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Developing an integrated conceptual framework for the interaction between bionic architecture and digital twin technology

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Abstract

Bionic architecture, inspired by nature's adaptive and efficient systems, is increasingly being explored in conjunction with digital twin technology to simulate and optimize built environments before physical implementation. This emerging synergy promises enhanced architectural intelligence; however, current approaches often lack a cohesive conceptual integration between bionic principles and digital twin components. This study aims to develop an integrated conceptual framework that enables a structured interaction between bionic architecture and digital twin systems, incorporating both bioinspired and digital elements within a unified model. Adopting a descriptive–analytical methodology based on a systematic literature review and thematic synthesis, the research identifies and classifies key components from each domain—such as biomimetic algorithms, sensor feedback loops, physical–virtual entities, and data-driven control mechanisms. These elements are organized into a three-layered process diagram and synthesized into a dual digital twin model comprising a biological twin (Twin A) and an architectural twin (Twin B). The framework is grounded in two core mechanisms: real-time feedback and iterative learning, supported by the integration of reinforcement learning (RL) and transfer learning (TL) algorithms. RL enables Twin A to optimize behavioral strategies through continuous environmental interaction, while TL allows Twin B to adapt architectural responses across different scenarios without retraining. The proposed closed-loop system enhances adaptability, responsiveness, and efficiency across both physical and digital domains, thereby establishing a novel paradigm of bio-cyber-architectural cognition. This framework not only contributes a theoretical foundation for intelligent architecture but also opens pathways for empirical experimentation, advanced BIM–digital twin integration, and interdisciplinary architectural innovation.

Keywords: Bionic Architecture; Digital Twin; Integrated Conceptual Framework; Real-time Feedback; Continuous Improvement

1. Introduction

With the increasing adoption of biomimetic approaches and the advancement of digital technologies, the need to develop sustainable and efficient architectural structures has become more pressing. Bionic architecture—drawing inspiration from nature's efficient and resilient mechanisms—and digital twin technology—with the ability to create precise virtual replicas of physical structures for simulation and optimization prior to construction—have each delivered remarkable innovations in their respective domains. However, the systematic integration of these two fields remains conceptually fragmented, and there is a notable gap in the development of a unified framework that concurrently encompasses bio-inspired processes and digital twin components (Asghar & Naghvi, 2019; Umorina, 2019; Varshabi et al., 2022).

Bionic architecture focuses on intelligently mimicking natural forms and mechanisms, whereas digital twin technology provides an ideal virtual platform for testing, refining, and validating nature-inspired designs (Lin et al., 2022; Tekinerdogan & Verdouw, 2020). The complexity of human and environmental variables in architectural contexts, combined with technical challenges such as integrating vast sensory data, bio-based content, and the significant computational power required to simulate biomimetic system behavior accurately, presents substantial barriers to developing precise and efficient digital twins for bionic designs (Mitkov et al., 2024).

Although many current digital twin systems focus primarily on technical aspects and pay less attention to the behavioral principles of nature, this technology holds considerable potential for integrating bioinspired strategies into the design and implementation cycle. The purposeful exploitation of proven natural strategies can lead to the development of architectural systems that are more flexible, responsive, and optimal.

Despite independent progress in bionic architecture and digital twin technology, there is a lack of focused studies systematically overlapping the two domains. This research gap results in the conceptual fragmentation of strategies and prevents repeatability and empirical validation. From this perspective, the central research question is: How can a unified conceptual framework be designed to systematically embed nature-proven strategies into digital twin components to maximize sustainability and dynamic adaptability in architecture? The primary aim of this study is to develop such a model, providing a solid theoretical and practical foundation for future studies and

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implementations in the fields of smart and energy-efficient architecture.

2. Research Background

2.1 Bionic architecture

Bionic architecture, an interdisciplinary branch of biomimicry, creates modern and sustainable structures by emulating natural mechanisms and forms. Biomimicry—bridging biology and engineering—offers practical solutions to technological and environmental challenges (Chayaamor-Heil, 2023). This approach promotes minimal environmental impact and structural harmony with the surrounding ecosystem (Contreras et al., 2023; Umorina, 2019). It is based on observing and understanding natural entities, deriving functional principles, and applying them in human activity (Huang et al., 2011; Umorina, 2019). Examples include self-regulating termite mound ventilation systems used to optimize building energy consumption and suspended cable or thin-shell structures inspired by spider webs and eggshell architecture (Yuan et al., 2017).

The evolution of bionic architecture has unfolded in stages, each introducing notable structural innovations. A milestone in this trajectory was the introduction of fractal geometry by Benoît Mandelbrot in The Fractal Geometry of Nature (1982), which established a mathematical basis for analyzing complex natural forms and enabled fractal-driven architectural morphogenesis (Vorobyeva, 2018).

This field has progressed from simple biomimicry to advanced designs such as bioprocessing and biohybrid systems (Raman & Bashir, 2017). Initially, architects focused on mimicking natural esthetics and logical forms (Huang et al., 2011). In the contemporary era, bionic architecture integrates function and material adaptation from biological systems. For instance, plant-inspired mechanisms—such as active leaf-like shells—are used to guide morphology, enhance structural flexibility, and improve energy efficiency (Mei et al., 2024). This evolution has also led to the development of adaptive building envelopes and smart responsive coatings that emulate natural organismal adaptability (Al-Obaidi et al., 2017; Sangtarash et al., 2022; Asefi & Aram, 2018). Drawing inspiration from polar bear fur and lotus leaves, architects have developed self-regulating, self-repairing, and self-cleaning materials to maximize durability and sustainability (Yuan et al., 2017).

The history of bionic architecture reflects our deepening understanding of natural mechanisms and our growing capability to translate them into architectural innovations. The field continues to evolve, emphasizing structural biomimicry, climate-sensitive design, and energy optimization (Jamei & Vrcelj, 2021). As bionic architecture advances, integrating insights from advanced biology with design creativity becomes essential, facilitating collaboration between architects and biologists (Chayaamor-Heil, 2023).

2.2 Digital twin background

Digital twin technology has emerged as a breakthrough in the era of the Internet of Things and industrial innovation, integrating machine learning, artificial intelligence, cloud computing, big data, and analytical software to transform the structure of processes and systems (Gopinath et al., 2019). By bridging the physicalphysical and virtual worlds and producing dynamic data-based models from real-time, historical, simulation, and AI data, digital twins are revolutionizing the structure and performance of industries ranging from manufacturing to architecture (Htet et al., 2023).

Originating in 2002, digital twin technology has evolved continuously since then (Jeong et al., 2022). In architecture, the growing emphasis on data-centricity and smart construction powered by computational advances has made digital twins a key tool (Zhou et al., 2021). The integration of digital twins into architecture enables the creation of comprehensive and accurate virtual models that reflect the entire lifecycle of physical structures. Initially applied in manufacturing with established frameworks and architectures (Aheleroff et al., 2021), digital twins have now become a pervasive technology of Industry 4.0, especially in architecture and construction (Duan & Tian, 2020).

