THE ART OF REUSE IN THE DATA AGE

CULTURE, PRACTICE, TOOL

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I would like to thank my supervisor, Elham Mousavian, for going above and beyond in assisting me with this writing.

For the research the following software and libraries were used:

Python 0.13.0

Pandas 2.2.3

OpenAI 1.52.2

Scikit-learn 1.5.2

Rhino 8 - 8.13.24317.13001

Grasshopper 1.0.0008

Phoenix3D 0.1.1

A public repository was presented for the tool developed:

Semantic-Search-Grasshopper

I acknowledge the use of AI in the form of ChatGPT 4o, 4o1 and OpenAI API in this writing.

Abstract

The reuse of architectural components remains a marginal practice, hindered by cultures of design and economy, regulation, and above all, complexity. For all their rhetoric, current small scale efforts are not stemming the tide of demolition waste. This dissertation argues that AI might offer a catalytic solution, addressing the core challenge of data complexity rather than attempting to overturn these entrenched cultural and economic forces. Through a critical review of literature on reuse in design, the research situates AI within broader debates, comparing its potential with alternative drivers of change. A bespoke tool, developed in Grasshopper and leveraging OpenAI's language models, tests AI's capability to streamline the integration of reclaimed components into architectural workflows. The tool facilitates early design-stage decisions by matching components based on geometry, material properties, and design intent, bridging gaps in current workflows and fostering broader adoption. In a limited sense, the findings demonstrate AI's ability to upscale reuse, though cultural, regulatory, and practical limitations remain. It concludes by framing reuse as more than a technical challenge, but a dogma which values the histories of objects previously destined for the scrapheap.

Contents

1 – Introduction

A Mandate for Reuse

An obsession with standardised production has been intensified by the digital tools we use today. As many have identified, parameter-based design has grown, beyond the distinctive style, Parametricism, into an all-encompassing software-driven approach by which most contemporary buildings are realised.[1] The ability to produce ever more objects started with industry and now permeates design tools. Further, the gravitation towards production pervades an interdisciplinary mindset. BIM and increasingly AI are making massive data quantities digestible. In personal practice and in studying the cutting-edge work of the Parametricists, a naïve question was incited. Why are these data tools only being used to create ever more rather than to use what we already have?

Whilst the term adaptive reuse has existed since 1973, the circular economy today is limited.[2] At one end, designers are making admirable yet bespoke attempts to reuse found components. At the other, industry violently recycles. Energy intensively, and favouring mechanistic production, often-reusable waste is instead recycled into standard products. In short, with 1/3rd of global waste arising from demolition, we are not doing enough.[3]

Our arguments of moral intention have driven little change in the context of reality. The recognition of embodied craft and carbon in a reused object's history is not compelling enough of an argument to shift the massive forces of established industry and economy. The dissertation considers how AI, what many have pitched as the 'intelligence revolution', may propel reuse into the mainstream. More importantly, encompassing everything from the attitude to scientific exploration, what cultural assumptions drive and limits its uptake? It does not examine designing for reuse. Though important, we cannot produce more to reduce waste. Neither is it a justification of reuse. Extending beyond purely scientific questions, it hopes to ask why the science was never deemed worthwhile in the first place.

As with many sustainable goals, the complexity of reusing varied components is far from a simple task. Here, Europe emerges as a hotbed of research, but this mandate extends to other developed nations and increasingly, developing countries which inherit globalised software.

1 Bottazzi, Digital Architecture beyond Computers, 83.
2 Wong, Adaptive Reuse in Architecture, 6.
3 Menegaki and Damigos, 'A Review on Current Situation and Challenges of Construction and Demolition Waste Management', 8.

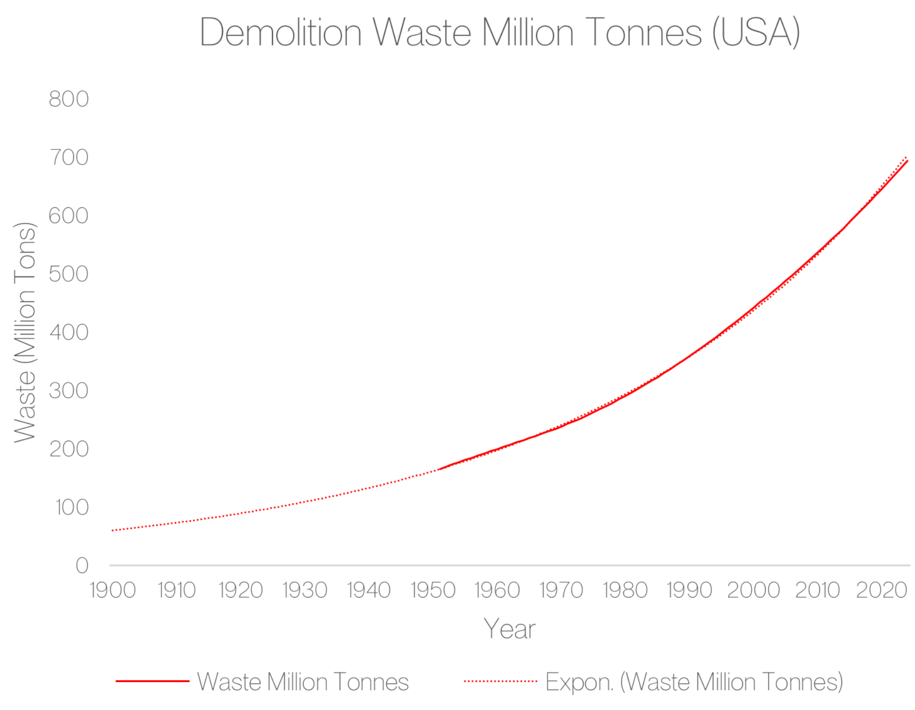


Figure 1 - Demolition waste since 1900 in the USA (dashed - extrapolated) [Miatto]

An outline summarises the key components of the research:

Culture - First examined are the arguments on how we arrived at a culture of non-reuse. This establishes a basis for understanding what needs to change, how we can most effectively form a solution and the context within which we must do it.

AI - A brief section explains some of the technicalities related to this catch-all term. It was found, understanding of the many field of AI, and their implementations and limitations, was essential to be an effective judge.

Literature Review - Two of the key design stages of reuse, measure and track, are evaluated through the existing body of literature. The hypothesis, shortly established, is a question which has, as of yet, not been asked for many key areas by academics.

Proposed Approach - Building on the insights gained through the literature review, a key area is narrowed in upon. It delves deeply into design literature to understand the specific challenges and opportunities within architectural workflows. Many of these tools are tested. Recognizing that reuse often falters due to the complexity of integrating reclaimed components into design processes, the study develops a targeted tool within the Grasshopper environment, a ubiquitous visual coding environment for Rhinoscerous3D.This leverages OpenAI's language models.

The tool explores how AI can facilitate the early stages of reuse-led design. It offers suggestions for reclaimed components based on design requirements like geometry, material properties, and aesthetic considerations. Its contribution is research into the ability for ChatGPT to understand architectural form through language. The aim is to demonstrate AI's potential to transform reuse from a niche practice to a scalable mainstream solution through accessible tools. By synthesizing insights from reuse-specific and design-focused literature, the approach bridges gaps between theory and practice, rigorously testing how AI might resolve logistical challenges while reshaping attitudes and workflows.

Discussion and Results – The tool and review are evaluated for their effectiveness and findings. Assessing the limitations of the tool given its brief development timespan, a suggestion of where future research might go next is made.

Central Argument

Current attempts to apply reuse are the subject of rich debate, but before any research, as a designer, it was possible to predict limiting factors for each stage of reuse. As will be identified, the notion of differing stages of reuse is both essential and well-established.[4] [5] Throughout the paper, these are termed Demolish, Measure, Store, Track, Design, Procure. Within Figure 2, the respective tasks and challenges are outlined.

Through the Proposed Approach it was hoped to substantiate a hypothesis:

Regardless of positive intentions, the organisation of many varied components into a coherent design is an enormous task. Consider further, the entrenched challenges of a regulatory-heavy, financially-driven and time-sensitive society. This study argues that, rather than overturning immutable societal realities, the most addressable common problem is one of data complexity. In this light, AI's scalability and ability to consider a vast dataset of parts, constraints, codes and other factors will catalyse reuse in the mainstream more than any other limitation.

In this cultural context, through examining existing approaches and those proposed by academia, I address:

Could AI be the solution to the problem in its most addressable sense?

How does AI's potency vary for differing reuse stages compared to other factors?

What are the implications, debates and methods surrounding AI's implementation?

4 Keulemans and Adams, 'Emergent Digital Possibilities for Design-Led Reuse within Circular Economy', 4 July 2024, 2–3.
5 De Wolf et al., 'A 5D Digital Circular Workflow', 3.

Deconstruct

How do we remove objects from buildings in order to preserve their contextual information before they enter the mass of others? How can we deconstruct non-

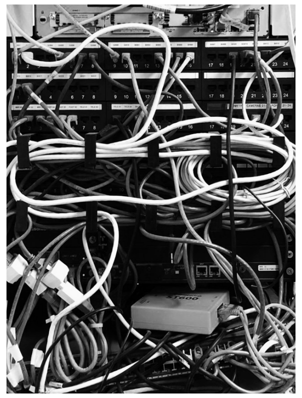
Measure

What processes allow us to figure out the attributes of these components without measuring each individually? Can we rely on these assumptions?

Store

Which middleman holds or distributes these objects? Are they incentivised to be part of this process financially? Are these sites accessible?

Track



What online databases can designers search to find these objects? What descriptors and search functions should a database provide?

Design

Can design tools help to solve this searching problem? Further, can they incorporated the varied geometries of components into our visions?

Procure

Is it possible to practically source this objects if they come from varied sources? If reprocessing is required, the timescales might be affected.

Process

Limitation

Deconstruct	Measure	Store	Track	Design	Procure
			– Complexity	– Complexity	– Complexity
– Cost	– Cost	– Cost	– Cost	– Cost	– Cost
– Time	– Time	– Financial Feasibility	– Value	– Sourcing	– Time
– Responsibility	– Cost	– Responsibility	– Responsibility	– Time	– Workflow
– Safety	– Responsibility	– Space	– Space	– Workflow	
	– Reliability		– Workflow	– Standardisation	
	– Regulation		– Standardisation	– Performance	

Limitations are Unified by Complexity

Figure 2 - An in depth description of each of the stages and the associated challenges identified at the start of writing.

Culture

In pre-industrial vernacular architectures across the world the simple rubble wall was an intuitive solution. Walls, set out by designers, skilled or unskilled craftsmen and labourers alike were assembled from varied stones processed minimally and sourced locally. A simple knowledge of the rules of aggregation – how these parts fit together in a desired overall form were the base requirements. Use of the available was the driving force and in every stone placed, the thought behind its positioning was embodied. Perhaps then, with the advent of Modernism, an architecture of the machine age, this was lost. Supplied by plentiful energy, mechanised industrial processes allowed us to address rapid population growth with standardised, measured, reproducible components. Designers increasingly became freed from the question of resource availability and trained to consider only what to do with bountiful options.

In 1936, Walter Benjamin's writing recognised this phenomenon. Through the theme of 'auratic loss', his statement reflected humanity's withering interest in objects' craft and history in the modern world: [6]

'The role of the hand in production has become more modest, and the place it filled in storytelling lies waste.'

–The Storyteller, 1936

Building Information Modelling
Design software which has structured data at its core. One could interpret BIM as a database which is tied to 3D objects which a designer conventionally models.

Benjamin invites us to extend this metaphorical hand to understand our loss of interest in craftsmanship, a creator of the objects' aura. He wrote this against a backdrop of standardisation. National standards institutions were young and electrification of factories was rising. This codification of design would be come so entrenched that today, it is integral to practice. Now, any stakeholder or designer expects construction products to be reliable, certified and adherent to performance standards. In essence, that which does not conform, like many reclaimed objects, is simply rejected.

The landscape of design became far removed from 1936 with the advent of computers. CAD allowed for the rapid reproduction of drawings, BIM added by letting us tie data to these digital geometric models. To understand Benjamin's idea in the context of digital production, it becomes helpful to introduce a second key concept: 'Cosmopolitan Localism'.[7] Ezio Manzini, the design researcher, uses this to describe thinking and tools distributed globally, but applied in local contexts. His concept postulates increasing

6 Benjamin, Arendt, and Zohn, Illuminations, 108.
7 Manzini and M'Rithaa, 'Distributed Systems And Cosmopolitan Localism', September 2016, 279.

Figure 3 - Rubble wall built through intuition, age unknown [The Smell of Water]

local resilience (positively) or dependence (negatively) through globalised interconnectedness.[8] In the context of reuse, small attempts at reclamation are working against massive 'cosmopolitan' forces. BIM, both a facilitator but a rigid tool for design is a classic example of a distributed tool by transnational corporations like Autodesk and Graphisoft. Here lies a formidable point - that AI, is equally affected. In strength, it is formed off rich transnational data, but concerningly, in weakness, only by large conglomerates with the power to handle it.

