From Structure to Action: AI-Guided Repair

AI-supported Repair Guidance Framework for the Built Environment

Introduction: Why Repair Matters

While **recycling** and **reuse** address the afterlife of materials, **repair** enables direct and situated interventions in existing buildings, extending their lifespan, avoiding premature replacement, and opening opportunities for upgrading. Yet in contemporary practice, repair is often deemed uneconomical and regarded as undesirable work. Replacement of parts, elements, or entire buildings has become the norm. Maintenance and repair are delegated to those whose labor remains undervalued, carried out in the background, lacking authorship and visibility. Conventional BIM and CAD systems are oriented toward new construction and offer no structured workflows for diagnosing, planning, guiding, or documenting repair.

Artificial intelligence offers flexible solutions to such challenges. It can interpret diverse and unstructured inputs from text, documents, images, and scans, and translate them into coherent structures that support reasoning and decision-making. For individuals without prior knowledge of repair, as well as for professionals seeking inspirational guidance, the question arises: How can AI help initiate repair as a fundamental step in sustainable construction and maintenance?

From Structure to Action proposes a digital workflow that uses AI to structure repair into a coherent, repeatable, and creative process. The project demonstrates how vision supported language models (VLMs) can reason and guide assessment, planning, and execution of repair, providing a foundation for repair as a systematic design strategy. The AI-supported framework is validated through two case studies, from canonical objects to buildings, and implemented as a mobile application that turns repair into an interactive and data-driven design practice.

Framework: From Perception through Reasoning to Action

A five-step digital pipeline is developed to enable users to generate geometric and semantic knowledge of intended objects or buildings, assess damages, formulate action plans and guidance, and document the process, leveraging Multimodal AI in every step.

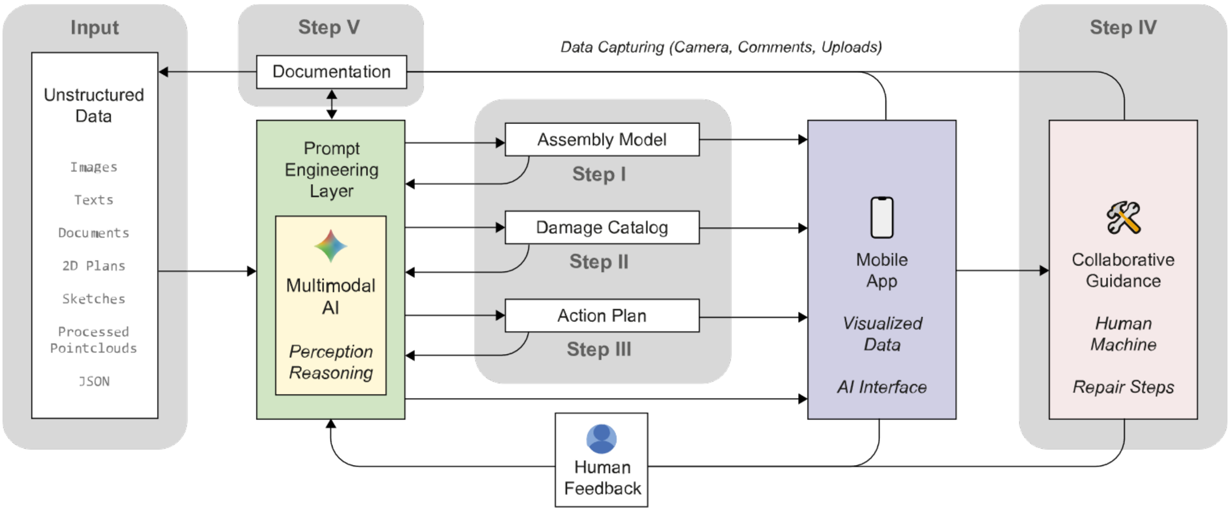

Figure 1: Workflow diagram of AI-assisted repair, from unstructured input to collaborative human–machine guidance.

I. Assembly Generation

Multimodal AI translates unstructured inputs, such as images, text, or point cloud scans, into geometric and semantic knowledge, stored within a graph-based *assembly-model* data structure, where each part is described with a unique identifier, dimensions, pose data, and material information. This step transforms real-world complexity into a digital assembly, containing the topological semantic structure of the building or object.

II. Damage Cataloging

Using the assembly as reference, the multimodal AI detects and classifies cracks, missing parts, corrosion, and other damages. The output is a list of all damages with metadata such as exact positions, severity, extent, and confidence scores. Overlaid on the assembly-model, the current state of the structure is revealed.

