecological objective	A meaningful role for energy, carbon, comfort, daylight, environmental performance, habitats, biodiversity, or non-human requirements.
I4 Design function	A contribution to generation, prediction for design, evaluation, optimisation, comparison of alternatives, or decision support.

2.4. Purposive Study Selection and Scope

Following title and abstract screening, the scope of the review was narrowed through purposive selection, and a final selection of 19 studies was established from the 184 eligible candidates. Selection considered conceptual contribution,

diversity of methods and design scales, the representation of nature, and the nature of the evidence presented. The remaining 165 eligible candidates and 32 uncertain records were not included in the final selection. This selection makes no claim to statistical representativeness or theoretical saturation.

The studies are presented according to their conceptual roles in the review under environmental performance and decision support (A: 7), the relationship between artificial intelligence and ecological design (B: 5), and computational ecological design (C: 7) (Table 4). Search group membership comprises seven records in S1, six in S2A, and ten in S2B. Because S2A and S2B share four records, the selection consists of seven S1 records and twelve records from the combined S2 groups. R-codes are internal record identifiers used for compact cross-referencing across tables. Table 4 maps each identifier to its author–year citation; the codes do not indicate study quality, ranking, or assessment level.

Table 4 Final study selection and the conceptual roles of the studies in the review (Designed by Author 2026).

Group	Study	Search	Role in the selection
A	Radziszewski and Waczyńska 2018 (R192)	S1	Early-stage daylight prediction and validation
A	Wortmann 2019 (R183)	S1	Algorithm comparison and method selection
A	Zou et al. 2021 (R168)	S1	Future climate and design uncertainty
A	Zhou et al. 2023 (R146)	S1	Trade-offs between embodied and operational carbon
A	Fenton et al. 2024 (R121)	S1	Embodied emissions prediction and data coverage
A	Qiu et al. 2025 (R094)	S1	Façade performance and model explanation
A	Zhang et al. 2026 (R012)	S1	Review context for surrogate modelling
B	Cantrell and Zhang 2018 (R205)	S2A	Relationships among humans, non-human agents, and AI
B	Zhang and Cantrell 2021 (R252)	S2B	Technodiversity and ecological agency
B	Wei and Herr 2025 (R220)	S2B	AI-based façade generation using local plant knowledge

Group	Study	Search	Role in the selection
B	Davidová et al. 2026 (R195)	S2A + S2B	The relationship between participatory habitat design and AI monitoring
B	Luan and Yang 2026 (R209)	S2B	Distinguishing visual quality from ecological claims
C	Weisser et al. 2023 (R202)	S2A + S2B	Multispecies building envelopes and requirements
C	Lange, Ratoi, and Co 2020 (R253)	S2B	Translating coral requirements into fabrication
C	Herr and Li 2023 (R240)	S2B	Microorganisms and façade parameters
C	Barnes and Barnes 2024 (R199)	S2A	Incorporating living growth into design
C	Maiorano et al. 2024 (R201)	S2A + S2B	Seasonal requirements of species
C	Levitzky et al. 2025 (R197)	S2A + S2B	Habitat prototypes derived from dead tree features
C	Kim et al. 2025 (R222)	S2B	Distinguishing LCA impact scope from local ecology

Purposive selection was undertaken by a single reviewer using the considerations outlined above; no independent review of the selection decisions was conducted. The resulting corpus therefore reflects the reviewer's interpretive judgement and may be subject to selection bias. The selection was intended to support a focused conceptual synthesis rather than to represent the distribution of the wider literature. The eligible studies not retained are not characterised individually, which limits the extent to which readers can reconstruct the purposive selection.

2.5. Full-Text Review and Thematic Synthesis

The full texts of the 19 selected studies were examined. Together with a supplementary publication describing the implementation stage of the coral habitat research, a total of 20 documents were assessed. Publications from the same line of research and primary studies included in reviews were not counted as independent evidence.