The writing of both creates a kind of disclaimer for 3- proposed approach. Benjamin identifies the powerful culture which favours standardisation. Manzini, describes the interconnectedness which distributes our tools. Both are contexts and limitations which are critical to the consideration of AI in reuse because the issue must be considered within the realities of modern design. It shortly appears AI has a potential to not only facilitate reuse applications but also enhance the scalability of reuse-based design. But without examination of culture first, it is impossible to work pragmatically. Further, the hidden ethical and practical implications it has on design practice, are likely to be cemented without necessary interrogation.

8 Manzini and M'Rithaa, 277.

Artificial Intelligence

A required stage of the literature review was understanding the complex terminology used to describe AI. In its widespread use today, the vagueness of 'AI' as a marketing term is clear. Armeni, referenced earlier, provided a concise overview of the subtypes as concepts.[9] (Figure 4) It was clear intelligence could be defined in many ways but always required the ability to learn patterns.

Two learning methods reflected very different implementations. Supervised models are taught by human-labelled data yet unsupervised learn, without this guidance, off labelled training inputs and outputs. This is explained by Figure 5. These distinctions were important to the involvedness of creating an AI model and therefore its ability to catalyse reuse. Relevant models were detailed extensively in Figure 6.

Consider that many implementations of NNs and GAs have existed theoretically for decades within the exclusive walls of financial industry. These models for instance were first mathematically hypothesised in 1958 and 1976 respectively.[10] [11] As much of this dissertation shows, the practical use of research has been catalysed by cosmopolitan tools like ChatGPT. Regarding the thesis, this expansion into widespread or upscaling was critical for assessing an AI's potential. Thus, an effective but obscure model was not considered a catalytic one.

9 Armeni, Raghu, and De Wolf, 'Artificial Intelligence for Predicting Reuse Patterns', 38–39.
10 Rosenblatt, 'The Perceptron'.
11 Holland, Adaptation in Natural and Artificial Systems.

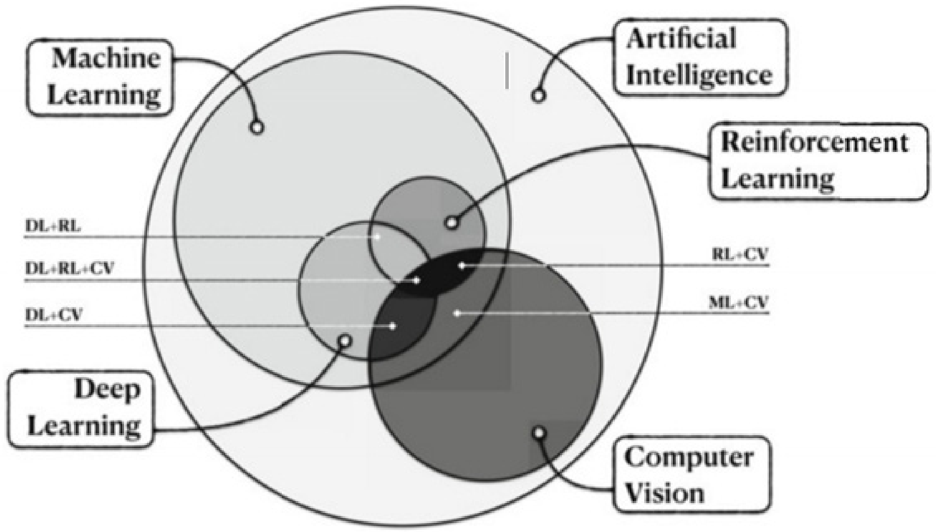


Figure 4 - AI subsets [Armeni]

Learning Types

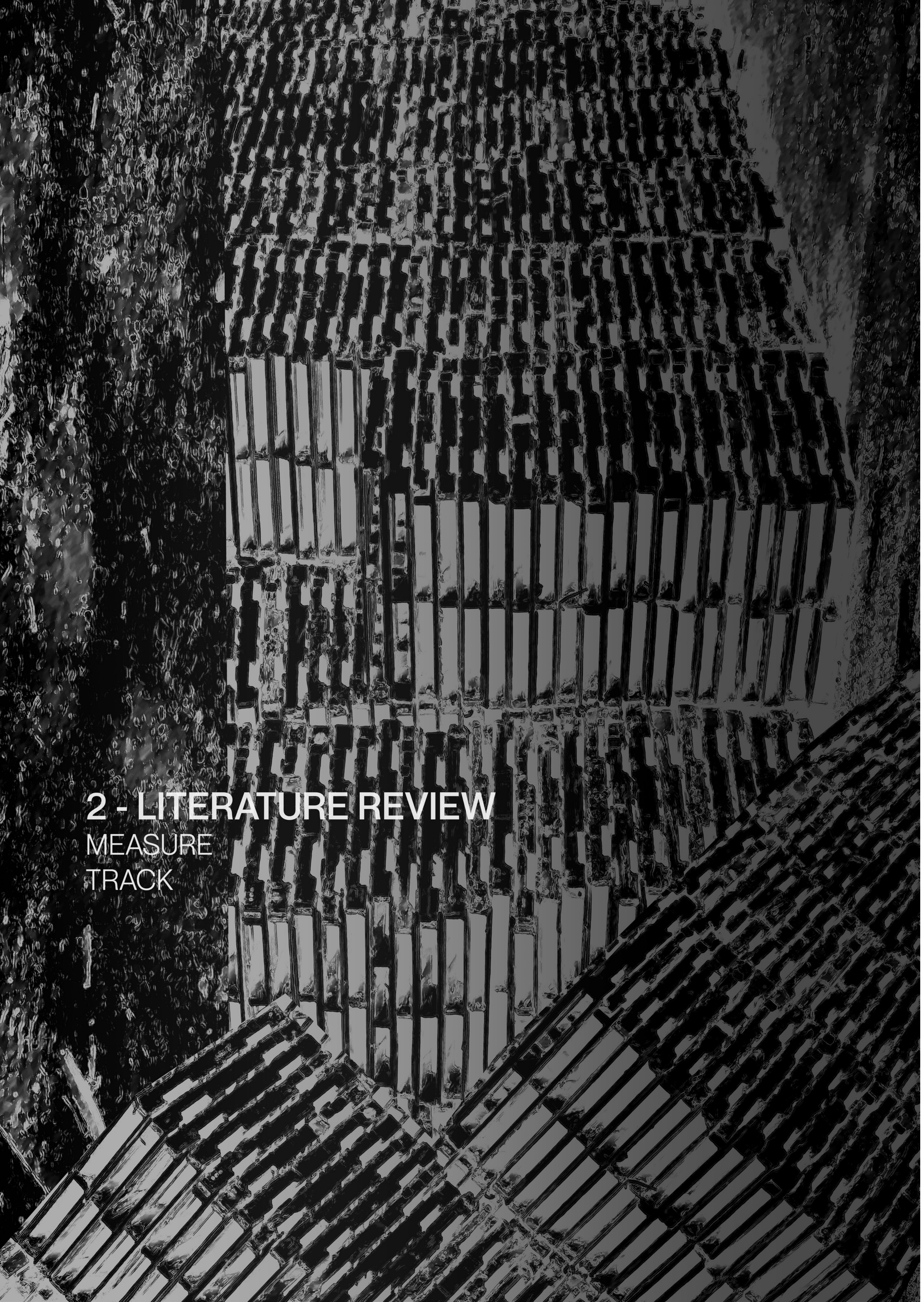
	Supervised	Unsupervised
Training	A human labels data with understanding. The system is taught how to behave.	A system recognises patterns in data to teach itself how to respond.
Data	Human-labelled. Input data and the corresponding output in each case	Labelled input data only
Example	An algorithm is taught to describe images. A human provides images with corresponding descriptions.	An algorithm teaches itself to classify images into different categories without human guidance.

Figure 5 - Supervised and Unsupervised Learning

Models

	Genetic Algorithm (GA)	Computer Vision (CV)	Neural Networks (NN)	Large Language Model (LLM)
	An algorithm, closely related to generative design, which generates many possible options by varying multiple	A model which identifies features in images, often by segmenting into regions.	A model which takes inputs and returns outputs. The model adjusts itself learning the pattern which achieves the correct output most closely.	A form of NN which recognises language patterns to predict how to respond.
Training	Does not require traditional training but instead iteratively optimises based on defined objectives.	Requires hand-labelled image datasets for supervised learning tasks.	Requires preprocessed data and tuning to train models with example inputs and outputs.	Pre-trained on general data, but fine-tuning may improve domain-specific performance.
Example	Cycling through many design options to find ones with the lowest waste metrics.	Segmenting images of demolished structures to predict reusable material volumes.	Predicting material performance from lab tests of other objects.	Providing suggestions for component reuse based on textual descriptions of materials.
Limitations	– Parameters tweaked on the fly – Computationally intensive given many iterations – Presents many optimal solutions	– Requires high-quality labelled datasets – Struggles to extend to untrained scenarios	– Not a matching algorithm – Language must be represented numerically – Hard to tweak once trained	– Relies on text inputs and outputs; limited integration with visual data – Requires vast datasets and resources
Reuse Cases	– Waste stream optimisation – Stock matching into structures	– Material recognition and sorting (e.g., wood, brick, concrete) – Automated documentation of reusable material properties	– Waste stream optimisation – Database management/ categorisation – Complex calculations with nonlinear correlations. – Material property prediction	– Search for reusable components from a database – Generating design narratives or sustainable reuse strategies

Figure 6 - A brief description of some of the AI types explored.



2 - LITERATURE REVIEW
MEASURE
TRACK

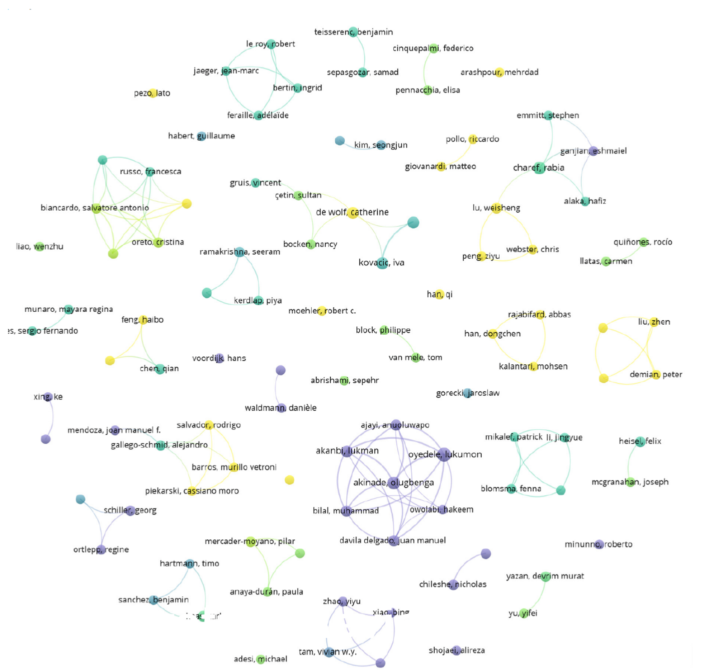


Figure 8 – Dervishaj's review identifies spheres of research within the field. Colours indicate the year of publication [Dervishaj]

Several of the leading researchers in the field have combined their precise technical research with expansive discussion or exploration of reuse at scale. Whilst earlier stages of reuse will be analysed in the literature review, the design stage is addressed in the proposed approach to link directly to the tool developed. Given their intensity of research, the measure and track stages were the focus.

Current attempts to apply reuse in architecture are the subject of fractious debate. Yet, these reuse stages, earlier outlined in Figure 2 are generally accepted.[12] [13] [14] Each presents unique challenges with unique implications. It was found that academics agreed in principle that any reuse at all was progress – the field was not combative. However, research on reuse is often fragmented, with academics and specialist studios focusing on perfecting scenario-specific solutions within their respective circles. This has resulted in an unwieldy collection of solutions, with no cohesive framework for integrating reuse into everyday practice.

Many have presented multi-disciplinary articles, straddling cutting-edge science and cultural analysis. Keulemans wrote an exploratory paper on digital tools in reuse including a subsection which applies a tool.[15] This identified the unexplored potential of AI. De Wolf produced a short qualitative review of the many problems related to the stages of reuse, exploring AI in part.[16] Dervishaj, presented a quantitative review focusing on available software for reuse.[17] (Figure 8) The only author with complete focus on AI was Armeni, whose review concluded on unanswered ethical and technical considerations. It overlooked points which this dissertation, alongside others, deemed relevant. Therefore, a comprehensive (but not exhaustive), overview of the sprawling topic, specifically oriented towards AI was felt to be valuable.