Digital twins transform building lifecycle management—from design through operation. During the design phase, comprehensive function simulations enable pre-emptive optimization. In construction, the early detection of anomalies enhances the project quality and efficiency. In operation, real-time monitoring and analytics simplify maintenance and enable predictive protocols (Zhou et al., 2021).

By converging physical and virtual spaces throughout a building's lifecycle, digital twins facilitate more active control, optimal management, and environmental sustainability (Nie et al., 2019). Their application in architecture has led to the development of smart building management frameworks based on digital twin technology, which are usable across various design and operational scenarios (Nie et al., 2019). This technology represents a fundamental milestone in architectural history by overcoming the limits of digitalization and smart integration in the design and construction processes.

3. Research Methodology

This study employs a descriptive–analytical methodology to critically and systematically review the literature related to bionic architecture and digital twin technology, thereby developing an integrated conceptual framework for their interaction. The researcher systematically extracts information and performs comparative analysis to identify the key mechanisms and components.

- Step 1. Systematic Literature Review: Databases in both Persian and Latin languages were searched using keywords such as "bionic architecture," "digital twin," and "biotechnology."
- Step 2. Thematic Content Analysis: The principal components within each domain were categorized. The reviewed texts were sorted into subthemes based on criteria including the nature of the bio-inspiration,

the physical–virtual structure, and the data–processing–feedback cycle. The behavioral and structural patterns of each category were then identified and compared.

- Step 3. Synthesis and Conceptual Model Development: Based on the identified relationships, a process diagram and final conceptual model were designed to illustrate the linkage between the bio-inspired components and the digital twin elements in a closed-loop data–processing–feedback cycle. Symbolic equivalents and explanations of each process stage were incorporated into the model.

4. Theoretical Foundations

4.1 Bio–technology interaction

In the bionic domain, the interaction between biological systems and technology is defined as a continuous feedback loop comprising the following key stages:

- Biological Sensing and Data Collection: Sensory systems in living organisms (e.g., chemical receptors in bacteria or sensory neurons in animals) capture environmental inputs and provide initial data to initiate the bionic feedback cycle (Bar-Cohen, 2005).
- Analysis and Modeling: Once the data are collected, researchers use analytical and simulation methods (such as fractal algorithms or evolutionary computation) to extract the functional principles of biological systems and reproduce them as conceptual or mathematical models (Mandelbrot, 1982).
- Technological Implementation: These models have been translated into technological prototypes, such as biomimetic flying robots with butterfly-wing aerodynamics or optimization algorithms for building envelopes derived from plant structures (Bar-Cohen, 2005; Mei et al., 2024).
- Integration and Deployment: Conceptual models and localized technologies are integrated into physical construction or bio-hybrid systems, realizing the biological–technological interface in practice (Wilson & Dorman, 2008).
- Monitoring and Feedback: The performance of the implemented technologies is continuously monitored in interaction with the biological context or environment. These observations are fed back into the original model to inform necessary refinements (Lebedev & Nicolelis, 2006; Kovatchev et al., 2010).

This cycle repeats continuously, with iterative feedback strengthening the development of more optimized and adaptive bionic technologies. Such elastic feedback underpins high-functioning self-regulating intelligent systems.

As illustrated in Figure.1, the interaction between biological systems and technology is organized within a continuous feedback cycle. This cycle begins with biological data collection (right side, yellow section), proceeds through analysis and modeling, and is then transferred to the technological model (left side, blue section). The results of technological implementation are integrated into the real environment and subjected to monitoring and feedback. The resulting data re-enter the cycle, thereby establishing a repetitive and self-optimizing structure.

The lower part of Figure.1 further illustrates the different modes of interaction between biology and technology. In biomimetic systems, the relationship between the biological components and the technology is classified into unidirectional and bidirectional structures. In a unidirectional structure, information flows one way—from biology to technology or vice versa—whereas in a bidirectional or closed-loop structure, continuous feedback between the biological context and engineered systems is maintained.

Examples include unidirectional biology-to-technology transfer—such as flying robots modeled after butterfly wing shape and motion to optimize aerodynamic performance (Bar-Cohen, 2005)—and reverse unidirectional applications, where technology supports or repairs biological function, such as cochlear implants that convert sound into neural pulses to restore deep hearing in deaf individuals (Wilson & Dorman, 2008).

In bidirectional or closed-loop systems, biological signals are read and technological interventions are written simultaneously. In bidirectional brain–machine interfaces, concurrent neuron recording and stimulation enable precise prosthetic control with sensory feedback (Lebedev & Nicolelis, 2006; Pasquale et al., 2014).

4.2 Bionic architecture in the digital age

To achieve a truly biomimetic architecture, we must move beyond the mere replication of natural forms and integrate biological principles into the functional design (El-Zeiny, 2012; Ramzy, 2015). This architecture solves complex design challenges and optimizes architectural solutions through computational algorithms based on biological processes (Chayaamor-Heil, 2018). Architectural algorithm software that combines bioinspired ideas with architectural design produces innovative, sustainable, and efficient structures, enabling the optimization and validation of bionic designs (Huang & Siao, 2016).

Bionic principles optimize architecture by mimicking natural structures, enabling architects to benefit from optimal structural solutions while achieving form diversity (Mayatskaya et al., 2020). Structural topology optimization allows the creation of unconventional yet efficient architectural forms; it enhances creativity and performance, fosters early collaboration between architects and engineers, and enables the evaluation of plant- and animal-inspired solutions through both visual and quantitative analysis (Mizobuti & Junior, 2020).

In environmental-performance-based design, environmental performance data are used to optimize the form and environmental interaction of buildings simultaneously. This holistic approach—beyond local biomimetic optimization—considers multiple environmental criteria in tandem (Song & Sun, 2021), aligning with green bionic architecture, reducing energy consumption, and promoting sustainable development (Mei et al., 2024). The shift toward performance-based design reflects the growing need for adaptive architecture that goes beyond mere form imitation (Mei et al., 2024; Song & Sun, 2021).

In the digital age, bionic architecture is defined by the integration of natural principles and digital technologies to create sustainable and innovative designs (de Oliveira et al., 2023). This approach applies evolutionary strategies from nature, translating biological principles into practical architectural applications through biomimicry (de Oliveira et al., 2023). Digital tools (such as Rhino, Grasshopper, and Ladybug) enable parametric modeling and environmental simulation, allowing the exploration of complex natural forms and processes in architectural design (Asghar & Naqvi, 2019).

Using computational methods, architects can develop biomimetic design processes specific to architecture (Menges, 2012). For instance, designing kinetic facade shading inspired by *Aldrovanda vesiculosa* has produced geometrically complex architectural mechanisms, while parametric modeling of orchid-inspired forms in landscape architecture has led to innovative urban furniture design (Körner et al., 2016; Jovic et al., 2021).