The review examined the design problem, computational method, beneficiaries, the role of indicators in decision-making, the validation

approach, and limitations. Conceptual proposals, simulations, expert assessments, physical prototypes, living growth experiments, and field observations were treated as distinct types of evidence. Quantitative results were interpreted with regard to the basis of comparison and system boundaries.

The thematic synthesis examined performance and decision-making, life cycle boundaries, non-human representation, habitat geometry and materials, time and maintenance, and visual generation and ecological validation. The preliminary framework was applied illustratively to Qiu et al. (2025), Weisser et al. (2023), Maiorano et al. (2024), and Davidová et al. (2026), covering contrasting design approaches and evidence types. Coding recorded the highest supported level within each assessed domain, together with its source evidence and implementation status. A single reviewer conducted the assessment without independent coder validation. The profiles were interpreted separately, without an aggregate score or ranking.

The selected corpus was complemented by contextual literature supporting the theoretical framing and discussion. Mirra et al. (2022) was not identified in the retained database export files and was included as a contextual example of habitat-oriented AI already known during the chapter's development before the structured search. These sources were distinguished from the 19 selected studies and the supplementary coral-habitat publication. The database search restrictions did not apply to this contextual literature.

3. Findings and Discussion

The findings are discussed in relation to the extent to which AI-supported architectural design approaches incorporate ecological considerations into design processes and decisions. Particular attention is given to the distinction between improving environmental performance through computational methods and adopting an ecocentric orientation that recognises ecological systems as integral to architectural decision-making.

3.1. Environmental Performance and Ecocentric Orientation

Environmental performance has become an important area of application for AI in architectural design, particularly through predictive modelling, simulation, and optimisation. These methods enable the assessment and comparison of environmental impacts across design alternatives. However, the integration of environmental indicators into computational processes does not necessarily indicate an ecocentric approach. This distinction raises questions

about how nature is represented in AI-supported design systems and whether ecological considerations influence design priorities or remain primarily parameters for performance evaluation.

3.1.1. The technical representation of nature

AI-based surrogate models support the evaluation of numerous design options by learning the relationships between the inputs and outputs of computationally expensive simulations. Elwy and Hagishima (2024) examine this approach in sustainable building design. Zhang et al. (2026) address performance-oriented parametric optimisation alongside surrogate modelling and decision-making processes. The speed provided by these methods makes it possible to compare more options; however, the criteria used to select an option are a separate matter from model speed.

Fenton et al.'s (2024) early-stage prediction of embodied greenhouse gas emissions illustrates this distinction. Predicting emissions from a building's descriptive characteristics provides information about the environmental consequences of the design. The availability of such information does not automatically demonstrate that it is used as a mandatory condition or a priority objective in the selection process. Separate links must be established between prediction, comparison, and decision-making.

Nature can be represented within a system as a data source, a performance indicator, or a design constraint. These functions do not constitute a necessary sequence of progression; they may coexist within the same model. Furthermore, habitat protection can be defined as a constraint while also reflecting the value assigned to non-human beneficiaries. The technical representation of nature and its ethical status are therefore separate subjects of examination. Systems that use data cannot invariably be assigned a low level of ecocentrism, nor can systems that use constraints invariably be assigned a high level.

3.1.2. Ecocentrism and non-human beneficiaries

Washington et al. (2017) describe ecocentrism as an approach that recognises the intrinsic value of ecosystems and their abiotic components alongside living organisms. This definition establishes a broader domain of value than anthropocentrism, which prioritises human benefit alone. The distinction between biocentrism, which focuses on living organisms, and ecocentrism, which also considers ecosystem integrity, is important for architecture. Designing a structure suitable for a single bird species takes non-

human beneficiaries into account but is insufficient to demonstrate a positive effect on the entire ecosystem.

Gürdür Broo et al. (2024) propose reconsidering the design of intelligent machines along a continuum between anthropocentric and ecocentric orientations. In an architectural context, this approach can connect ecological concerns to the definition of design objectives rather than treating them as a characteristic of a distinct type of technology. A system's environmental sophistication does not imply normative coherence. Conversely, a design intention directed towards non-human life also requires technical competence and evidence of implementation.