12 Dervishaj and Gudmundsson, 'From LCA to Circular Design'; Dervishaj and Gudmundsson.
13 Moussavi et al., 'Design Based on Availability'.
14 Armeni, Raghu, and De Wolf, 'Artificial Intelligence for Predicting Reuse Patterns'.
15 Keulemans and Adams, 'Emergent Digital Possibilities for Design-Led Reuse within Circular Economy', 4 July 2024.
16 De Wolf et al., 'A 5D Digital Circular Workflow'.
17 Dervishaj and Gudmundsson, 'From LCA to Circular Design'.

To methodically evaluate against each of the stated key questions, a method of approach was essential:

Could AI be the solution to the problem in its most addressable sense?

Evaluate how each AI tool is a catalyst. Is it simple to use, integrated into practice, accessible and scalable or are there large trade-offs?

How does AI's potency vary for differing reuse stages compared to other factors?

Compare the limitations of the most effective research. To what extent is AI the limiting factor in reuse uptake?

What are the implications, debates and methods surrounding AI's implementation?`

Speculate what problems AI might cause. Assess these tools' ability to change design practice both positively or negatively.

In a single field or reuse, one review identified 252 papers.[18] Therefore the approach taken was generally qualitative over quantitative. For some stages, the review of reuse-specific literature was exhaustive. In others, a non-exhaustive approach was suitable for getting a picture of the field. For all literature, the reading at a minimum, covered the summarising sections. From here, those with more citations by others and greater distribution outside of academic institutions were preferred for in-depth analysis. By pitting the various arguments against each other, debate relevant to the overarching thesis could be better analysed. By, tying together literature beyond the architectural domain, a selection of fewer sources but with particular quality painted a better picture of the landscape of reuse.

Over three months, the corpus of reading was expanded through searching Google Scholar, academic collections such as JSTOR, the University's physical collection, correspondence with authors themselves and the mining of references from texts. Additionally, ChatGPT search, released a month into the dissertation, was essential in expanding research into personally alien but related fields such as robotics, programming and sawmilling.[19]

18 Dervishaj and Gudmundsson, 4.
19 'Introducing ChatGPT Search'.

What processes allow us to figure out the attributes of these components without measuring each individually? Can we rely on these assumptions?

- Cost
- Time
- Cost
- Responsibility
- Reliability
- Regulation
- Complexity

Measure - Materiality

The current lack of reuse stems in part from a lack of knowledge about the performance of discarded components. Stakeholders and designers require known metadata about objects, or they risk under-performance or worse, catastrophic failure. An examination of culture established our societal obsession with quantitative performance over qualitative selection of building parts. Yet, modern reality demands objectivity in the measurable strength of components. We cannot simply ignore U-value, acoustic rating or weight because an object is reclaimed. For measuring these properties, the review analysed relevant subtopics. Firstly, the current research on AI-led material assessment. Then comparatively, the industrial implementations of AI outside of reuse. Finally, the political issue of whom the burden of responsibility falls on. Research was critically compared at many scales. At the macro considering material waste flows for national waste processing. Simultaneously, at the micro comprehensive testing of objects for performance metrics.

Metadata
Information which is attached to the objects. In BIM this is different to a parameter, it is a form of data storage.

The key challenges emerge as ones of liability, cost, complexity and responsibility. To what extent can AI, particularly CV help us to visually classify building waste with reliable certainty?

Academic Reuse-Specific Research

Research started within the confines of the topic of reuse in academic publications. Considering the established reality, one argument believes this process should be economically viable. By encouraging manufacturers to collect and process reclaimed components, reuse might be incentivised by market forces over unlikely governmental intervention. Exploration of this pragmatic argument was fruitful. It was found that Raghu, a researcher of circular architectural engineering at ETH Zurich, has presented multiple methods for classifying building waste at city-wide scale with AI.[20] With a key focus on identifying local material quantities for diversion into reuse, her tool uses publicly available data such as street maps, LIDAR, satellite imagery and photographs. Training a Neural Network to recognise materials such as brick and stucco, it was possible to accurately chart quantities and geographic distributions of material. (Figures 9 & 10) The tool was tested to be effective in multiple cities and continents with varying architectural styles.[21 22 23]

20 Raghu, Bucher, and De Wolf, 'Towards a "Resource Cadastre" for a Circular Economy – Urban-Scale Building Material Detection Using Street View Imagery and Computer Vision'.
21 Raghu, Bucher, and De Wolf, 5–7.
22 Raghu and De Wolf, 'India's Informal Reuse Ecosystem Towards Circular Construction'.
23 Byers et al., 'From Research to Practice'.

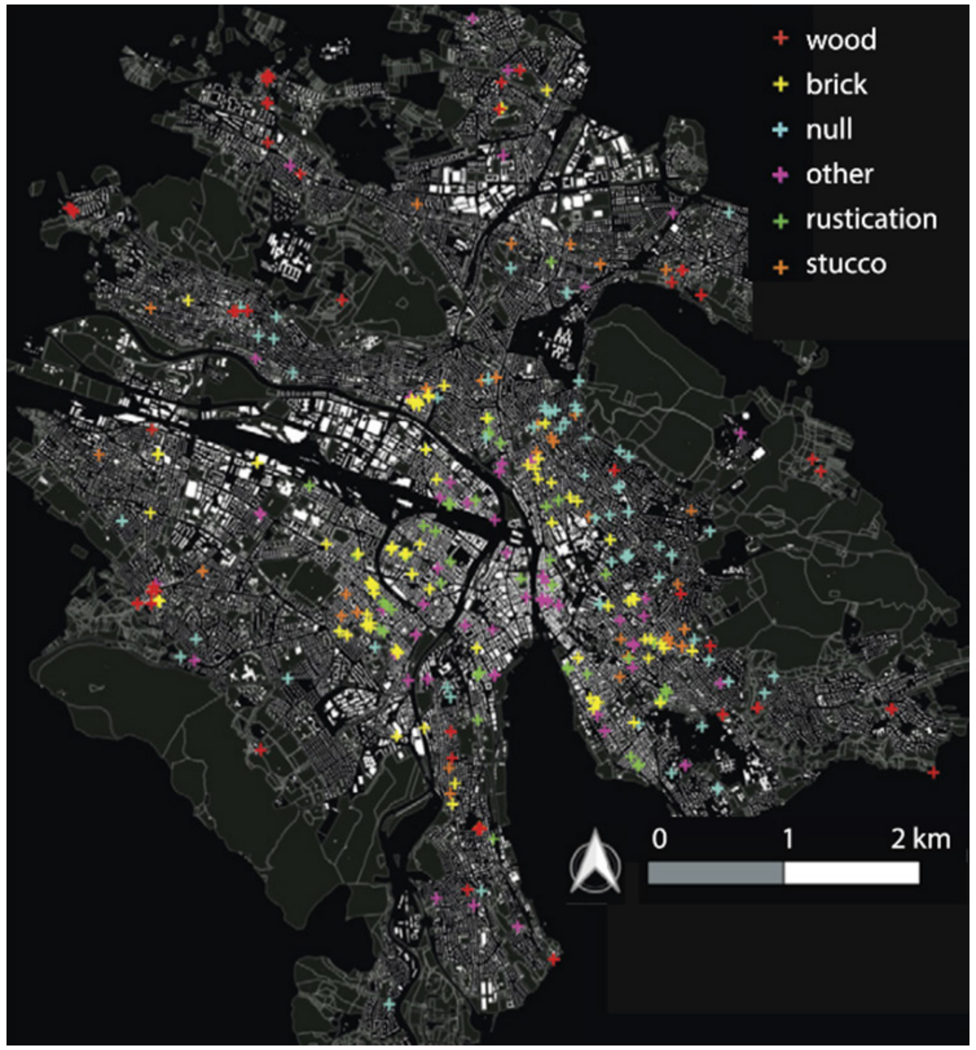


Figure 9 - Citywide map of identified resources [Raghu]

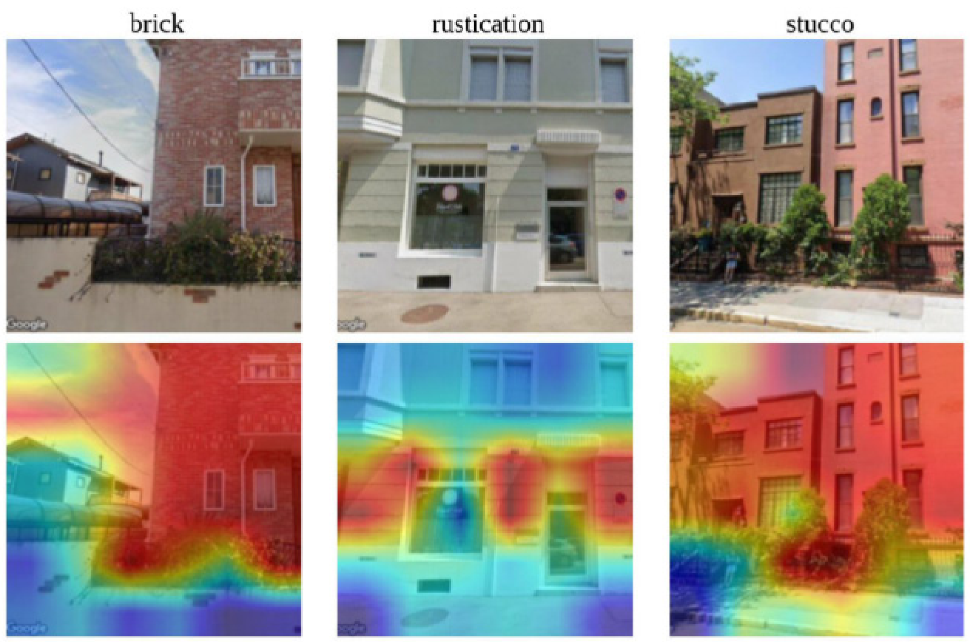


Figure 10 - Heatmap showing image material recognition [Raghu]

Like many others, she presents a tool for material detection at city-wide scales. [24] [25] Her position was vital to the research question: giving manufacturers and designers the ability to make informed decisions about material availabilities may increase reuse's viability as a business model. It gives designers an understanding of potential materials for a specific macro locality. [26]

Simultaneously, it was vital to extend analysis to the performance of individual objects on the micro scale. How had others tackled the problem of assessing material attributes in objects with unknown history? As identified beforehand, engineers primarily rely on controlled testing during manufacturing for performance. Secondarily, numerical calculations extend our design capabilities beyond what has been tested. AI however, with experience-taught ability to handle unseen materials, is yet to be recognised as a robust option beyond academia. The review found that those such as Keulemans, an artist and reuse-focused researcher, assessed CV's role in categorising structural timber.[27] Through non-intrusive methods, properties could be ascertained without destruction. His research took laser-scanned reclaimed timber to effectively extract properties such as grain direction, defects and structural grade. With emphasis on workflow, this allowed timbers to be directly imported into widely used softwares like Rhino3D.[28] Comparatively, for both reuse in-situ and for isolated reclaimed objects, it was found that others had successfully explored this. The research extended to steel, minerals, concrete, masonry and timber. Numerous studies achieved an accuracy extremely close to the reliability of lab-based testing.[29] [30] [31] Keulemans identifies this rift between practice and research stating that 'the problem of waste and its assorted complexity must come into the remit of professional designers with skills ... to capacitate the design of waste.' [32] AI's prowess in assessing materials partially answered the question. Yet, in balance, it was concluded, there are more structural issues. A combination of regulatory mistrust, lacking application beyond academia and inaccessible tools have enclosed reuse from practice. At both micro and macro scales, these researchers identified data-availability as a widespread problem. Responsively, many made efforts to use public data for training. AI's efficacy as a tool to simplify the complex task of assessing reclaimed components however, was not extended into practice.