Biomimetic algorithms, which emulate natural processes and integrate empirical data with computational parameters in specialized software, enable the precise force simulation and optimization of complex architectural designs (Chayaamor-Heil, 2018; Menges, 2012).

Digital tools and computational algorithms in bionic architecture serve as bridges between biological patterns and design processes by analyzing vast datasets and uncovering semantic relationships among variables. These techniques enable efficient data handling, hidden-pattern detection, and evidence-based insights, supporting decision making from ideation through strategic design (Ushizima et al., 2016).

Data-mining methods combined with visual analytics—identifying atypical patterns and relationships in biological data—support hypothesis testing and exploratory research platforms (Cvek et al., 2009; Cvek et al., 2011). By integrating pattern-discovery algorithms (e.g., clustering, principal component analysis, network mining) with dynamic visualization tools (such as Cytoscape, Gephi, or visual modules in Grasshopper), researchers gain deep insights into biological structures and processes. This approach not only renders big data visually analyzable but also facilitates the integration of diverse data sources, empowering researchers to identify complex relationships and generate new hypotheses (Khennak & Drias, 2018; Santhaiah & Reddy, 2014).

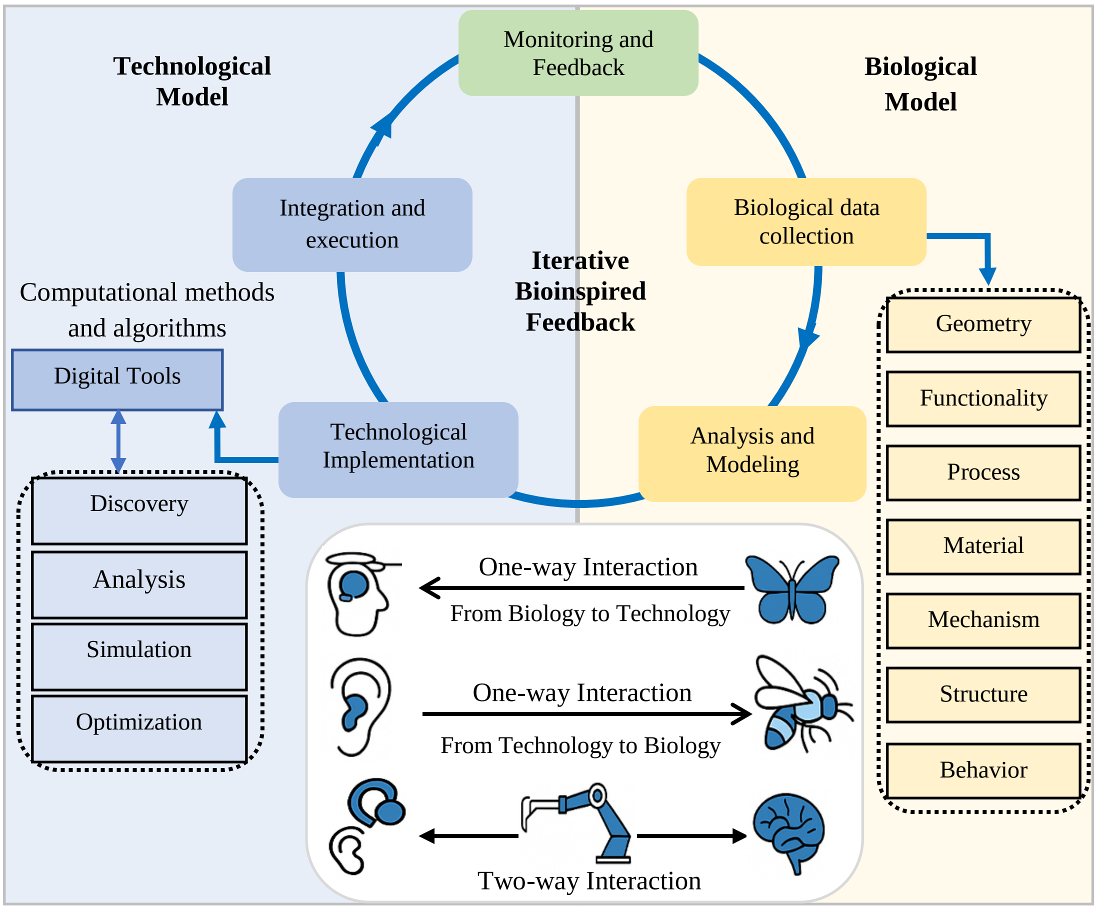

Fig. 1. Integrated bio–technology interaction model. The diagram illustrates the continuous feedback loop between the biological model (right) and the technological model (left). Each stage—from biological data collection to technological implementation and monitoring—forms part of an iterative cycle. The lower section depicts possible modes of interaction: one-way (biology → technology), one-way (technology → biology), and two-way (closed-loop feedback).

4.3. Components of the digital twin

Digitization significantly enhances performance and efficiency within the architecture, engineering, and construction (AEC) industries. The digital twin refers to the creation of a highly accurate three-dimensional digital replica of a physical object or system in a computer-based environment. This virtual counterpart can be used for simulation, performance evaluation, and monitoring of the physical system for various purposes—ranging from behavior prediction and performance analysis to process optimization (Naudet et al., 2021).

By providing precise simulations, the digital twins offer deep insights into the internal system functions, component interactions, and future behaviors of their physical counterparts. They generate practical data for users and stakeholders. Currently, research and applications of digital twins are rapidly expanding across domains such as smart cities, urban environments, transportation logistics, healthcare, engineering, and the automotive industry (Botín-Sanabria et al., 2022).

A digital twin is an informational construct that optimally collects and stores all data related to a physical entity in digital form (Grieves & Vickers, 2017). It is a real-time, updated digital model of a physical object and its surrounding environment, incorporating data such as geometry, location, function, behavior, structure, and movement. Through simulation, predictive analytics, and real-world data processing, it provides a multidimensional and analytical view of system performance (Autodesk, 2021).

By transforming conventional workflows in design, construction, planning, simulation, and forecasting, digital twins enable researchers to optimize design and production. They achieved the original intent of the concept by offering an accurate reflection of real-world conditions at reduced cost and increased implementation efficiency (Agrawal et al., 2022).

As illustrated in (Figure.2), a digital twin consists of three interconnected components: the physical entity (right, orange section), the virtual model (left, blue section), and the data that integrates them (center, green section). Raw data are collected from the real environment and transferred to the virtual model, where they undergo simulation, analysis, and processing. The resulting insights are then fed back to the physical model as processed information, enabling continuous synchronization between real and virtual systems. This cyclical exchange forms the basis for real-time monitoring, predictive analysis, and decision-making in digital twin applications (Agrawal et al., 2022; Campos et al., 2019; Liu et al., 2023).