Hernández-Santín et al. (2023) discuss how biodiversity can be positioned in passive, indirect, or active stakeholder roles within urban design. Grobman et al. (2023) extend this issue to the multispecies design process at the building scale. The identification of target species' life cycle requirements at the outset of design in the Animal-Aided Design approach also exemplifies this shift (Weisser & Hauck, 2025). By considering trees, birds, and humans together, Holland and Roudavski (2024) question whose knowledge informs design and how that knowledge is produced. These approaches provide a basis for broadening the definition of the architectural user; not all of them are AI methods.

In this chapter, stakeholders are entities positively or negatively affected by a decision, whereas beneficiaries are entities intended to benefit from it. This distinction is necessary to avoid listing only the species to be supported while overlooking those that may be harmed. Non-human requirements can be represented through observation, ecological research, and expert interpretation. However, this representation is not a direct and infallible "voice of nature". The species selected, the origins of the data, and the allocation of decision-making authority must be made explicit.

Cantrell and Zhang (2018) understand intelligence in landscapes through relationships among humans, non-human agents, and the environment rather than through the capacity of an individual machine. This approach demonstrates that stakeholder scope cannot be defined solely through the human–AI pairing. Weisser et al.'s (2023) "ecolope" proposal incorporates the requirements of animals, plants, and microorganisms into multi-criteria building envelope design. Relating ecological knowledge to design variables makes the connection between the availability of environmental data and its influence on decisions more concrete. This proposal is not, in itself, a machine learning application.

3.1.3. The difference between explanation and responsibility

Rong et al.'s (2024) review of 97 studies examines evaluations of explainable AI in terms of trust, understanding, usability, and human–AI collaboration. These criteria are valuable for architectural decisions; nevertheless, identifying a variable that influences a prediction and explaining the ecological consequences of a design are different operations. For example, an explanation showing the importance of material selection in an energy prediction does not automatically explain the material's effects on habitats or water systems.

UNESCO (2022) addresses traceability, auditability, and impact assessment in relation to responsibility. In this chapter, ecological responsibility extends beyond explanation to include who reviews a decision and how it is corrected in response to unforeseen harm. It is a conceptual synthesis of explainability and environmental impact assessment for architectural decision-making.

3.2. An Ecocentric Assessment Framework

The framework comprises three dimensions: Stakeholder Scope, Environmental and Ecological Impact Integration (hereafter, impact integration), and Ecological Responsibility. The first examines the domain of value, the second the decision mechanism, and the third justification and accountability. Figure 1 illustrates how the three assessment dimensions apply throughout the design-to-monitoring process, with feedback informing the revision of requirements and decisions.

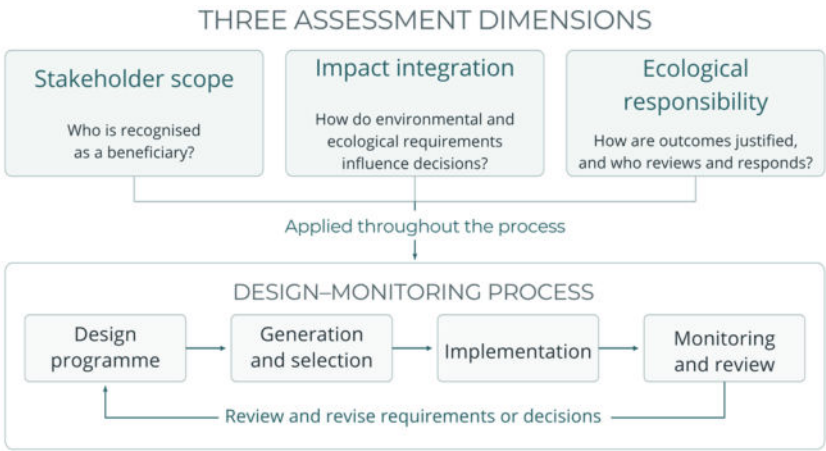

Figure 1 Three complementary assessment dimensions applied throughout the design-to-monitoring process (Designed by Author 2026).