III. Action Planning

AI generates repair strategies based on the combined assembly and damage data. Users can guide the reasoning process by commenting on their own thoughts and consulting help of AI-Agents that represent expert knowledge. Draft plans are fully editable, keeping human expertise central. Approved strategies are stored and visualized as procedural repair action-graphs.

IV. Interactive Guidance

The mobile-phone interface offers immersive 3D visualization, interactive action-graphs, and conversational AI support. Users can follow steps sequentially or navigate non-linearly, receiving contextual instructions at each stage. This transforms the repair site into a digitally augmented workspace.

V. **Review and Documentation**
The user can record all interventions via the interface within the data structure, creating a transparent digital history. This record can support facility management, certification, and long-term monitoring of interventions.

At every stage, the human remains in control. The system augments rather than replaces expertise: each generated assembly, damage catalogue, or repair plan is presented for inspection and can be refined through simple textual input. This ensures that digital representations remain both accurate and aligned with design intent. By structuring these steps into a coherent workflow, repair becomes repeatable and data-rich rather than ad-hoc. Crucially, all of this happens directly on site via a mobile-first interface. Designers and craftspeople can capture, verify, and adapt data in real time, documenting damages in context, checking assemblies against the object, and testing repair plans against immediate constraints. This immediacy reduces delays, prevents misunderstandings, and turns repair into a live, iterative process rather than a disconnected sequence of paperwork.

Technical Set-up

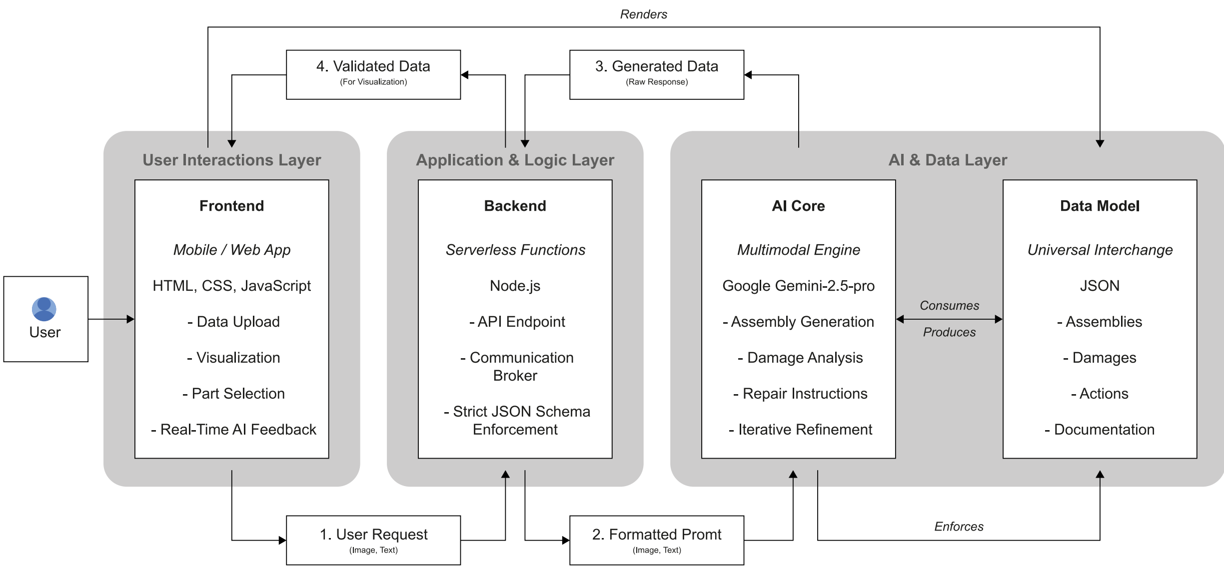

Figure 2: System architecture of the AI-assisted repair workflow from user input to validated repair data.

A functional prototype has been implemented and evaluated, comprising the following modules:

Frontend: A mobile- web application built with HTML, CSS, and JavaScript, allowing users to upload data, generate assemblies, inspect damages, and interactively visualize repair plans. Features include explode views, part selection with metadata, and real-time AI feedback.

Backend: Serverless Node.js functions handle communication with a multimodal AI model. The backend enforces strict JSON schemas to ensure robustness and interoperability.

AI Core: Comparative testing identified Gemini-2.5-pro as the current most effective engine for assembly generation. It produces coherent, part-based models from single images and responds reliably to iterative refinement via natural language prompts. A trained or fine-tuned model is yet to be implemented.

Data Model: JSON serves as a universal interchange format, lightweight, human-readable, and platform-independent, storing the assembly model, damages, action model and documentation. The schematic structure effectively supports AI communication in terms of input and output, while also facilitating visualization and documentation.