Industrial Applications Beyond Reuse

Expanding the literature beyond academic research was equally important. The tools applied in industry for production with virgin material are relevant but not applied to reuse. This extension, gave clear insight into the societal forces limiting the directing of these tools towards reuse. In timber production

24 Markopoulou and Taut, 'Urban Mining. Scoping Resources for Circular Construction'.
25 Harrison, Hollberg, and Yu, 'Scalability in Building Component Data Annotation'.
26 Raghu, Bucher, and De Wolf, 'Towards a "Resource Cadastre" for a Circular Economy – Urban-Scale Building Material Detection Using Street View Imagery and Computer Vision', 8.
27 Keulemans and Adams, 'Emergent Digital Possibilities for Design-Led Reuse within Circular Economy', 4 July 2024.
28 Keulemans and Adams, 4, 8.
29 De Wolf, Çetin, and Bocken, A Circular Built Environment in the Digital Age, 45–55.
30 Mahami et al., 'Material Recognition for Automated Progress Monitoring Using Deep Learning Methods'.
31 Kim and Cho, 'Automated Vision-Based Detection of Cracks on Concrete Surfaces Using a Deep Learning Technique'.
32 Keulemans and Adams, 'Emergent Digital Possibilities for Design-Led Reuse within Circular Economy', 4 July 2024, 3.

for instance, CV is used extensively. In Sweden, Biometria, a firm handling the vast majority of sawmill and forestry data, had developed an entirely automated AI grading and measurement process.[33] Previously, forests were assessed for growth manually and cut timber was dimensioned, graded and assessed for deformities by hand. Using the data from 3 million hand measurements per annum, Biometria worked with Microsoft to entirely automate the process. Similarly to Raghu's research, the resulting tool could perform this process with photographs to a remarkable accuracy, greater than error-prone humans.[34] (Figure 11)The tool's efficacy, trained on a private dataset, for the purpose of private producers illuminated AI's efficacy and implications. Relying on big data, inherently held by large corporations, it risks control by an oligarchy. In this case, parties with a financial interest in manufacturing ever more carbon-producing material. A tool like this remains bound to the powerful party who creates it.

Returning to the theory of cosmopolitan localism, a common theme of 'siloed thinking' resonates here. Many private parties take ownership of their technological advances and knowledge is clutched within organisations. Reasonably, one could assume this hinders reuse. The issue is found to be endemic to AI. For one, AI models which have been used by large financial institutions for decades are only emerging into the public sphere now.[35] Yet, a key question remains, how might we incentivise reuse through market forces whilst simultaneously deterring anti-collaborative practise? AI alone cannot overcome self-serving Capitalism. Therefore, a clear argument for slow-moving regulation exists. Legislation should attribute economic cost to waste and emissions to steer the tides of industry towards reuse. Perhaps this points towards a question of responsibility. Which parties should the legislation direct this towards?

Identifying Responsibility

An assessment of responsibility, considered counter arguments to industry-led reuse. Indeed, many have questioned the suitability of this argument for capitalist-driven reuse. More interestingly, some have debated whether responsibility should be held by the original producer of waste. Gorgolewski, professor of architectural science, identifies 'closed' and 'open' cycle systems. The former describes the responsibility and knowledge of reuse/recycling held by the original producer. The latter describes reprocessing by other parties where information about the products is freely circulated.[36] He argues closed cycles are more effectual. Large-scale industry is encouraged to develop end-to-end, or as some have termed, cradle-to-grave, programmes for handling waste. Reframing this argument towards AI suggests otherwise. Asking whom the responsibility of repurposing demolition waste lies upon is paramount. Should the liability be with the original producer, designer or contractor who, in the case of older buildings, may no longer exist? Should governmental bureaucracy handle the task? Or, as established in contrast with Gorgolewski's argument, might the reframing of demolition as a financial opportunity rather than a burden be more productive in our current context? Indeed, many have presented tools to

Cradle-to-grave
A consideration of a product's entire life cycle from the material used to create it, to its final disposal.

33 Björklund, 'Automate Timber Measurement With AI'.
34 Björklund.
35 LoanWorks, 'Artificial Intelligence in Financial Services'.
36 Gorgolewski, Resource Salvation, 27.

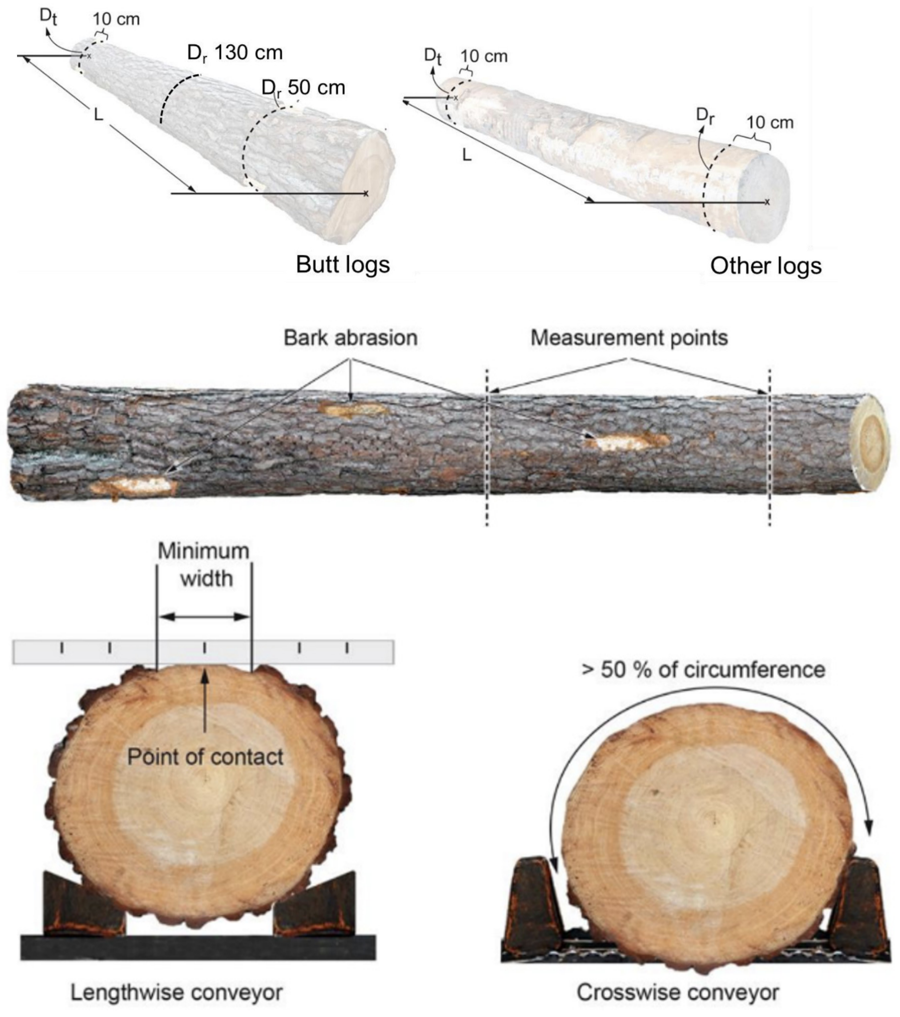


Figure 11 - Examples of Biometria's scanning methods which understand the organic nuances of timber. This includes the bark thickness. [Biometria]

glean data from buildings both pre-demolition and from construction drawings.[37][38][39] This intends to forecast the financial opportunities of reuse before irreversible deconstruction is performed. As I explore further, ineffectual measurement at early stages intensifies the problem of reuse in later stages. A lack of data on deconstructed components should not fall on the cost-conscious marketplace or the time-conscious designer as they will inevitably deem the task to be too complex.

In evaluation, AI has catalytic potential when comparing the measurement stage with others. However, with caution, the effort to develop AI-based measurement for industry should not be glossed over. Such a task, requiring immense training data, may be challenging to scale into widespread practice. AI may cast certainty upon objects normally discarded but it cannot act alone. The attitude, particularly in regulation, formed by decades of counter-reuse culture, is a hindrance. Incentivisation of reuse within the Capitalist mode of business is essential, it would be unwise to overturn the entire system. Yet, it must start with regulatory acceptance of AI's force as a tool in charting reclaimed objects.

37 Gordon et al., 'Automating Building Element Detection for Deconstruction Planning and Material Reuse'.
38 Yu and Fingrut, 'Sustainable Building Design (SBD) with Reclaimed Wood Library Constructed in Collaboration with 3D Scanning Technology in the UK'.
39 UNSW Art and Design et al., 'Design Considerations for the Transformative Reuse of a Japanese Temple'.

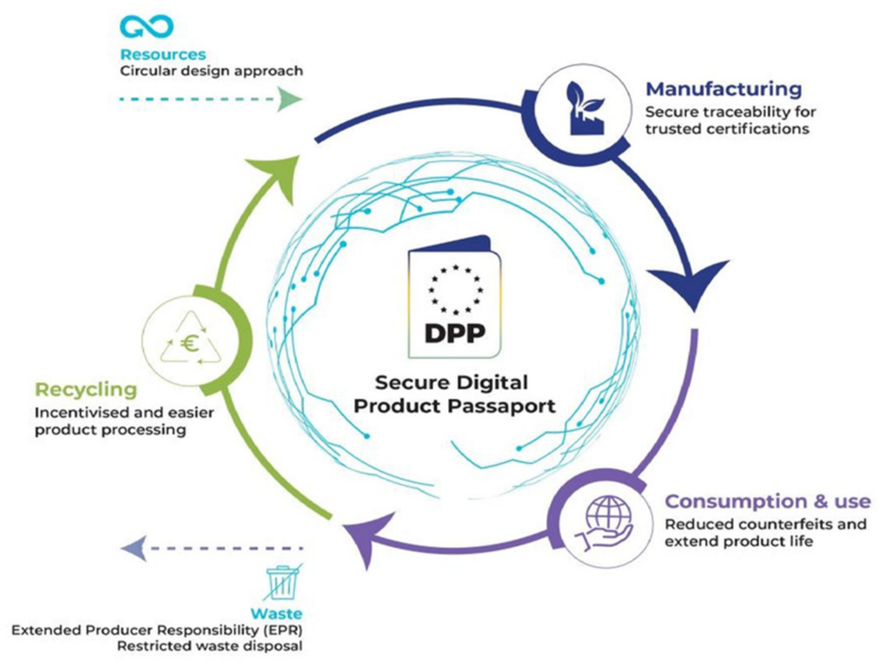
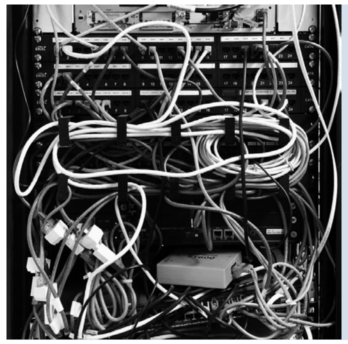


Figure 11 - Example data included in the DPP [Certilogo]

Figure 12 - Attachment of DPP QR code identifiers



What online databases can designers search to find these objects? What descriptors and search functions should a database provide?

- Complexity
- Cost
- Value
- Responsibility
- Space
- Workflow
- Standardisation

Track - Database

Considering how we track our reclaimed objects is a critical stage of reuse. What information should a marketplace-style database provide? What role in helping designers to find parts? Further, is AI effectual in this stage? Given the numerous pre-existing reuse marketplaces, found during research, clearly, these databases were already entirely feasible.[40] [41] [42] [43] [44] [45] Analysis discovered concentration in North-western Europe owing to ambitious governmental reuse targets. [46] Debate emerged in firstly, the properties and metrics we use to describe these materials on the database. Secondly, the unique identifier tags used to keep track of these objects. A loose method involved personally browsing these databases as a potential shopper.

Properties and Metrics

For a reuse marketplace or database, consider what properties might be important to designers. Like any construction product, there are minimum quantitative standards to meet – many of these properties were established in the measure section. But beyond this, a designer requires qualitative properties like texture, appearance and quality. Core to the concept of circular economy, the representation of components' environmental properties, as important metrics within a database, were found to be ill-defined. De Wolf, a heavyweight of the field, identifies a key issue alongside others. [47] [48] Life Cycle Assessment (LCA) has become a ubiquitous term for assessing CO2 both emitted and in savings potential through reuse. Yet, disjuncture exists as researchers market ever more effective metrics. Despite the importance of LCA, its technicalities are irrelevant to the research question. Pertinently, it is characteristic of the nebulous circular economy metrics which designers must navigate. This analysis found AI to be a peripheral issue. Structural issues limiting the standardisation of metrics were overriding because they fundamentally limited the ability to make informed selections of components for purchase. A clear need for unified metrics to make databases clear and useful was established.

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40 'useagain'.
41 Iwadmin, 'Homepage'.
42 'Enviromate | Free Leftover Building Materials Marketplace'.
43 'Excess Materials Exchange'.
44 'Products | Rotor Deconstruction – Reuse of Building Materials Made Easy'.
45 ReLondon, 'Home - Material Reuse Portal'.
46 Khadim et al., 'Critical Review of Nano and Micro-Level Building Circularity Indicators and Frameworks', 5.
47 De Wolf, Pomponi, and Moncaster, 'Measuring Embodied Carbon Dioxide Equivalent of Buildings', 68.
48 Dervishaj and Gudmundsson, 'From LCA to Circular Design', 4.

Identification

Relatedly to unification, the review unearthed fragmented approaches to the methods for tagging and identifying individual components. Design researcher, Arlind Dervishaj, synthesised the existing literature to compare numerous methods.[49] Digital Product Passports, proposed by the EU, leverage BIM's ability to store object-related data. (Figures 11 & 12) The proposal to mark products with irrefutable metrics such as repairability, manufacturer and embodied carbon is laudable. Yet, the implementation is unresolved.[50] [51] [52] Tellingly, others were led to develop their own methods. Blockchain, initially developed for currency transactions, improved reliability further by storing a secure interconnected ledger of object properties and histories. [53] Evidently, analysis found the standardised implementation of technically straightforward methods to be most limiting to reuse.