Table 5 Preliminary coding rules for the ecocentric assessment framework (Designed by Author 2026).

Level	Stakeholder scope	Impact integration	Ecological responsibility
0	The stated design aims concern human beneficiaries only, without an environmental or ecological rationale.	The process under examination explicitly excludes environmental or ecological assessment.	Assessment of these outcomes is explicitly excluded from the process under examination.
1	The environment is considered in terms of human comfort or resource benefits.	An impact indicator is calculated but is not linked to the comparison of design options.	Outcome indicators are reported, but their connections to the rationale for the decision are not explained.
2	Non-human entities are identified as affected parties; their status as independent beneficiaries is unclear.	Indicators are used to compare options or support expert selection.	Outcomes, justifications, significant trade-offs, and uncertainties within the impact domain are related to one another.
3	Non-human life or ecosystems are explicitly recognised as beneficiaries possessing value independently of human benefit.	Impacts are incorporated as objectives or constraints in generation, screening, or optimisation mechanisms.	In addition to the preceding level, a responsible party and a process for review, monitoring, and corrective intervention are defined.

Table 5 presents the preliminary coding rules used in the illustrative assessment. The levels are ordinal, and the differences between them cannot be assumed to be equal. Within each dimension and specified impact domain, the highest level supported by the publication is recorded. Insufficient information is coded as "not reported" (NR), rather than as level 0. The status of the supporting evidence is recorded separately so that a proposed mechanism is not mistaken for an implemented process or a demonstrated ecological outcome.

Stakeholder scope is assessed from the stated design aims and intended beneficiaries. Level 2 identifies non-human entities as affected parties; level 3 requires their well-being or ecosystem integrity to be an explicit design end, supported by the description of their requirements. Ecological terminology alone does not establish this distinction. Impact integration concerns the role

of environmental or ecological information in the workflow: comparison and expert-guided selection support level 2, while incorporation into generation, screening, or optimisation supports level 3.

Ecological responsibility concerns the relationship between outcomes and their justification. Level 2 connects reported or predicted outcomes with decision rationales, trade-offs, and uncertainties. Level 3 additionally identifies a responsible actor and a process linking review or monitoring to corrective action. Level 0 requires explicit exclusion of outcome assessment; insufficient information is recorded as NR. Model explanations and routine maintenance are considered within this assessment but do not independently establish ecological accountability.

The unit of analysis is the workflow described in a publication. Each profile identifies the impact domain, source evidence, and implementation status. Domains include building and resource performance, species and habitat relationships, ecosystem processes, and the environmental burden of the computational workflow. A code assigned in one domain does not extend automatically to another. Conceptual proposals, simulations, prototypes, and field observations are therefore distinguished throughout the assessment.

The location-based assessment of dependencies and impacts in the Taskforce on Nature-related Financial Disclosures (TNFD) LEAP approach provides a related perspective on connecting ecological information to decisions (TNFD, 2023). Here, integration is established by tracing information to a documented decision mechanism. Testing whether changes to an indicator alter the preferred solution could provide further evidence of its influence in future applications.

Table 6 presents four illustrative profiles covering building performance, conceptual multispecies design, habitat optimisation, and participatory prototyping. Profiles record stakeholder scope (S), impact integration (I), and ecological responsibility (R) within the stated domain, using the rules in Table 5.

Table 6 Illustrative assessment profiles of four selected studies (Designed by Author 2026).