Digital twins transfer raw data from the physical component to the virtual model, where it is processed into actionable insights. This synchronous combination of data and analytics enables real-time monitoring and comparison between physical and virtual systems. During the construction phase, it significantly enhances efficiency, cost-effectiveness, and quality (Grieves, 2014). Overall, the digital twin operates through a cyclical analytical process (Liu et al., 2022). While all three stages are essential, the precision and speed of decision-making are the most critical factors impacting the overall system performance (Liu et al., 2023).

Digital twins integrate the physical world—including the object or process, sensors, actuators, and edge computing—with the digital world—comprising the virtual model, machine learning, data analytics, and databases. This is achieved through various communication protocols (e.g., Wi-Fi, Bluetooth, and wired connections). As a result, traditional construction processes have evolved into systems driven by the Internet of Things (IoT), artificial intelligence (AI), and continuous data analytics, enabling real-time performance monitoring and visualization for end users (Botín-Sanabria et al., 2022).

Digital twins are not limited to visual models alone. By incorporating augmented reality (AR) and virtual reality (VR), they enable safer, more immersive simulations with features such as remote access and interaction within hazardous environments (Rassölkin et al., 2021).

Two general types of interaction between the physical and digital models are identified in the literature:

- Full Digital Twin (Real-Time, Bidirectional Synchronization): In this configuration, the physical and digital models are continuously linked via embedded sensors. Real-time sensor data are transmitted to the digital model, and its simulations or analyses provide feedback or corrective commands to the physical system. This bidirectional loop supports continuous monitoring, predictive maintenance, and even autonomous control. Scholars such as Kritzinger et al. define the digital twin as a multiphysics and multiscale model with real-time, bidirectional data exchange (Kritzinger et al., 2018). Similarly, Tao et al. highlight its role in "real-time monitoring, control, and optimization" (Tao et al., 2019).
- Passive or Delayed Synchronization (Unidirectional): This state, referred to as a "digital shadow" (as categorized by Kritzinger et al.), involves one-way data flow from the physical entity to the digital model. Updates to the virtual model must be entered manually or periodically following changes in the real-world system. No automatic or corrective feedback is transmitted from the digital model to the physical system (Kritzinger et al., 2018). Grieves and Vickers describe the digital shadow as an initial developmental stage of the digital twin, where sensor data is merely transferred to the model without dynamic interaction (Grieves & Vickers, 2017).

Improving conditions and product quality via Digital Twin requires a stepwise, hierarchical framework rather than simply identifying improvable components. As outlined by Agrawal et al. (2022), five sequential questions guide this process:

- Which components to improve – e.g., process optimization, prediction/prevention, resource efficiency.
- What data are needed – sensor readings, historical records, environmental inputs.

- What algorithms are needed – machine learning, simulation, optimization to turn data into insights.
- What software is needed – platforms, simulation tools, data management systems.
- What models are needed – mathematical, physical, or data-driven to represent system behavior.

This chain—components → data → algorithms → software → models—ensures each stage builds on the last, enabling Digital Twins to deliver measurable performance and quality gains.
(**Table 1**) summarizes potential answers to each of these five questions, presenting concrete insights derived from the reviewed literature.

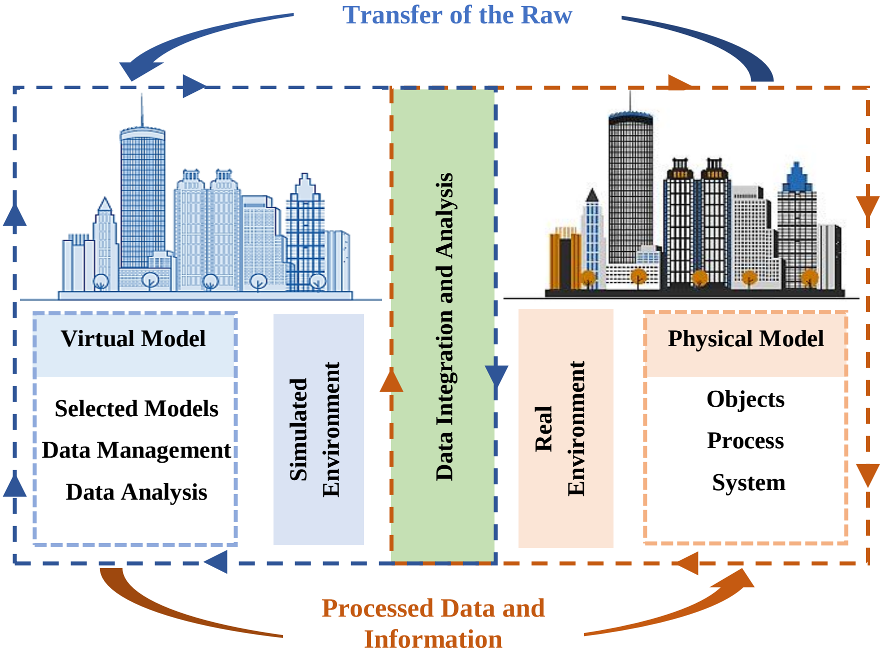

Fig. 2. Core components and data flow in a digital twin system.
The diagram illustrates the interaction between the physical model (right) and the virtual model (left). Raw data are collected from the real environment and transferred to the digital environment for simulation and analysis. Through data integration and processing (center), actionable insights are generated and transferred back to the physical system as processed information. This cyclical exchange ensures synchronization between real and virtual systems, supporting real-time monitoring, predictive analysis, and decision-making.

Table 1
Key Questions and Possible Responses Regarding the Use of Digital Twin Technology

Key Questions	Some Potential Answers
Which components can be improved using a digital twin?	• Process optimization: Digital twins enable process optimization by analyzing data and simulating different scenarios, helping to reduce time and costs (Luo et al., 2023; Soori et al., 2023). • Prediction and prevention: Using machine learning algorithms, digital twins can predict future system behavior and identify issues before they occur (Iliuţă et al., 2024). • Quality management: Continuous monitoring and simulation allow digital twins to improve the quality of products and services (Luo et al., 2023). • Data-driven decision-making: Providing accurate, data-based insights for faster and better decisions (Botín-Sanabria et al., 2022). • Maintenance cost reduction: Predicting maintenance needs to minimize unnecessary expenses (Soori et al., 2023). • Resource optimization: Reducing waste and improving resource efficiency through data analysis. • Testing and innovation: Enabling experimentation with new scenarios and innovations in design and processes without physical risks (Xuan et al., 2023).
What data are required for using a digital twin?	• Sensor data: Information collected from physical sensors such as temperature, pressure, vibration, and other relevant parameters (Liu et al., 2023). • Historical data: Data related to past system performance, including failures, repairs, and optimizations (Al-Ali et al., 2020). • Operational data: Real-time information on system operation, including inputs and outputs (Stadtmann et al., 2023). • Environmental data: Information about the environmental conditions that influence system performance (Al-Ali et al., 2020).