Blockchain
a system in which a record of transactions, especially those made in a cryptocurrency, is maintained across computers that are linked in a peer-to-peer network.

A drift towards fragmented tracking of objects is clear. By developing metrics, often in a vacuum, without consideration of their standardisation, little practice-based change is made. The reading found issues of standardisation to be particularly limiting in reuse database design. Before considering AI's ability to maintain databases, more fundamental issues must be tackled. De Wolf's position, that reuse marketplaces 'should act as catalysts' for reuse, is fitting.[54] She represents one side of a debate on whether AI-led component matchmaking should be performed either within BIM itself or conversely by databases which act as comprehensive tools. Moreover, the analysis will not ignore the essential connection between database and BIM. The linking together of tools and databases is further explored in 3 – Proposed Approach. The integration of workflow should be considered as equally significant as the tools themselves.

This section engages with the challenges of tracking reclaimed objects and designing effective reuse databases, an issue affected by identifying objects and translating their properties into interpretable metrics. Perhaps, this concern overrides considerations of AI. The question, of object identity returns, once again, to the notion of auratic loss. In representing these objects, who chooses what aspects of an objects history are catalogued? Will it be programmers, stakeholders, designers or regulators? Databases have a role to play in deciding what story stays with the object and what is forgotten in the scrap heap and designers risk isolation if they do not contribute to these databases. A purely technical evaluation is perhaps more hopeful, these marketplaces are, in many other industries, already widespread.

49 Dervishaj and Gudmundsson, 'From LCA to Circular Design'.
50 Dervishaj and Gudmundsson, 2.
51 De Wolf, Çetin, and Bocken, A Circular Built Environment in the Digital Age.
52 Byers et al., 'From Research to Practice'.
53 ETH Zurich and Hunhevicz, 'Blockchain for a Circular Digital Built Environment'.
54 De Wolf et al., 'A 5D Digital Circular Workflow', 4.

3 - PROPOSED APPROACH

DESIGN

RESEARCH OBJECTIVE

Whilst the literature found varying suitability and implications for AI in preceding stages, design was felt to be the most intriguing for methodological research. This went some way in analysing AI's potency for reuse when compared with sweeping cultural factors. Simultaneously, a deeper investigation into the design stage combined with measured scientific research was essential to test the hypothesis. This approach mimics how others in the field have approached research as both exploration and validation.

The term academia is wielded frequently. This camp describes work which is confined to the walls of universities or institutions often practised in conjunction with closed-off corporate research and development. Such tools might never be considered by a trained designer, let alone an investor or policymaker. This is foundational to the question of scaling up reuse.

Hypothesis
An open proposition, without any assumption of its underlying truth.

Objective
A defined goal with resolution sought after.

In language, the distinction is made between a research hypothesis which addresses architectural discourse broadly and a research objective which attempted to narrow down on a modest tool as a response. Simply put, architectural practice is not a science to be validated or predicted and objective research has its limits.

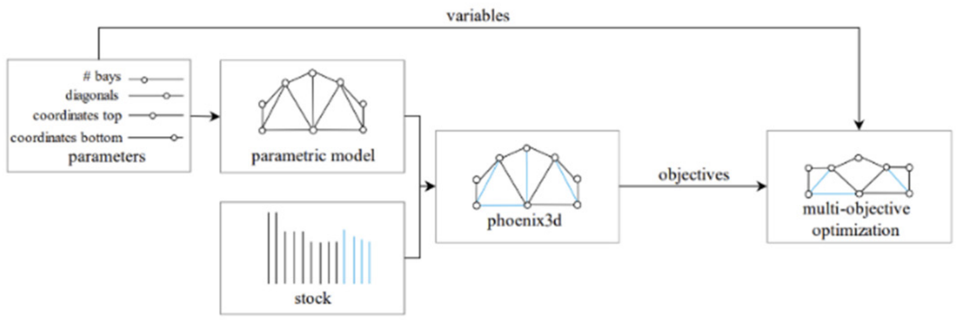


Figure 13 - Design workflow proposed by Brutting [Brutting]

Design

Initially, in similar style to 2 - Literature Review, the literature of the design stage was explored. This emerged to be the stage of most multifaceted debate. Further, it exposed points which formed the research objective. Beyond the tribulations of sourcing reclaimed objects, the process of putting them into architecture is riddled with complexity. Some common limitations emanate throughout design, many passed on from earlier stages: the sourcing of objects with known performance, the lack of integration into design workflow, the geometric complexity of the task and above all the time cost. For the discussion of subtopics termed representation and hierarchy, it was useful to compare two collectives with differing philosophies. Superuse studios, a Dutch practice is one leader in executing reuse in the real world.[55] Their work reflects the truth of reuse in practice. Their process must integrate with existing, timescales, regulations, tools and parties involved in construction. By contrast, Brutting et al., a group of structural optimisation researchers at EPFL, have presented a cutting-edge yet complex tool called Phoenix3D.[56] Extensive personal testing was involved and it came to symbolise the forefront of reuse-based design within academia.

Representation vs. Replica

Argument on BIM's purpose in reuse has separated researchers from designers. The rift is endemic to the generally evolving status of BIM in practice. For reuse, where flexibility is often required, should BIM be a 'digital twin' to represent a design in every detail? Or conversely, is it simply a tool for vague representation, a way to track design intentions loosely? Many, particularly those in the field of engineering have developed solutions which take reclaimed objects, with complete metadata and optimise for a known geometric goal.[57] [58] [59]The review found 15 papers of relevance. As will be argued, AI has diverse implications here.

Digital Twin
A virtual replica of the building itself.

55 kayleighlettow, 'Harvest! Collect! Re-Use!'
56 Warmuth, Brütting, and Fivet, 'Computational Tool for Stock-Constrained Design of Structures'.
57 Huang et al., 'Algorithmic Circular Design with Reused Structural Elements'.
58 Haskell et al., 'Generation of Elastic Geodesic Grid-shells with Anisotropic Cross Sections'.
59 Amtsberg et al., 'Structural Upcycling: Matching Digital and Natural Geometry'.

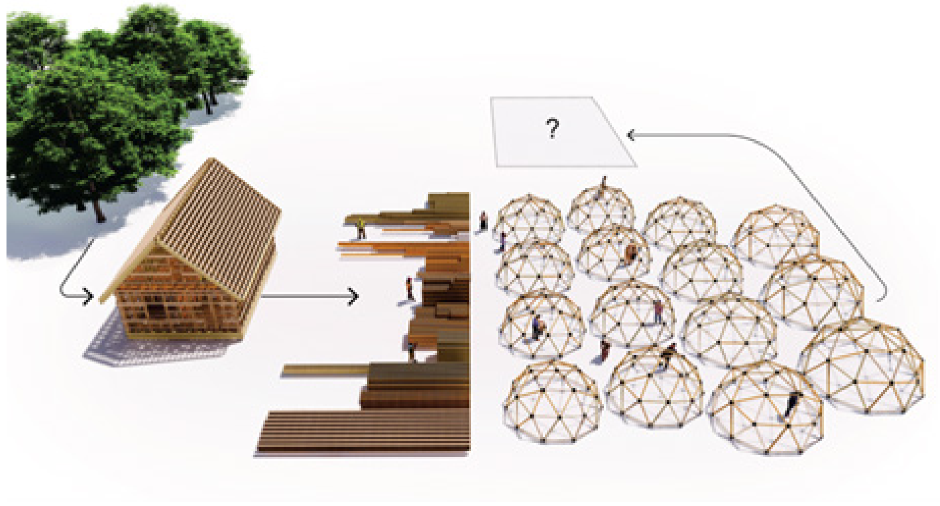


Figure 14 - A timber house is deconstructed to form many domes [Huang]

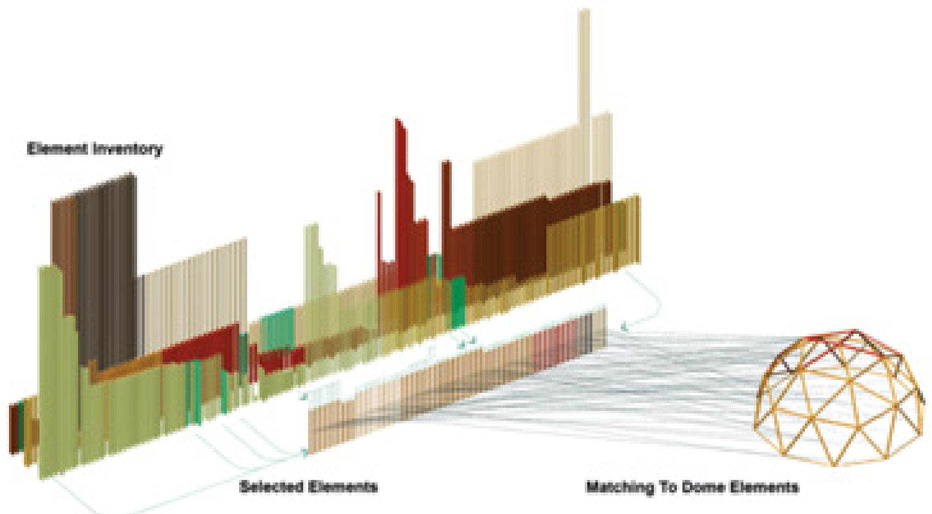


Figure 15 - The available stock, matched into the dome by trying many iterations, is shown graphically [Huang]

Below: Figure 16 - Grid shell structure developed computationally from reclaimed skis [Fivet]

Phoenix3D for one, could take a target structure geometry with calculated design loads. (Figure 13) Then, considering many reclaimed structural elements of differing sections and lengths, it could find an optimal arrangement. Here, the tool is simplified but it can be considered in the context of a workflow. Generative design, a form of ML, created many possible design options by adjusting input parameters. Combined with a best-fit algorithm, the tool tested many possible arrangements of reclaimed components. This way it could find a solution structurally optimised for strength-to-weight. Output metrics like the strength and embodied carbon were able to steer the generative design tool to learn which designs could work. In a personal project, extensive exploration of the tool allowed for the building of a model truss bridge from entirely reclaimed timber. (Figures 17 & 18) To navigate the tool, correspondence with Jonas Warmuth, one of the creators, was ultimately required.

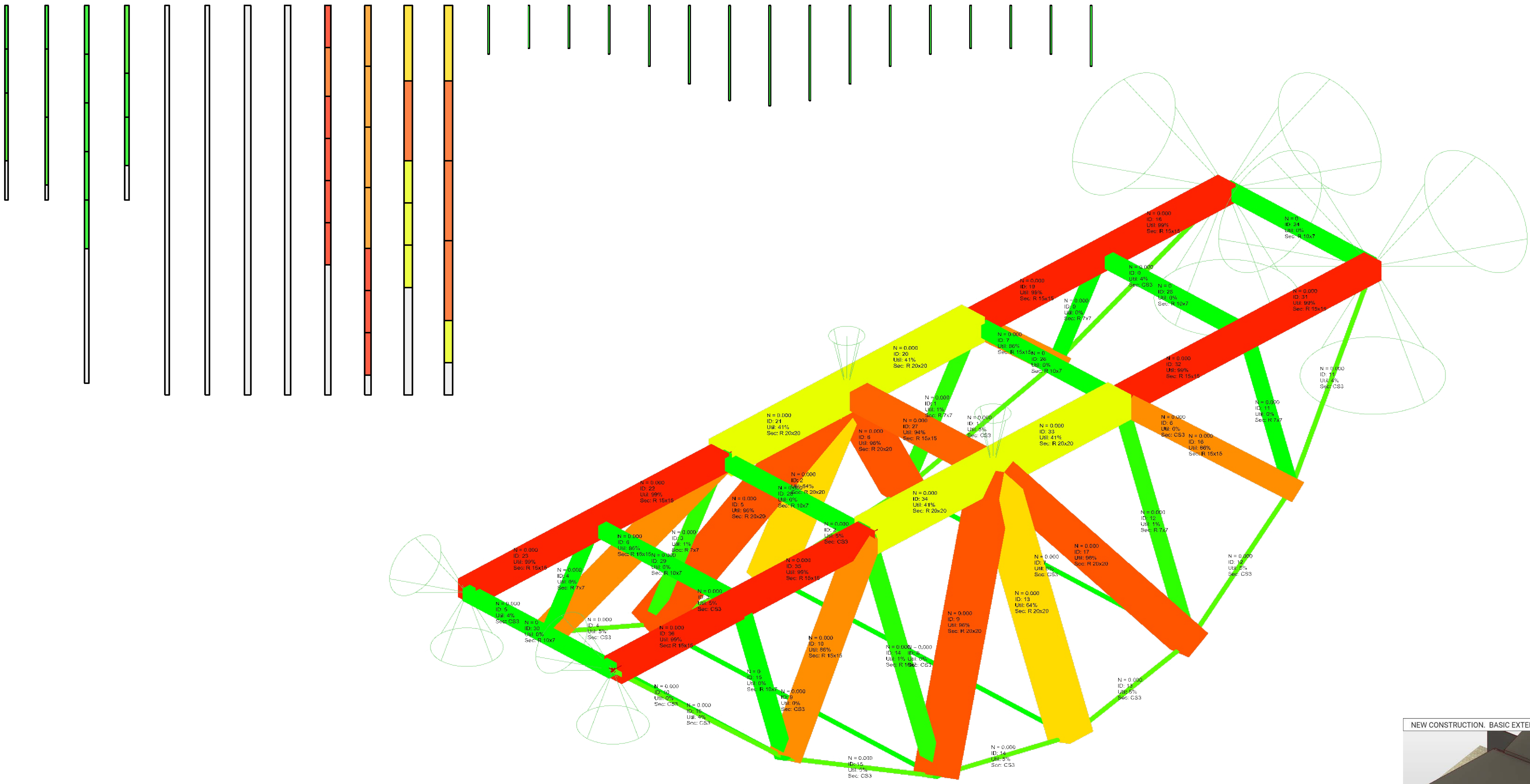
Generative Design
A process which generates and evaluates copious design options. Iterations are guided by user input and self-learning.