Study and assessed domain	Profile (S/I/R)	Evidence and principal limitation
Qiu et al. (2025): building energy, daylight, and photovoltaic potential	1 / 3 / 2	Human-oriented performance objectives enter optimisation directly. Design choices are examined through predicted outcomes, trade-offs, and model limitations. Evidence is simulation-based; habitat effects fall outside the assessed domain (Sections 3.5 and 4).
Weisser et al. (2023): multispecies building envelopes	3 / 3(P) / NR	Non-human inhabitants are explicit beneficiaries, with stakeholder-specific indicators informing the proposed optimisation workflow. The mechanism remains conceptual, and an applied outcome assessment is not reported (Sections 4.1–4.4 and 5–6).
Maiorano et al. (2024): species-specific shelter conditions	3 / 3 / 2	Shelter shading enters optimisation; temperature and humidity guide subsequent selection. Seasonal suitability failures, species conflicts, and material limitations are disclosed. Long-term habitat outcomes remain untested (Sections 5.4, 5.6, and 6–7).
Davidová et al. (2026): pollinator habitats	3 / 2 / 2	Pollinator requirements inform expert-guided planting and prototyping. Observations support revisions and reveal ecological and organisational limitations. Maintenance roles are identified, while AI monitoring remains planned and corrective responsibilities are incompletely specified (Sections 3, 6–7, and 9).

Note: P = proposed integration mechanism; NR = insufficient reported evidence for a level assignment. Codes apply to the specified domain and workflow. Maiorano et al.'s integration level 3 refers to shelter shading; temperature and humidity inform selection at level 2. Section references refer to the assessed publications.

The profiles distinguish beneficiary recognition from decision integration and responsibility. Direct integration can support human-oriented performance goals, while multispecies objectives may remain at the conceptual stage. Implementation status and evidence type, therefore, remain essential to interpreting each profile.

The three dimensions apply across learning-based and rule-based or parametric workflows, but the evidence required differs. For stakeholder scope, learning-based systems require scrutiny of which species, sites, and conditions are represented in training data, while rule-based systems require scrutiny of the ecological assumptions encoded by designers. For impact integration, the assessment traces either model predictions or explicit rules into objectives, constraints, and selection decisions. For ecological responsibility, learning-based workflows raise questions about data provenance, model explanations, and transfer beyond training conditions; rule-based workflows raise questions about the justification and revision of rules and parameters. Explicit rules may be easier to inspect, but inspectability alone does not establish ecological validity. Hybrid workflows require both forms of scrutiny.

3.3. Thematic Findings from the Full Texts

The full-text review examines the incorporation of environmental and ecological objectives into design decisions through six themes. Each theme considers the methodological contributions of the studies alongside the scope of the evidence they present.

3.3.1. Learning environmental performance and linking it to design decisions

Performance-oriented studies accelerate the comparison of alternatives at the early design stage. Radziszewski and Waczyńska (2018) predict daylight indicators using artificial neural networks for an office context in Denver's climate. Variations in accuracy across indicators and deviations in glare predictions demonstrate the need to define a model's application domain according to context. Wortmann's (2019) comparison of seven architectural optimisation problems shows that, despite the strong results achieved by RBFOpt, methodological success depends on problem characteristics and the evaluation budget.

Fenton et al. (2024) predict embodied greenhouse gas emissions from building characteristics that can be known at an early stage. Across related datasets comprising 319 dwellings in France and 524 buildings in France and

Belgium, the reported success rate of approximately 92–93% represents the proportion of predictions falling within ±15% of the reference value. This result demonstrates predictive adequacy within a particular data scope, rather than emissions reduction.

Zhou et al. (2023) connect embodied and operational carbon with surrogate modelling, multi-objective optimisation, and alternative selection. However, in the residential example examined, the solution with the lowest total impact reduces the number of storeys from eight to four, requiring the building service provided to be considered in the comparison. No overall savings rate was inferred because of numerical discrepancies between the study's table and narrative.

Qiu et al. (2025) assess daylight, solar radiation, heating, and cooling indicators using models developed from simulations of 1,800 photovoltaic façade alternatives, and explain the contribution of variables to model outputs through Shapley additive explanations (SHAP) analysis. The exclusion of lighting energy from the energy calculation and the restriction of transferability tests to similar climates define the scope of the results.

Zhang et al.'s (2026) review of 114 publications identifies data generation, transfer across contexts, explainability, and validation beyond simulation as common challenges for these approaches. This theme demonstrates that predictive accuracy, design preference, and realised environmental gains require separate assessment. In addition to model performance, ecocentric assessment requires examining which beneficiaries and impacts are included within the scope of decision-making.