What algorithms are required for using a digital twin?	• Machine learning algorithms: For data analysis and predicting future system behavior (Goodwin et al., 2022). • Simulation algorithms: For simulating system behavior and evaluating various scenarios (Chiachío et al., 2022). • Optimization algorithms: For enhancing system performance and reducing costs (Luo et al., 2023 Khalili et al., 2018).
What software is required for using a digital twin?	• Data analytics software: For processing and analyzing collected data (Luo et al., 2023). • Simulation software: For modeling and simulating system behavior (Wang et al., 2021) • Digital twin platforms: Tools that integrate data, models, and algorithms (Lehner et al., 2023). • Data management software: For storing, managing, and retrieving data (Pang et al., 2021).
What models are required for using a digital twin?	• Mathematical models: To describe system behavior and the relationships between variables (Huang et al., 2024). • Physical models: To simulate the physical characteristics and interactions of the system (Huang et al., 2024). • Data-driven models: To analyze and process data to extract useful insights (Liu et al., 2023).

5. Results

5.1 Bionic–digital twin comparison

The convergence of digital twin technology and bionic architecture has created a new paradigm in the design of the built environment. By integrating advanced computational capabilities with evolutionary strategies inspired by nature, this approach enables the development of adaptive, self-regulating, responsive, and resource-optimizing architectural systems (Li et al., 2021). The integration of Internet of Things (IoT) sensors with virtual models enhances data transparency and strengthens the feedback continuum (Agrawal et al., 2022).

The concept of the Biological Digital Twin in this study refers to a system that models and simulates biological entities in a digital format (Lin et al., 2022), while the Architectural Digital Twin executes adaptive environmental responses based on those interpretations.

In bionic architecture, digital twins enable complex virtual representations of natural systems, facilitating multivariate analysis and control of building processes. They operate beyond traditional, one-dimensional simulations by unifying geometric, behavioral, and process sub-models within a single computational framework (Liu et al., 2021). Performance-based design, supported by digital twins, marks a shift from purely mimetic approaches toward design methodologies that consider evolutionary processes and environmental adaptations as design drivers. This approach allows the development of optimized architectural solutions through the simulation of complex ecosystem interactions and data-driven optimization (Song & Sun, 2021). For example, biomimetic building envelopes can be designed and tested through digital twin simulations (Al-Obaidi et al., 2017).

Several fundamental concepts in digital twin technology align with the strategies observed in nature. For instance, digital twins facilitate predictive insight and self-awareness (Lee et al., 2021), reflecting the adaptive and evolutionary behaviors of natural systems. A comparative analysis of living organisms and digital twin systems revealed two core shared mechanisms:

- **Feedback Mechanism:** Like living organisms, digital twins receive feedback from their environment, adjust their behavior accordingly, and evolve. Early-stage feedback allows for self-regulation and optimization. Bionic architecture incorporates this nature-inspired mechanism to enable buildings to respond and adapt to environmental changes, allowing structures to interact actively with their surroundings (Ilieva et al., 2022). The digital twins continuously update their models on the basis of incoming data and environmental shifts, enabling real-time adaptation and improving system responsiveness. Their functional logic mirrors biological learning processes, which are continuously refined and optimized (Liu et al., 2023).
- **Iteration and Improvement:** As living organisms continually adjust and optimize their behavior through growth and environmental interaction, digital twins operate through repeated feedback cycles that perpetually support repair and decision-making improvement (Liu et al., 2023). Both natural systems and digital twins rely on gradual changes and continuous behavioral refinement to develop adaptive optimization strategies, gradually enhancing the performance of intelligent cyber-physical systems (Gabor et al., 2016). Recent studies have demonstrated that multi-objective genetic algorithms integrated into feedback loops can significantly reduce the energy consumption in bionic structures (Zheng & Wang, 2024).

By leveraging these analogies, digital twins can effectively model and simulate complex systems and biomimetic components. Through dynamic, self-learning mechanisms that integrate sensor data, expert knowledge, and historical records, digital twins provide valuable insights and predictive capabilities in architecture, continuously enhancing the performance of cyber-physical systems (Bottani et al., 2020). This cycle of continuous improvement enables digital twins to predict the behavior of complex systems with greater precision and ensure adaptive decision-making based on constant feedback (Pires et al., 2019; Santos et al., 2022).

In living organisms, learning and behavioral adjustment are ongoing processes. Similarly, digital twin models employ iterative loops of data collection, analysis, model updating, simulation, and evaluation to achieve continual improvement and adaptability (Bottani et al., 2020; Viola & Chen, 2020). The stages are as follows:

- **Data Collection:** Similar to the complex sensory systems of organisms, digital twins use multivariate sensor networks to gather quantitative data from the physical environment (Bernhardt et al., 2020). For instance, the use of ultrasonic and LiDAR sensors allows for the capture of micro topographical surface details, improving the feedback fidelity (Oliveira et al., 2024).
- **Analysis, Learning, and Model Updating:** Following actions or responses, living organisms learn from past experiences to adjust future behaviors (Botton-Amiot et al., 2023). Similarly, digital twins analyze the collected data and identify patterns to continuously update their models and implement the necessary optimizations. Recent research emphasizes the importance of transfer learning frameworks in reducing model update time (Goodwin et al., 2024).
- **Testing and Simulation:** Organisms routinely test new behaviors and adjust based on the outcomes. Digital twins can simulate various scenarios to evaluate the results and identify the optimal solutions.
- **Adaptive Prediction:** Living beings predict behavioral outcomes based on prior experiences and learning (Bernhardt et al., 2020). Digital twins use collected data and updated models to forecast physical system behavior and plan appropriate responses (Iliuț ă et al., 2024).
- **Performance Evaluation:** In the digital twins, the simulation and prediction outputs were compared with the actual performance of the physical model to assess the model accuracy. This phase can reveal the need for further calibration and, using multi-criteria decision analysis techniques, optimize the overall performance (Zhang & Li, 2023).

5.2. Conceptual Framework of the Interactive Process

Building upon theoretical foundations and the identified intersection between digital twin technology and biotechnology, this study proposes an interactive and hierarchical conceptual framework. As illustrated in (Figure.3), the framework consists of two parallel and synchronous layers: the Biological Digital Twin (Twin A) and the Architectural Digital Twin (Twin B). Each layer independently follows five sequential stages (Stages 1–5), after which they converge in a central Integration and Implementation Layer (Stages 6–11). This structure ensures a systematic progression: from initial pattern selection and data extraction to parametric modeling, integration, and continuous adaptive optimization.