Despite the extremely rewarding results, as a research tool, it had engineering limitations beyond the scope of this dissertation. Further, it required both complete knowledge of material properties and design loads and a complex setup process. By flexibly installing and testing similar Grasshopper plug-ins its ease-of-us could be compared.[60] [61] [62] This identified that a phenomenal tool for reuse-based optimisation it was, but a practical design tool for the average architect, it was not. (Figures 14-15) In every case, the issue of data availability held true. These tools relied on complete reclaimed material data, for exact results to guarantee a geometric fit. (Figure 16) It was identified that generative design was essential for the testing of the myriads of potential forms. The ability to cycle through many variations, given the myriad of components, is fundamental to reuse design. Whilst a lesser argument can be made for catalytic effect of other forms of AI here, it still emerges as a core technology applied to the process.

In contrast, Superuse studios and Keulemans were some of the few analysed to agree on a more loosely representative approach in contrast to absolute geometric accuracy. Considering the erratic predictability of found component data-completeness, BIM was viewed as a more flexible way of tracking design needs rather than realities. These approaches were examined in Revit, the most popular BIM software globally, used in standard configuration. Here, an early building design's parts were tagged. Figure 19 They might be marked with reuse intents: 'reuse', 'might be reused' or 'should not be reused' along with other metadata such as the required U-value, fire rating, cost or material. In this way, the designer could easily visualise and present reuse opportunities with the ability to adapt as the project develops. The approach was basic enough for any Revit user to apply.

Despite this simplicity, at odds with current reuse practice, it relies fully on a designer's intuition and motivation to reclaim. Superuse Studios embody reuse culture, but what about the majority who do not deem it worthwhile? Identified, was the critical importance of integration with databases to transform component-searching, beyond a conscious process, into a

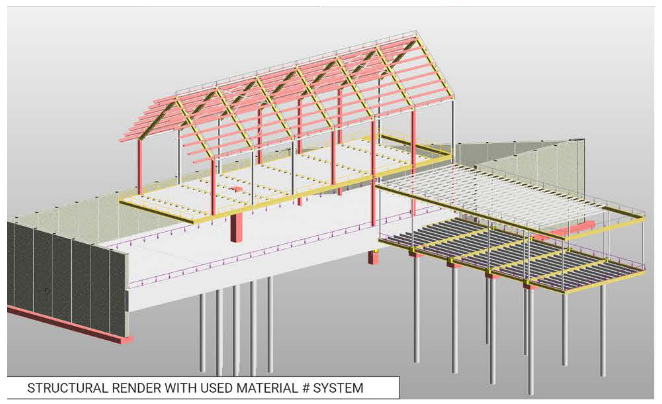
60 kjl, keithjlee2, and soerensenkarl, 'Keithjlee/DigitalCircularityToolkit'.
61 Huang et al., 'Algorithmic Circular Design with Reused Structural Elements'.
62 Rossi, 'Wasp'.

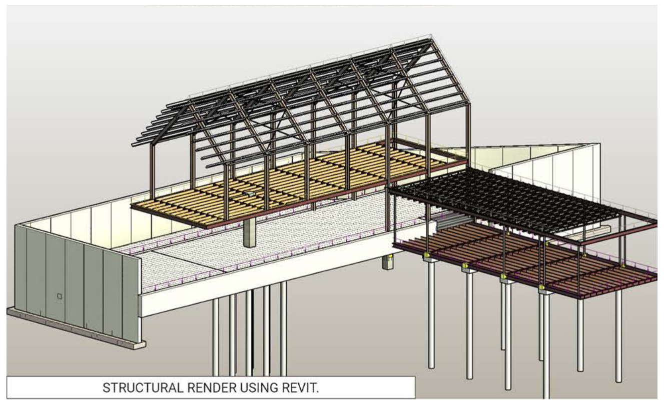


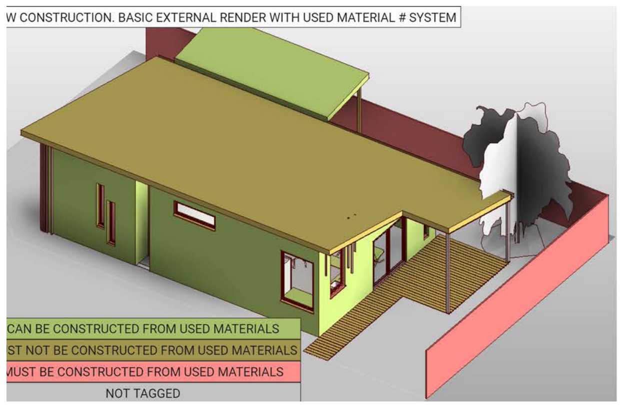
Above: Figure 17 - Final bridge model

Right: Figure 18 - Bridge design using Phoenix3D showing structural analysis of element capacity utilisation

Right: Figure 19 - Using BIM with targets and placeholders. Colour coding identifies which objects must be reuse, can be reused, or must not be reused [Keulemans]







semi-passive activity. In Dervishaj's review alone, 52 papers cited BIM as a core focus. The perception of importance in facilitating design changes at early stages is pervasive. Through review, this was found to be a motivator in countless BIM-related research papers.[63] [64] Indeed, AI's ability to make database suggestions is promising yet unexplored, and heavily applicable into BIM. This premise formed the backbone of the dissertation's scientific objective where the user interface was largely inspired by this representative approach. Here AI was a weapon. It could easily make suggestions at design stages which both benefited from suggestion and were not sensitive to error.

Hierarchy

Aggregation
Earlier aggregation was described as a simple set of rules. One which a designer of a rubble wall used

Bottom-Up
The parts and connections create the overall form.

Top-Down
A designer-led form is divided into parts after conception.

Through review of academic articles, a further debate emerged on a hierarchy of parts, connections and form. As has been debated more generally in architecture, some tools took a top-down approach – a target form, conceived by a designer, was discretised or matched into with reclaimed parts. (Figure 22) Others aggregated discrete parts by a logic of connection and manipulation – an overall form was a product of the parts themselves. It was arrived at by predefining the rules of interconnection between discrete parts. These might be termed top-down and bottom-up approaches. Phoenix3D, already examined, a clear example of the former, presents an optimisation of a target form. Here, the designer rules and the algorithm follows. Indeed, during review this was the overwhelming approach. Kaicong Wu, researcher in architectural robotics, presents one of the rarer bottom-up examples.[65] Here, a robotic arm was trained using CV to scan, route joints into and stack together irregular birch logs. The model further ensured a structurally feasible arrangement. (Figure 20) With some difficulty, the ability for the robotic arm to learn from its poor choices allowed for continual evolution of its ability to stack.[66] A remarkable similarity, like that of a child learning to stack blocks, was apparent. Like other bottom-up examples, the tool lacked applicability to practice. Yet, the approach of designing from the bottom up, facilitated by AI, is a fundamental shift to standard architectural practice, one which is suited to reuse.

The implications of this hierarchy are structural to architectural discourse. Firstly, referring once again to a the battle between industrialisation and craftsmanship – will our tools consider how varied reclaimed components fit together from the bottom up? Or, will business carry on as usual with designers specifying ever more complex forms from the top down. In this approach, tools like Phoenix3D would enable existing top-down design practices? Further Wu's research epitomises the implications of AI. Its intelligence, learnt off a cosmopolitan scale of data, allows it to respond to local, individual problems. As with the measure stage, at every use of these tools, if data is made public, the model learns to reuse more effectively. An absence of a middle ground. Which tools could be developed which mediate the bottom-up aggregation of discrete parts with the guiding hand of a top-down form.

63 Cavieres, Gentry, and Al-Haddad, 'Knowledge-Based Parametric Tools for Concrete Masonry Walls'.
64 Wang et al., 'Collaborative Conceptual Design—State of the Art and Future Trends'.
65 Wu and Kilian, 'Designing Natural Wood Log Structures with Stochastic Assembly and Deep Learning'.
66 Wu and Kilian, 28.

Figure 20 - A robotic arm, trained through AI, learns how to assemble logs. It understands both joint design and structural feasibility. [Wu]

Semantics – Language & Physicality

Semantic Search
An engine looks for the meaning behind words rather than trying to find exact matches. In a philosophical sense, the term semantic extends to how we interpret interpret linguistics.

Semantic search, relating to the study of language, overwhelmingly informs the proposed approach which ultimately developed an actual tool. De Wolf, a figurehead of reuse, advocates for the importance of integrating reuse databases with BIM. Her statement, referenced earlier, identifies this lacking integration once again: [67]

'Circular platforms should act as catalysts, linking those dealing with building disposal to those starting new constructions.'

Evidently, this link is essential but during extensive research, the literature on reuse database search was absent. The problem goes beyond conventional database search because beyond linguistics alone, it must consider complexities unique to design.[68] How to incorporate geometry, availability, timescale, materiality and form, where most databases consider only direct language matches?

Large Language Models
A form of neural network which predict language patterns to offer responses.

Therefore, the proposed approach importantly considered examples outside of reuse which could be considered extensible. For legibility, more technical explanations of computational methods related to language are consigned to the research objective. However, the following key points were considered: 1) the research into adapting LLMs for a specific understanding of construction, 2) the ability for these models to understand the physical form which language describes.

For database search, publicly available LLMs are accessible but not construction-specific. Natural language researchers like Antoine Tixier are some of the few to improve the AEC-specific research.[69] Using semantic methods, detailed later, he was able to train a model on construction reports which outperformed Google's construction terminology understanding 50% of the time.[70] Moreover, in conversation with Tixier himself, it was clear that in the 8 years since publication, LLMs have rapidly developed in understanding of this terminology. Samar Abusaleh, within the same field, illustrates this rapid development in AI. His research bears further relevance. A model, for examining global heritage sites natural, and man-made was trained on multifaceted data.[71] This included not only text descriptions (historical background, structural stability, cultural importance, visitor attendance statistics, and current conservation) but also numerical data (age, visitor attendance, location). Further, in a second stage, it was able to suggest conservation strategies.[72] Relevantly to reuse, Abusaleh evidences a model which is both adapted to architecture and able to consider numeric and geometric data beyond a conventional search engine. In fact, both academics, within their research, identified predominant limitations in the architectural field. Firstly, the effort to gather training data from public sources. Yet, more importantly, the siloed separation between this computational research and architectural discourse.

67 De Wolf et al., 'A 5D Digital Circular Workflow', 4.
68 Abusaleh, 'Enhancing Preservation Outcomes for Architectural Heritage Buildings through Machine Learning-Driven Future Search Optimization', 5282.
69 Tixier, Vazirgiannis, and Hallowell, 'Word Embeddings for the Construction Domain'.
70 Tixier, Vazirgiannis, and Hallowell, 11.
71 Abusaleh, 'Enhancing Preservation Outcomes for Architectural Heritage Buildings through Machine Learning-Driven Future Search Optimization'.
72 Abusaleh, 5283, 5286.