3.3.2. Life cycle boundaries and the scope of ecological impact

Kim et al.'s (2025) BIM-IGL approach combines rule-based layout generation with optimisation, building information modelling (BIM), and life cycle assessment (LCA). Fourteen layout alternatives were examined for a hypothetical two-storey dwelling, and 60 material combinations were evaluated for the walls of the selected layout. Because ecological impact analysis takes place after layout selection, not all impact categories are direct objectives of layout generation.

The 40-year assessment is limited to the production, maintenance, and replacement of walls. Monetising damage to human health, biodiversity, and primary production broadens the scope of impacts considered but does not provide direct outcomes concerning the lives of species at the building site. This

makes the distinction between calculating life cycle impacts and incorporating local habitat requirements into design more explicit.

System boundaries also affect the interpretation of computational efficiency. Qiu et al. (2025) exclude approximately 150 hours of initial simulation data generation from the 60.6-hour comparison reported for their machine learning approach. Data generation, model development, and reuse should therefore be considered together when assessing speed gains. A reduction in computation time cannot be directly equated with energy consumption or net environmental benefit.

3.3.3. The representation of non-human life and decision-making authority

Cantrell and Zhang's (2018) "third intelligence" approach locates design knowledge within relationships among humans, machines, materials, and biophysical processes. Zhang and Cantrell (2021) extend this approach through environmental feedback and techno diversity, discussing the place of different forms of knowledge and understandings of nature in the design process. These conceptual studies reveal the limitations of positioning the designer as an actor who fully controls the environment.

Weisser et al. (2023) incorporate the requirements of humans, animals, plants, and microorganisms into the design programme of a multispecies building envelope termed an "ecolope". The connection among species pools, local conditions, ecological models, and generative design is intended to enable the evaluation of alternatives from the perspectives of different beneficiaries. The proposal is a research framework requiring further development rather than an implementation test demonstrating the success of a completed system.

The shared contribution of these studies is to broaden the domain of value in architectural decisions to include non-human life. Nevertheless, humans remain the actors who determine target species, indicators, and acceptable trade-offs. The basis of representational authority should therefore be assessed alongside the scope of representation.

3.3.4. Translating habitat requirements into geometry and materials

Herr and Li (2023) use cellular automata to generate façade patterns conducive to microbial colonisation. Their approach makes microbial life a subject of architectural form and surface design while leaving the testing of biological colonisation to later stages. Levitzky et al. (2025) translate the characteristics of dead tree habitats into parametric design through interviews with four experts and field observations. Wood-based and ceramic prototypes

reveal the relationship between habitat geometry and fabrication possibilities. Both studies incorporate ecological requirements into computational design without presenting a learning-based habitat model.

Lange, Ratoi, and Co (2020) translate coral attachment and water circulation requirements into habitat tiles produced through robotic clay printing. Material use, printing behaviour, and monitorability were assessed together. A supplementary publication from the same research documents the underwater installation and placement of coral fragments in Hoi Ha Wan Marine Park (Lange, Ratoi, Lim, et al., 2020). These publications demonstrate the transition from fabrication to field installation but do not report long-term survival or growth outcomes.

Maiorano et al. (2024) connect temperature, humidity, and solar exposure conditions in multispecies residential environments in the Galapagos with evolutionary optimisation and designer selection. The inability to provide suitable conditions for land iguanas and sea lions during certain months demonstrates that species requirements may conflict. Furthermore, the experimental strength of the fabricated bioceramic differs from the literature value used in the structural analysis; the material test cannot be regarded as validation of the entire architectural proposal.

Outside the selected studies, Mirra et al.'s (2022) learning-based abstractions of tree forms and the FloaTree application also support the relationship between computational representation and fabrication (Pugnale et al., 2024). This theme demonstrates that habitat design is not completed through geometric generation alone; connections must be established among materials, the requirements of living organisms, and observations following use.