Real-time data streams from sensors and actuators ensure that both digital twins remain synchronized with actual environmental conditions. At the integration stage, a set of interconnected feedback loops (real-time, short-term, and long-term) enables the system to continuously recalibrate and enhance architectural performance. Thus, the model not only describes a linear progression of stages but also incorporates cyclical feedback mechanisms, providing adaptive intelligence to the overall framework.

To enhance clarity, a scenario-based illustrative example accompanies the diagram under the title “Ant-Inspired Pathfinding for the Design of Efficient Evacuation in Crowded Architectural Spaces.” This example demonstrates how each stage operates in sequence, showing how biological logic—such as ant foraging efficiency—can inform architectural design decisions. By walking through each stage in order, the scenario ensures that the hierarchical structure of the model is both conceptually transparent and practically grounded.

A. Biological Layer

- **Stage 1: Selection of Biological Pattern:** A suitable bio-inspired model is selected, whose structural and functional principles can be extracted for architectural application (Smith & Jones, 2019). The key selection criteria include the quantifiability of the mechanical and geometric parameters and the reproducibility of the dynamic behavior in the computational environments.
  Example: *In this stage, ant foraging behavior is selected due to its measurable and computationally replicable characteristics—specifically, optimal pathfinding (shortest path) using pheromone reinforcement and decentralized decision-making. The Ant Colony Optimization (ACO) algorithm, which emerges from this behavior, is identified as an effective tool for emergency evacuation planning in dense architectural environments such as passenger terminals.*
- **Stage 2: Data Collection and Extraction of Biological Parameters:** In addition to extracting data from scientific databases, experimental data—such as geometric, mechanical, hydrothermal properties, and motion patterns—are recorded in controlled laboratory environments using digital and thermal cameras, 3D scanning, temperature and humidity sensors, precision catalogers, and mechanical testing devices (Zhang, Kumar, & Chauhan, 2020). These data form the basis for subsequent modeling.
  Example: *Here, biological data concerning ant navigation (path pattern, movement speed, decision at bifurcations, response to congestion, obstacle avoidance, and density distribution) were collected from both the scientific literature and controlled laboratory experiments. This includes tracking ant behavior in maze environments to capture real-time decisions under pressure and obstacle conditions.*
- **Stage 3: Primary Data Integration:** The collected data were validated and standardized using statistical methods and structural integration algorithms. Normalized data sets are stored in a centralized, reliable database for use in parametric modeling (Stage 5) (Pauwels & Zhang, 2019).
  Example: *The movement and pheromone deposition patterns are statistically analyzed and encoded into structured datasets, which serve as behavioral templates in subsequent parametric modeling. These formats facilitate integration with the architectural datasets.*

- **Stage 4: Geometric Reconstruction and Digital Equivalency of the Biological Model:** Using sub-millimeter resolution 3D scanning, laser scanning, or manual modeling based on microscopic data, the geometry of the biological specimen is digitally reconstructed (e.g., in Rhino). The natural material properties—density, elastic modulus, and thermal conductivity—are then assigned to the digital components for accurate numerical simulation (Eastman, Teicholz, Sacks, & Liston, 2018).
  Example: *A digital behavioral model is developed based on observed ant trail geometries, representing pheromone gradients, decision nodes, and probabilistic movement. This forms a spatial network model that simulates decentralized collective pathfinding, which is suitable for parametric adaptation.*
- **Stage 5: Bio-Inspired Parametric Modeling (Twin A):** A dynamic parametric model is created to simulate the behavior and structure of the biological pattern. Its control function or governing algorithm is calibrated using experimental data from Stages 2 and 3 to minimize deviation and maximize alignment with real-world responses (Pauwels & Zhang, 2019).
  Example: *This parametric model—Twin A—is responsible for dynamically generating optimal evacuation paths in real time using the ACO logic. It reacts to environmental inputs such as crowd density or blocked exits and continuously recalculates escape routes under changing conditions.*

B. The Architectural Layer

- **Stage 1: Selection of Architectural Element:** The research scope is defined by selecting one or more architectural elements (e.g., building envelope, window frame, structural system, or HVAC). The selection criteria included functional alignment with bio-inspired strategies, availability of experimental data, and significance in improving building performance.
  Example: *In this case, the emergency evacuation system of a high-density transportation terminal is selected. The terminal consists of numerous exits, corridors, and congestion points, making it suitable for bio-inspired optimization strategies.*
- **Stage 2: Collection of Architectural Parameters:** All the performance-related parameters of the chosen element are collected. These include geometric features (dimensions, thickness, reflectivity), materials (density, elastic modulus, thermal conductivity), environmental conditions (indoor/outdoor temperatures, solar radiation, wind load), and performance requirements (acoustic insulation, structural demands, comfort criteria), sourced from BIM models, lab data, technical references, and environmental sensors.
  Example: *Key data include corridor width, door dimensions, occupancy levels, surface friction, and target evacuation times. These inputs serve as the architectural constraints and boundary conditions for the Twin B simulations.*
- **Stage 3: Data Integration:** The collected data are standardized using a common data structure. Raw data are first validated and cleaned statistically. Then, a data schema or BIM/IFC standards convert the information into consistent units and formats (e.g., SI), organized in a centralized database with metadata. This enables efficient retrieval and alignment with biological data.
  Example: *Architectural and biological datasets are mapped onto a common schema, enabling real-time correspondence between the ant-movement-inspired simulations and the actual architectural paths within the terminal.*
- **Stage 4: Geometric Reconstruction:** Using the integrated data, a precise 3D model of the architectural element is created. Techniques such as high-resolution laser scanning, photogrammetry, or parametric modeling in CAD/BIM environments are applied. The material properties and topological connections are assigned digitally.
  Example: *This digital twin includes route geometries, exit signs, and known congestion zones. It mirrors the layout in which Twin A's output will be tested and validated.*
- **Stage 5: Architectural Digital Twin (Twin B):** The refined 3D model is implemented as a parametric-analytical version capable of simulating structural, thermal, and dynamic behaviors using time-sensitive inputs (e.g., real-time temperature and wind load variations) and processing algorithms derived from Twin A. This twin forms the basis for feedback loops and architectural optimization.
  Example: *Twin B receives optimized evacuation paths from Twin A and simulates the crowd flow accordingly. It also generates responsive architectural behaviors—such as activating signage, adjusting barriers, or rerouting flow using smart guidance systems.*

C. Integration Layer

- **Stage 6: Activation of Real-Time Environmental Monitoring:** A network of high-precision sensors (temperature, humidity, solar radiation, wind pressure, and inclinometers) is installed on the architectural components. Real-time data are transmitted to both digital twins, enabling predictive and reactive responses and forming the foundation of intelligent architectural control (Lee, Bagheri, & Kao, 2021).
  Example: *In the terminal, IoT sensors track occupancy density, door status, crowd velocity, and environmental stressors (e.g., smoke or fire). These inputs trigger ACO updates in Twin A and real-time spatial simulations in Twin B.*
- **Stage 7: Data Transfer from Twin A to Twin B:** Twin A processes the real-time data, calculates the control parameters and optimal responses, and communicates them to Twin B via a digital twin

platform. This ensures that Twin B is continually updated with optimized parameters, thereby enhancing the simulation accuracy under real-world conditions.
Example: *For instance, if a corridor becomes congested, Twin A will redirect flows to alternative exits and send updated paths to Twin B. The system adapts continuously to crowd dynamics.*