Case Studies

The prototype is evaluated through two case studies spanning different scales: a set of 1960´s Santo chairs by the Swiss designer Edlef Bandixen, representing the canonical object scale, and a church by the German architect Hans-Uwe Rein, representing the architectural scale. A working demonstration (Figure 2) shows that a chair photographed with a smartphone can be transformed into a structured assembly, have damages detected, and a repair plan generated, all within minutes. With multiple copies of the chair available, several users were provided with the repair plan to evaluate both the effectiveness of the action strategy and the usability of the interface.

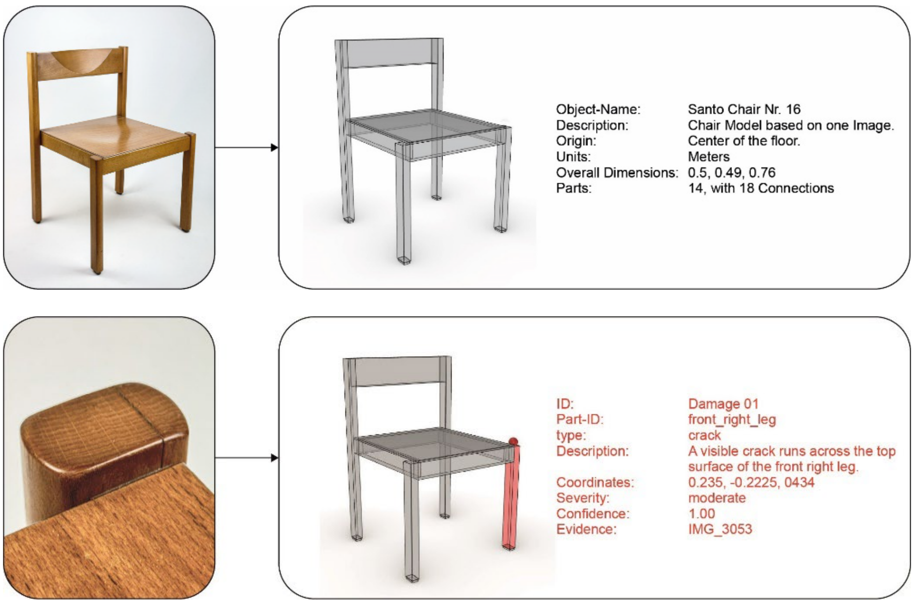

Figure 3: Generation of an assembly-model from a single reference image and user comments (top), as well as damage detection and annotation, linking a visible crack on the front right leg to structured metadata (bottom).

Testing with the church data highlights the potential for scaling this approach to larger, complex structures, where new challenges emerge compared to the smaller-scale chair example. The structure introduces a far greater number of elements, interdependencies, and spatial dimensions. At this scale, the workflow must not only capture and model geometric complexity but also account for historical data, material weathering, and site-specific conditions. The integration of multimodal inputs (historical photographs, pointcloud surveys, and on-site damage assessment) becomes essential to build a reliable assembly and action model. This larger case demonstrates how the system can move beyond isolated artifacts toward architectural environments, bridging detailed repair reasoning with broader questions of conservation strategy, material authenticity, and long-term maintenance planning.

Historical Data *Pointcloud Data* *Damage Assessment* *Assembly & Action Model*

Figure 4: From historical reference and pointcloud data to on-site assessment and structured assembly- and action-model for repair.

Applications in the Built Environment

The system has broad applications across the life cycle of buildings:

Architecture & Design: Supports adaptive reuse and repair into the early stages of design.

Engineering: Provides structured diagnostics and repair strategies for structural monitoring.

Construction: Offers on-site, mobile-based guidance, with potential for AR/VR extensions.

Operation & Maintenance: Documents interventions digitally, enabling predictive maintenance.

Education & Training: Prepares architects and engineers to treat repair as a central design strategy.

By embedding repair in digital workflows, the project directly contributes to **sustainability, resource efficiency, and cultural continuity**.

Outlook

From Structure to Action demonstrates how multimodal AI can transform maintenance, repair, and work with the existing building stock into a structured and creative design process. The framework translates unstructured input into assemblies, damage catalogues, and action plans, establishing repair as a systematic and data-rich practice. Its scalability from small artifacts to architectural structures suggests applications in heritage conservation, adaptive reuse, and contemporary construction. As datasets expand, models will gain precision, contextual understanding, and adaptability. In the future, structured and machine-readable outputs could connect AI reasoning with robotic fabrication or augmented reality guidance on site, revealing how architectural intelligence itself evolves when repair becomes a central mode of design.