3.3.5. Incorporating time, growth, and maintenance into design

Zou et al. (2021) assess the design of a classroom in Guangzhou using future climate scenarios, neural network surrogate models, and multi-objective optimisation. Improvements in certain objectives, without simultaneous improvement across all indicators, demonstrate that design suitability depends on time and priorities. Adapting this human-user-oriented approach to changing species requirements presents a research opportunity for ecocentric design.

Barnes and Barnes (2024) examine the responses of four plant species to different directional treatments and growth arrangements in separate eight-week greenhouse experiments. The failure of certain species to meet geometric expectations demonstrates that living behaviour can alter design assumptions.

The small number of replicates and the reliance on image-derived growth indicators limit the transfer of these findings to permanent architectural applications.

Davidová et al.'s (2026) POL-AI approach connects full-scale habitat interventions with pollinator gardens, local maintenance, and participatory fabrication. Although field observations and thermal images provide information about implementation, they do not demonstrate a comparative increase in biodiversity. As camera-based monitoring remains under planned development, the system cannot be regarded as a completed autonomous design control system.

These studies highlight the relevance of changing conditions, maintenance, and adaptation beyond design delivery. From an ecocentric perspective, these considerations extend responsibility to the continued use and management of an intervention.

3.3.6. Visual generation, locality, and ecological validation

Wei and Herr (2025) incorporate 500 plant and substrate images collected in Shenzhen into façade design through multimodal language models, expert correction, and generative image tools. Among the 60 images assessed by ten experts, the mean visual quality score was 8.83 out of ten, while the mean locality score was 6.13. The higher mean score for visual quality than for locality in the expert assessment demonstrates the need to evaluate these criteria separately. The assessment is based on images and does not encompass the survival or reproductive success of plants in the field.

Luan and Yang (2026) evaluate landscape images generated with ControlNet using image quality metrics. However, the calculation of the ecological index used and its relationship to target species are insufficiently explained. Inconsistencies in the reporting of sample sizes and speed further complicate assessment of the ecological effectiveness claim.

Outside the selected studies, Yang and Qian (2025) illustrate the role of generative tools in early architectural representation, while Khan et al. (2024) exemplify the connection of explainable models to energy, carbon, and comfort objectives. Considered together, these studies demonstrate that representational quality, performance assessment, and biological suitability require different validation processes.

Table 7 summarises the relationship between the six themes and ecocentric assessment. The themes focus on the identification of beneficiaries, the

Table 7 The relationship between thematic findings and ecocentric assessment (Records may be used in more than one theme. The table does not constitute a methodological quality score or an ecocentrism ranking) (Designed by Author 2026).

Theme	Source records	Main contribution	Limits of the evidence
Performance and decision-making	R192, R183, R121, R146, R094, R012	Prediction and optimisation support defined indicators.	Model performance does not constitute a realised environmental gain.
Life cycle and impact boundaries	R222; R146, R094, R183, R012	Computational and impact scope affect the outcome of the comparison.	LCA categories do not substitute for local habitat indicators.
Representation of non-human life	R205, R252, R202	The definition of beneficiaries and their requirements broadens the design programme.	A conceptual proposal is not an implemented multispecies system.
Habitat geometry and materials	R240, R197, R253, R201; Lange, Ratoi, Lim, et al. (2020)	Ecological knowledge is translated into form, materials, and selection conditions.	Fabrication experiments and field installation are distinguished from long-term biological success.
Time, growth, and maintenance	R168, R199, R195; R252	Suitability is assessed in relation to changing climate, growth, and maintenance.	Scenarios, greenhouse experiments, and field observations are different types of evidence.
Visual generation and validation	R220, R209	Local data and expert assessment influence the quality of representation.	Visual quality does not demonstrate species accuracy or survival success.

Note: R-codes refer to the studies identified in Table 4. Studies may contribute to more than one theme.

influence of their requirements on decisions, and the validation of outcomes rather than on algorithmic complexity.