- **Stage 8: Simulation and Prediction:** Twin B integrates the optimized parameters (target temperature, reflectivity, airflow rate, and structural performance) with the model's geometry and materials to simulate the structural, thermal, and dynamic behavior. The simulation output generates precise control commands for the embedded actuators (Kritzinger et al., 2018).
Example: *Simulations may include alternate evacuation patterns, traffic redistribution, or stress-response modeling to ensure minimum evacuation times across all zones.*
- **Stage 9: Actuator Execution:** Digitally defined control commands (e.g., speed, movement angle) are transmitted via IoT networks or PLC protocols to mechanical, hydraulic, or electronic actuators. Upon validating the message integrity, the actuators execute settings such as adjusting the apertures or modifying the structural stiffness to achieve architectural responses (e.g., reducing the wind load or improving the temperature distribution). The feedback data are relayed back to Twin B for synchronization.
Example: *For example, evacuation signs are updated dynamically, doors are opened or closed, and pressure zones are adjusted to support optimized crowd movement.*
- **Stage 10: Calibration and Model Updating:** Discrepancies between Twin A's simulated outputs and real-world sensor data are used to recalibrate Twin A's parameters. Based on these refinements, Twin B is re-optimized and updated instructions are sent to the actuators. The sensors then capture the post-adjustment data (displacement, stress, and temperature) and relay them to Twin B. This ongoing calibration maintains long-term accuracy and stability (Zhang et al., 2020).
Example: *If a bottleneck occurs despite the predicted clearance, both twins adjust their parameters. Updated commands are issued to refine the spatial responses while maintaining safety and performance.*
- **Stage 11: Continuous Learning and Adaptation:** Following execution, Twin A logs responses via sensor data, generating updated datasets. Reinforcement learning is applied to refine Twin A's decision-making over time. These updated insights are sent back to Twin B, where transfer learning enables rapid adaptation to new spatial or contextual conditions. This cycle continuously aligns the biological and architectural models, ensuring optimal configurations and improved system performance.
Example: *By integrating Ant Colony Optimization (ACO) with reinforcement learning (RL), Twin A gradually refines its path-selection strategy based on environmental feedback—such as adjusting evacuation routes under varying crowd densities or obstacle locations. Each emergency cycle improves its ability to identify the optimal behavioral responses. Meanwhile, transfer learning (TL) allows Twin B to reuse these optimized patterns in different architectural layouts (e.g., from a train station to an airport terminal) without starting from scratch, ensuring faster and more context-aware spatial adaptation.*

The proposed use of RL and TL within the feedback loops of the digital twin system is grounded in their demonstrated effectiveness in adaptive, data-scarce, and real-time decision-making environments. These characteristics align closely with the operational logic of the proposed bio-architectural framework, which relies on the dynamic interaction between biological and architectural digital twins.

Reinforcement Learning (RL) is particularly suitable for systems that must learn optimal decision policies through continuous feedback from their environment. In this study, RL is embedded within Stage 5 of the Biological Digital Twin (Twin A), where it enhances the Ant Colony Optimization (ACO)-based control mechanism by allowing the system to iteratively improve path selection in real-time under spatial uncertainty and environmental stress. The application of RL in adaptive building systems has been validated in prior studies—for example, Chen & Zhang (2023) demonstrated RL's capacity to optimize the behavior of kinetic façades based on environmental feedback, significantly improving energy efficiency and occupant comfort.

TL is applied within the continuous learning stage (Stage 11) to update Twin B by transferring previously learned control policies to new architectural scenarios. TL enables the reuse of learned behavioral control policies—such as evacuation response patterns or spatial flow optimizations—across similar typologies or user conditions, reducing the need for retraining from scratch. The use of TL in digital twin platforms has been shown to improve learning efficiency and cross-domain adaptability, as confirmed by Liu et al. (2023) in manufacturing systems.

Unlike traditional rule-based control approaches that require predefined parameters and manual updates, RL and TL enable self-adjusting architectural systems capable of reacting to unforeseen user behavior, environmental stimuli, or structural disturbances. These learning mechanisms form the basis for the three-tier feedback architecture of the proposed model, supporting autonomous calibration, continuous improvement, and long-term performance optimization.

By integrating these intelligent algorithms into the dual digital twin framework, the system moves beyond static simulation or one-time optimization toward a bio-cyber-architectural cognition paradigm—one in which design decisions evolve over time through experience, environmental interaction, and biologically inspired logic.