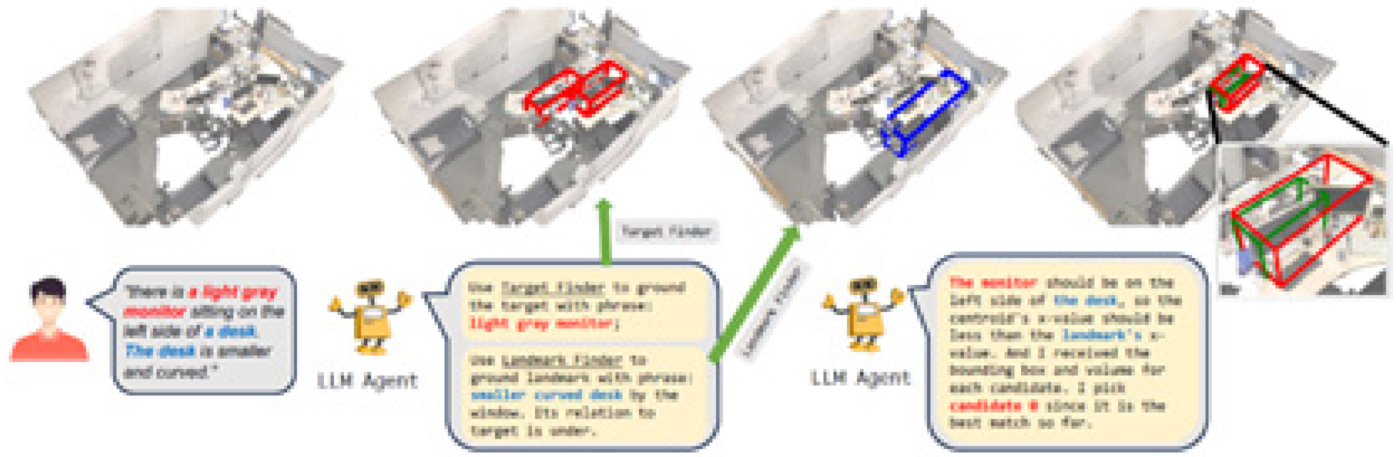


Figure 21 - A prompt provided by a user is understood and deconstructed by ChatGPT [Yang]

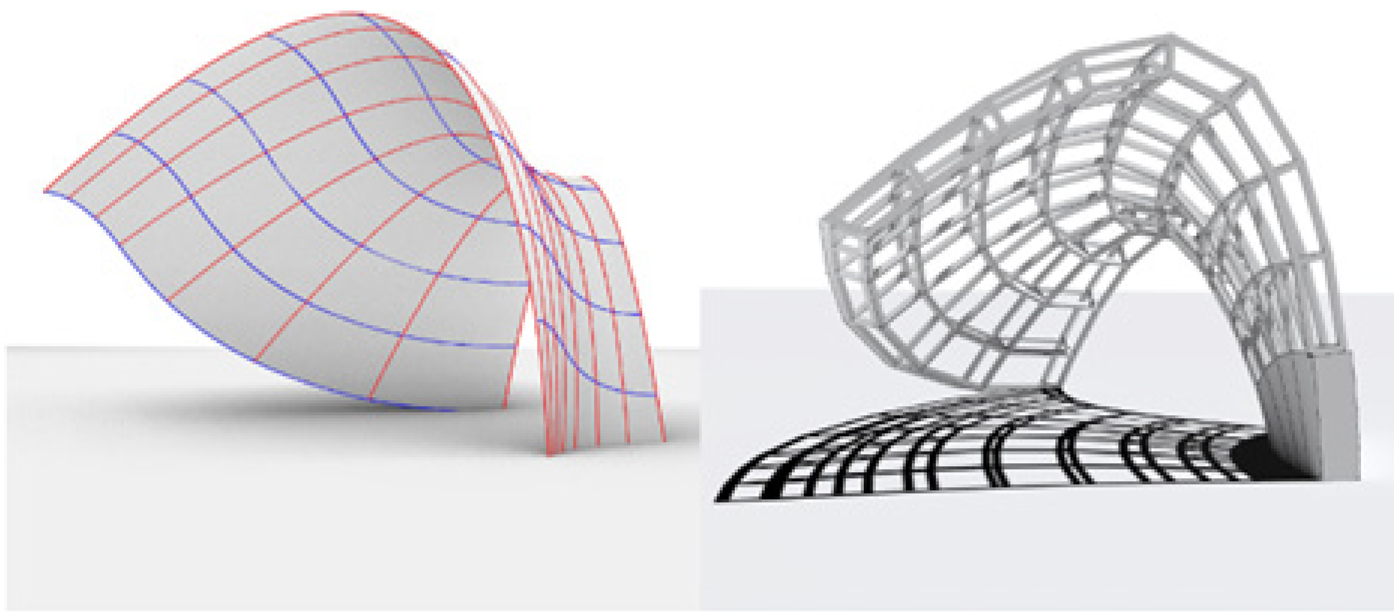


Figure 22 - An example where a provided surface form is discretised into

Reasoning
In AI, this is highly debated. Here it used to describe the ability to draw logical conclusions beyond the user inputs themselves. ChatGPT, recently version 4o1, reads its own responses to judge their suitability and expand upon them. This might be termed a chain of thought.

Quarrying online collections, it was possible to find examples of those who had taught LLMs to understand space and form. This level of reasoning, though potent, was equally unapplied to the searching of reuse databases for reclaimed components. In the field of robotics, a notable example was Jianing Yang's.[73] An objective, to allow home robots to understand simple prompts like 'a light grey monitor sitting to the left of the desk' was achieved through the use of ChatGPT 4. With a small delay, ChatGPT was able to decipher such language into clear prompts for the robot to act upon.[74] It could deconstruct such phrases into object, colour, position and movement. (Figure 21) Yang's achievement is crucial to the dissertation's proposed approach because it demonstrates, outside of reuse, the ability for LLMs to understand object attributes such as form and materiality. Only in this way, can searching a reuse database begin to capture the nuances of both a designer's requirements and reclaimed object attributes. The adequacy of a general tool, such as Google, despite its ubiquity, is unlikely to be enough.

The design stage, as most multifaceted, exposed a tension between pragmatic and cutting-edge approaches to reuse. Superuse Studios exemplified a manually-selective practice, guided by intuition, yet constrained by current tools, Contrastingly, while ML-driven systems like Phoenix3D highlighted the potential of optimisation. These remain limited by data completeness and technical complexity. Such contrasts underscore the central challenge of making reuse a viable part of scalable architectural workflows. Still to be achieved is a unification of powerful digital tools with the practical navigation of construction and regulation. AI's recent developments are perhaps most relevant to language and therefore make for low-hanging fruit.

The contrast of the catalytic propositions (in de Wolf's words) of reclamation search tools, against the sparse research is telling. Many of the self-described digitally cutting-edge Parametric studios like Zaha Hadid Architects are preoccupied with geometric research. Reuse, particularly the complex problem of language is rarely mentioned. Parametric architecture finds identity in its supposed ability to respond to place and environment dynamically. Benjamin's notion of aura finds a story in materials. Shall this story not be considered as one of a buildings defining 'parameters'?

AI promises to catalyse design reuse by streamlining tasks like generating designs, integrating databases, and addressing linguistic challenges, though the geometric issues of design lack solution refinement. The proposed approach unearthed that whilst AI can make reuse scalable and efficient, its catalytic potential is not universal. Other insurmountable barriers exist. During research however, it felt vital to transfigure the hypothesis into an objective before making any sweeping conclusion.

73 Yang et al., 'LLM-Grounder'.
74 Yang et al., 4–6.

Research Objective

Through research, this more precise objective became apparent. The limitations of current approaches, identified in th2 - Literature Review were formative:

– Existing research used a restricted set of reclaimed stock. In reality, reused components come from far-reaching sources and restricting this set is challenging.

– The tools rely on complete data (geometric, performance and visual properties) which do not exist today for most reclaimed objects.

– They are narrow in application, most papers applied complex tools effectively but to a narrow design problem. These specialised approaches are ripe for exploration. A potential designer should not have to negotiate complex methods.

– Contrary to direct reuse, repurposing and upcycling are rarely considered because this is a complex language problem related to understanding form.

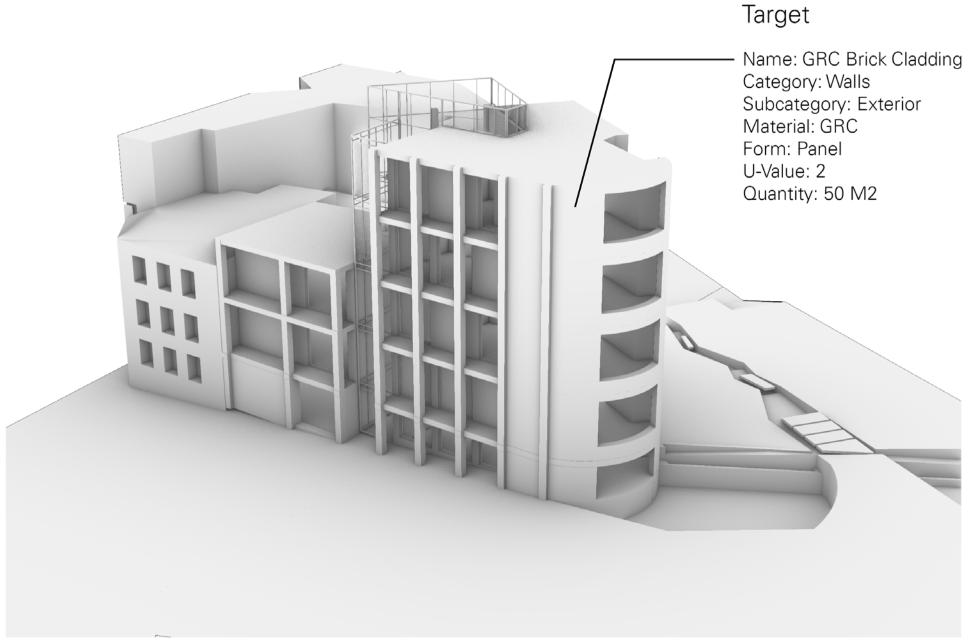


Figure 23 - Target and Match, the mechanism of the tool

The issue of indirect reuse is pertinent as a symbol for the challenging complexity of the task. A research objective emerged:

> Broadly, to prove AI is accessible and effective for suggesting reused components. An integrated workflow may enact change where a designer might not otherwise make the effort. By helping to understand the mass of potential options available, AI could help to identify suitable components.

> More narrowly, this research considers the linguistic difficulty of navigating reuse. By using LLMs, now ubiquitous, we can better search the innumerable available objects. How might public but unspecialised tools be weaponised and upscaled for designers?

Clear requirements were set out. The tool should be created in Grasshopper so it could be directly integrated with the widely-used Rhinoceros3D.[75] [76] It should make use of an LLM with far greater data sources than any one researcher could provide. It should work with databases of components to provide one-click matches without the need for complex configuration. To reiterate, BIM tools should be integrated with circular platforms to impact the early design stage.[77] The proposed approach avoided probing the database structure itself, being resigned instead to developing a parts-matching tool. Using standardised Revit categories for objects, I hoped to make the tool more extensible to other BIM softwares.[78]

75 Robert McNeel & Associates, 'Grasshopper'.
76 Robert McNeel & Associates, 'Rhinoceros 3D'.
77 Cavieres, Gentry, and Al-Haddad, 'Knowledge-Based Parametric Tools for Concrete Masonry Walls', 717.
78 Autodesk Inc., 'Revit 2025'.