3.4. Architectural Application and Discussion

The framework is analytical in use and ecocentric in orientation: it examines beneficiary recognition, impact integration, and responsibility without treating the resulting profile as proof of ecological benefit. The following recommendations develop the author's normative interpretation of the synthesis for architectural practice, extending from the design programme to post-implementation monitoring.

3.4.1. Incorporating ecological requirements into design

The design programme should encompass the site's habitats, seasonal use, and relationships with its surroundings. Alongside beneficiary species, species and ecological processes that may be harmed by the intervention should be identified. These requirements should be connected to decisions about layout, façades, materials, planting, lighting, and maintenance.

For each indicator, the conditions under which it eliminates an alternative or changes its preference ranking should be explicit. Energy and habitat impacts require separate assessment, since gains in one domain do not necessarily compensate for losses in another. The range of alternatives can include reusing existing buildings, reducing the scale of intervention, and retaining existing conditions without construction. This broadens assessment to the necessity and scope of the intervention.

3.4.2. Moving from model indicators to ecological outcomes

Holland et al.'s (2023) long-term assessment of natural and artificial habitat structures demonstrates the need to test design success over time. The presence of a structure does not mean that the target species can use it safely.

Monitoring programmes should specify a baseline, comparison conditions, and the expected ecological outcome. Different forms of use, including visitation, sheltering, and reproduction, require separate observation. The authority and maintenance resources needed to modify the design in response to adverse outcomes should also be identified.

3.4.3. The environmental burden of AI itself

Van Wynsberghe (2021) considers the use of AI for sustainability alongside the technology's own life cycle impacts. This scope includes energy, water, mineral use, and electronic waste (UNESCO, n.d.). Luccioni et al. (2024)

likewise show that energy consumption during use depends on the task and model selected.

The framework addresses these burdens through impact integration and ecological responsibility. The former examines whether resource information influences the choice of computational method or workflow; the latter concerns its justification, assessment boundaries, uncertainties, and arrangements for review. Data generation, training, inference, and hardware-related impacts should be considered alongside the expected environmental gains of the supported design. Comparisons require tasks of comparable scope and output quality, with attention to repeated generation or evaluation and to impacts that remain unmeasured.

3.4.4. Representation and decision-making authority

Representing non-human life in design does not resolve the question of who holds decision-making authority. When expert knowledge and local observations are used, the information sources, uncertainties, and accepted trade-offs should be made explicit.

Documenting design assumptions, the basis of ecological assessments, and responsibility for maintenance makes these decisions open to review. Accountability also requires a process through which emerging evidence can lead to changes in the design or its management.

4. Conclusion and Suggestions

This review suggests that ecocentric orientation in architectural AI and computational design is not adequately characterised by algorithm type or environmental performance alone. Its principal contribution is a framework that examines beneficiary recognition, decision integration, and responsibility for outcomes as distinct dimensions. The thematic synthesis and four illustrative profiles show how these dimensions can describe different design approaches while retaining their impact domains, evidence types, and implementation status.

The review is limited by its focus on English-language publications, the 2018–2026 period, database coverage, and full-text access. The purposive selection does not represent the statistical distribution of the field. Independent coder validation and reanalysis of original experimental data were not conducted. The proposed framework should therefore not be regarded as a validated scoring or project-ranking tool.

Future research should test the framework across different climates and design scales, examining assessment consistency and the relationships between design decisions and long-term ecological outcomes. In architectural practice, local species requirements, life cycle impacts, the resource use of AI, and post-implementation maintenance should be considered together.

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This chapter complies with national and international research and publication ethics.

Author Contribution and Conflict of Interest Declaration Information

Adil Yirmibeş is the sole author and assumes responsibility for the conceptual framework, methodology, interpretation, and final content of this chapter. The author declares no conflict of interest.

Declaration on the Use of Artificial Intelligence and AI-Enabled Technologies

Generative artificial intelligence tools were used to assist with bibliographic data processing and language editing. The author retains responsibility for the accuracy of the content and references, the interpretation of the literature, and the conclusions presented in this chapter.

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