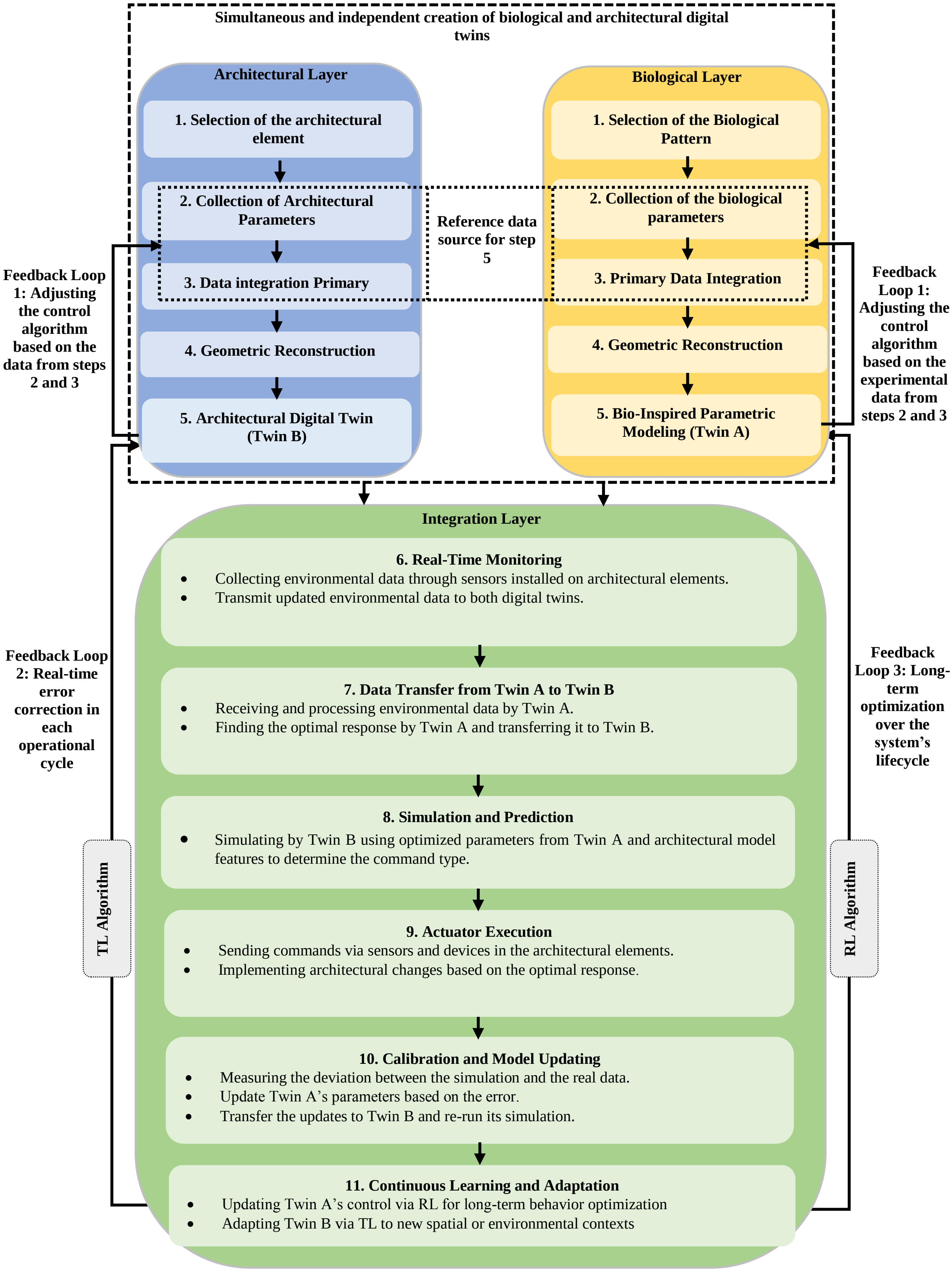

Fig. 3. Conceptual integration of the bionics and digital twin in architecture

6. Discussion

To strengthen the contribution of this study, we positioned our proposed framework in relation to two influential digital twin models: Jeong et al. (2022) and Chiachío et al. (2022). Both approaches have significantly advanced digital twin applications in industrial and structural engineering by focusing on relatively static domains—primarily structural monitoring, fault detection, and performance prediction. Jeong et al. introduced a multilayered framework anchored in technology readiness levels and manufacturing workflows, whereas Chiachío et al. proposed a structural digital twin framework emphasizing sensor integration and real-time analysis for civil and structural engineering systems. While effective in their respective contexts, these models do not address dynamic, biologically interactive environments.

In contrast, our framework introduces a dual digital twin structure—the Biological Digital Twin (BDT) and the Architectural Digital Twin (ADT)—explicitly designed for adaptive architectural responsiveness. Unlike prior static models, this system leverages physiological signals and behavioral patterns to drive real-time spatial transformations through continuous feedback loops. Its novelty lies in extending digital twin concepts from industrial monitoring toward bio-adaptive architecture, thereby creating an interdisciplinary bridge between bioinspired design, cognitive systems, and cyber-physical environments.

Although empirical validation remains pending, the framework is grounded in established research. Prior studies have demonstrated the feasibility of biological feedback control (Li et al., 2021; Chen & Zhang, 2023) and adaptive building systems (Nie et al., 2019; Pang et al., 2021), providing evidence that the integration of these elements into a closed-loop architectural model is technically plausible. The framework's logic aligns with core principles of cognitive architectures and cyber-physical systems (Grieves & Vickers, 2017), but its application to the architectural scale represents a novel conceptual advance.

This study, however, has several limitations. First, the framework has not yet been validated through full-scale implementation or simulation, limiting its immediate applicability. Second, while reinforcement learning and transfer learning strengthen its adaptive potential, these methods have not been tested on architectural datasets in real time. Third, the biological analogy of ant foraging, while illustrative, is domain-specific and may not fully capture the diversity of biomimetic strategies relevant to architecture. These limitations highlight avenues for future research: empirical prototyping, exploration of alternative biological paradigms, and practical integration of intelligent feedback mechanisms within built environments.

Ultimately, the contribution of this work lies not in replicating existing digital twin structures, but in reframing them for adaptive, bio-architectural contexts. By shifting from static monitoring toward dynamic responsiveness, the proposed framework offers a foundation for interdisciplinary inquiry and practical experimentation at the intersection of biology, computation, and architecture.

7. Conclusion

This study sought to bridge the domains of bionic architecture and digital twin technology by constructing an integrated conceptual framework that translates biological intelligence into architectural performance within a closed-loop feedback system. Unlike prior works that have treated biomimicry or digital twins as parallel but disconnected approaches, this research demonstrates how the two can be systematically combined through a hierarchical, multi-layered process model.

The proposed framework was developed through a stage-by-stage synthesis of data, models, and algorithms. Beginning with the extraction of biological parameters and their parametric reconstruction (Twin A), the study showed how these data can be mapped and synchronized with architectural datasets (Twin B). The subsequent integration layer established a coherent flow of sensor-driven data monitoring, simulation, and actuator feedback, thereby operationalizing the conceptual model into a dynamic and adaptive system. This sequence of stages illustrates how the model is directly derived from both the theoretical analysis and the structured organization of data, ensuring methodological transparency and conceptual rigor.

A key finding of this research lies in the incorporation of reinforcement learning (RL) and transfer learning (TL) as core mechanisms within the feedback architecture. RL enables Twin A to optimize bio-inspired algorithms, such as ant colony pathfinding, through continuous interaction with environmental data. TL allows Twin B to transfer previously learned response strategies into new architectural contexts, thus enhancing adaptability and reducing the need for retraining. Together, these learning mechanisms provide a pathway toward self-regulating and cross-domain architectural intelligence.

By integrating these components, the model advances beyond static biomimetic analogies or conventional simulation tools. It offers a new paradigm of bio-cyber-architectural cognition, in which built environments are capable of learning, responsiveness, and ecological adaptation. This contribution adds both methodological clarity—through the explicit stepwise model—and theoretical depth—by demonstrating how biological and architectural systems can converge into a unified adaptive framework.

Future research directions emerging from this study include:

- Development of integrated BIM–Digital Twin platforms with automated real-time monitoring and continuous model updating.
- Exploration of diverse biological analogies (e.g., plant cells, microscopic morphologies) to enrich the repertoire of transferable principles.

- Empirical field testing of bio-inspired systems at multiple scales and in different climatic contexts to validate simulation results.
- Advancement of machine learning algorithms to improve predictive accuracy in digital twin simulations.
- Design of intelligent, sensor-driven architectural systems capable of responding autonomously to environmental stimuli and user needs.

Through these directions, the framework proposed in this study can evolve into a robust foundation for future adaptive and ecologically intelligent architectural design practices.

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