Match Results

1.
Name: Concrete Brick Effect Cladding
Category: Walls
Subcategory: Exterior
Material: GRC
Form: Panel
U-Value: 1.8
Quantity: 60 M2
Certainty: 90%

2.
Name: London Brick
Category: Walls
Subcategory: Exterior
Material: Clay
Form: Block
U-Value: 1.8
Quantity: 3000 Units
Certainty: 80%

3.
Name: Timber Wall Panel
Category: Floors
Subcategory: Finishes
Material: Douglas Fir
Form: Plank
U-Value: 3
Quantity: 55 M2
Certainty: 55%

Mechanism

First, the mechanism was considered. The measure stage identified potential object attributes and the design stage evaluated a loosely representative approach to BIM. BIM can be understood as a data tool which attaches highly structured information to 3D objects. With the representative approach, metadata might be manually added to objects or in the case of area, quantity, volume and length, calculated by Grasshopper. This mechanism intended to respond with matching suggestions for the designer from a database of reclaimed components. (Figure 24) To conceptualise this process, with one-click suggestions for target objects, Figure 23 diagrams the mechanism. This is the front-end which appears to a user. Figure 25 simplifies the tool's inner workings, or rather, the back-end. Grasshopper, the visual coding tool is used. Its ability to link together components and run Python scripts within was essential.[79]

79 Van Rossum and Drake Jr, 'Python 3.13.0'.

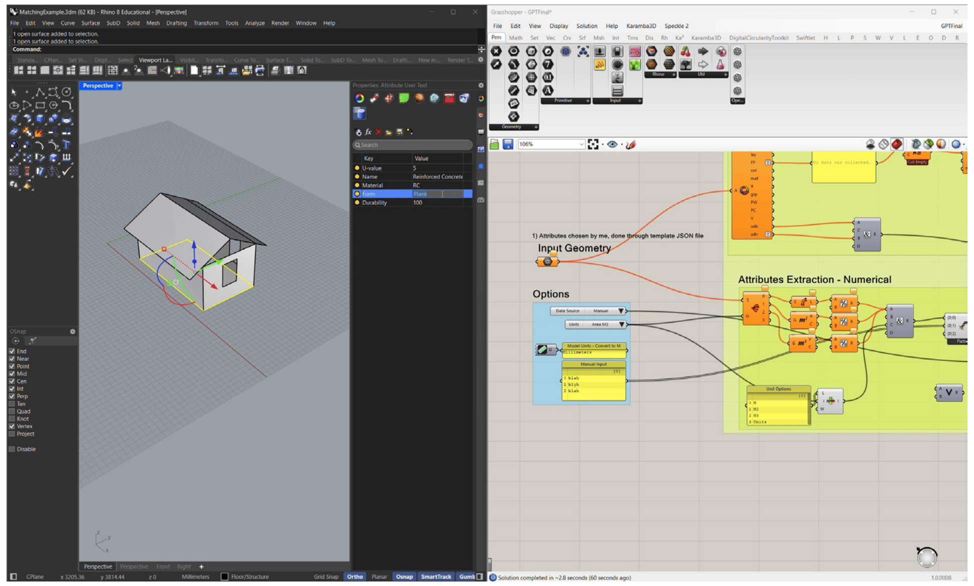


Figure 24 - Object selection: the user can manually or automatically set geometry units

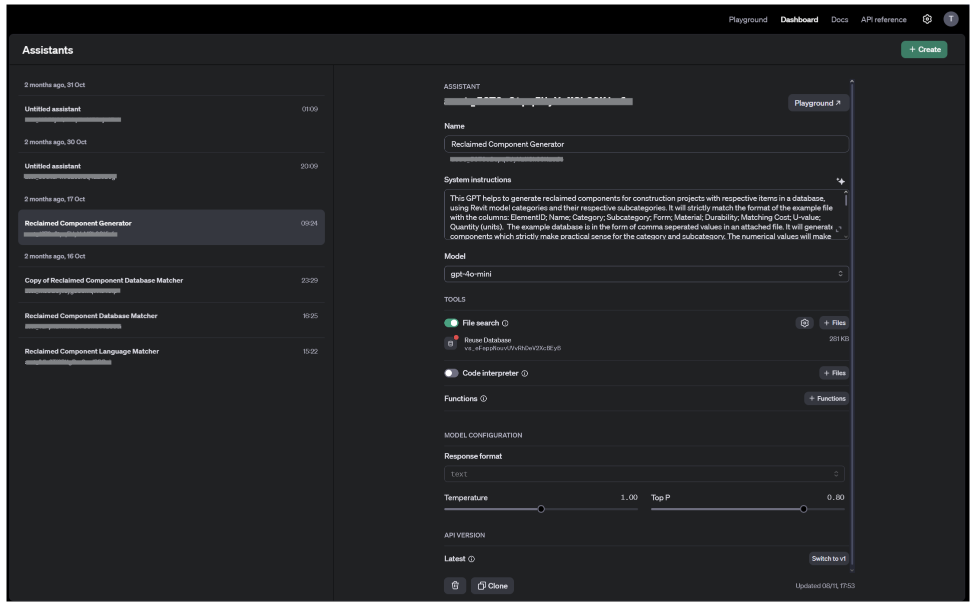


Figure 26 - OpenAI API dashboard, where assistants can be configured

OpenAI API

OpenAI's API is a tool for developers to integrate their chat tools directly into applications.[80] Simply, ChatGPT 4o, the most powerful GPT at the time, could be accessed, beyond the web platform, through languages like Python within Grasshopper.[81] The OpenAI's assistants API allows for a chatbot with preconfigured instructions, functions, databases and response formats. (Figure 26) At the time, no implementations of this existed in Grasshopper. To understand the structured input data from Grasshopper, this assistant was predefined to read the prompts' metadata fields (Category, Form, U-value, etc.) and to trawl a database for potential matches.

Linking to the review of databases, where a uniqueness to architectural object matching was identified, metadata was of two clear categories. For this metadata of numerical values (quantity & U-value) could easily be filtered for in the database. Language identifiers conversely, (form, name, material) which were key to the linguistic search, leveraged the LLM's reasoning skills.

Whilst numerical filtering was trialled in Grasshopper, it was simpler to perform the entire process in the API. The assistant allowed for definition of a filtering function in natural language which it would intelligently choose to use if necessary. Unlike a Python script, this function was flexible enough to understand units or remain inactive when numerical targets weren't provided. For example, in the case of U-value it understood, through reasoning, to filter for lesser values. For returning the responses, it was configured to respond in structured JSON, a widely recognised structured text format. This way, match results could be easily extracted in Grasshopper.

The Python specific to interacting with the API used various functions including runs, messages and threads. Given personal inexperience, tedious trial and error was required. Such, considerations are likely trivial for a competent Python user. Thus, definitions are only outlined in App. B. For efficiency, sections of code like the thread were written to remain constant, yet those such as messages would loop for every input prompt. (Figure 29 & 30)

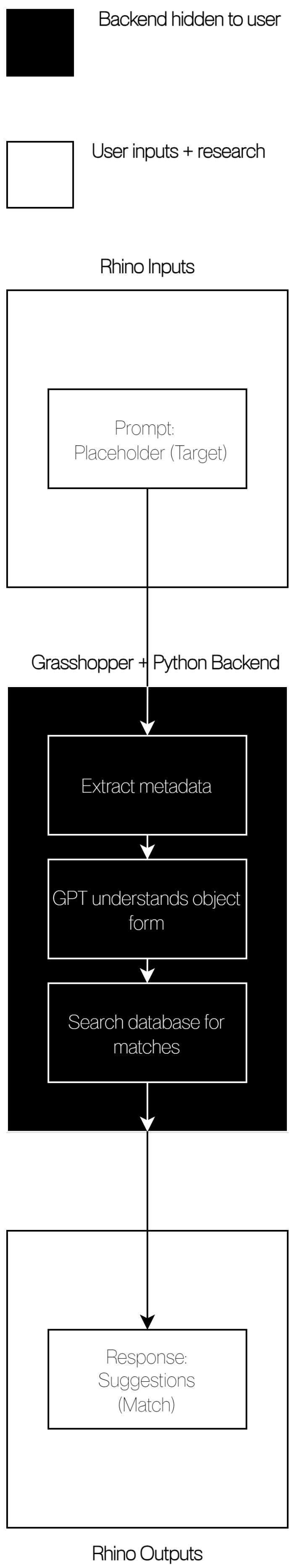


Figure 25 - Overall structure of the tool

80 'OpenAI Platform'.
81 'Introducing ChatGPT Pro'.

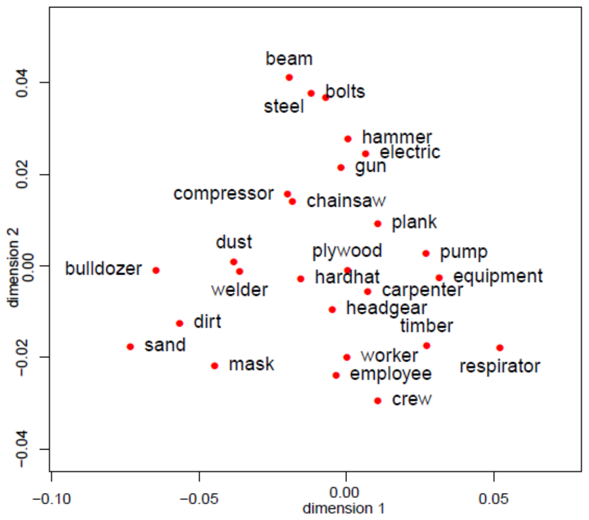


Figure 27 - Semantically similar words occupy similar vector spaces [Tixier]

Venetian [-0.10458385944366455, -0.014801296405494213, -0.30353015661239624, ..., ..., 0.22405271232128143]

Figure 28 - An example vector embedding

Semantically Expanded Search (SES)

The preceding research hypothesis explored (through review) LLMs breadth but lacking AEC specificity. ChatGPT 4 for instance cost over $100 million to train given its dataset.[82] However, as a generalised model, only a fraction of its material would have been construction-related. Identified further was the GPT's ability to understand form through descriptive prompts. Therefore, by expanding the search terminology, providing construction-specific synonyms was hypothesised to increase the GPT's understanding of the desired objects.

LLMs, as Neural Networks, understand words through conversion into numeric values. A common approach used by LLMs and search engines is word vector embeddings. Here, a vast list of terms are analysed for similarity by processing copious texts. The resulting vector embeddings describe the interconnectedness of words. (Figure 27) A vector of many dimensions represents each word. For example, (Figure 28).

Tixier's, article on language for the construction domain, earlier outlined, was deconstructed in depth. His research provided word vector embeddings for extremely specific construction terms which the GPT may lack training in. It was felt that these embeddings were a potent tool for semantic search for synonyms. Despite attempts, the 8-year-old project was hard to generate embeddings for. Instead, OpenAI's own embeddings model, 'text-embedding-3-large', the most up-to-date, was leveraged.[83] This generated new vectors for his original 32,689 construction terms.[84] Critically, it responded to Tixier's own self-criticism, that LLMs were now the way forward whilst using the diverse construction words his study had identified .

The gargantuan embeddings list returned had vector dimensions of 1024 with an impractical size of 1GB. The generating script was tweaked to request a smaller dimension of 256 and the size reduced to 180MB. Through Python, these embeddings were converted into a simple spreadsheet which could be searched with a script in Grasshopper - in this sense, they were a kind of dictionary. Python's cosine similarity function computes the angles between each search term's vectors and the many other terms in the spreadsheet.

82 'The Extreme Cost Of Training AI Models Like ChatGPT and Gemini'.
83 'New Embedding Models and API Updates'.
84 Tixier, Vazirgiannis, and Hallowell, 'Word Embeddings for the Construction Domain', 4.

(App.. A) Though complex, it is commonly used within Python to return similar terms. Here, it found the top 5 synonyms for every word in every prompt. This process was hidden in the Grasshopper back-end but would return results like:

Target Name: Joist

Name	Cosine similarity
joists	0.895057
rafter	0.610819
jointer	0.609660
jib	0.591910
corbel	0.589322

Using this construction-specific SES, the prompt was passed to the GPT for reclaimed component search. It was later clear that the tool was underutilised because it only computed similarity for individual terms rather than entire phrases such as 'London brick cladding'.

Match Parsing

Again, Python was used to extract (parse) the API's match results, which varied slightly in format, back into Grasshopper for clean display in Rhino. This script was written to handle inconsistent formatting, a common issue with ChatGPT. The approach centred round the assumption that database would be liable to change, and a rigid script may become obsolete. Flexibility was an essential consideration if the tool was to be used with varied databases with different table headings. Rigidly specific research would have perverted the entire research objective.

To summarise, the back-end, overwhelmingly written in Python, was split into three modules shown in Figure 29:

A) Input parsing and cosine similarity – to take the separate object attributes, perform semantically expanded search and combine them into a single prompt

B) OpenAI API – to send prompts and receive match responses

C) Response Extraction – to split the response into its constituent parts

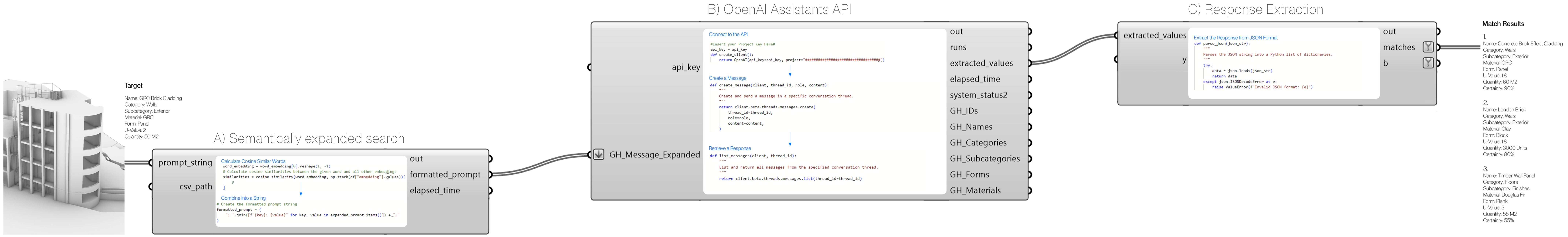


Figure 29 - Simplified diagram of the key Python components in Grasshopper shows code covered by sections A, B and C

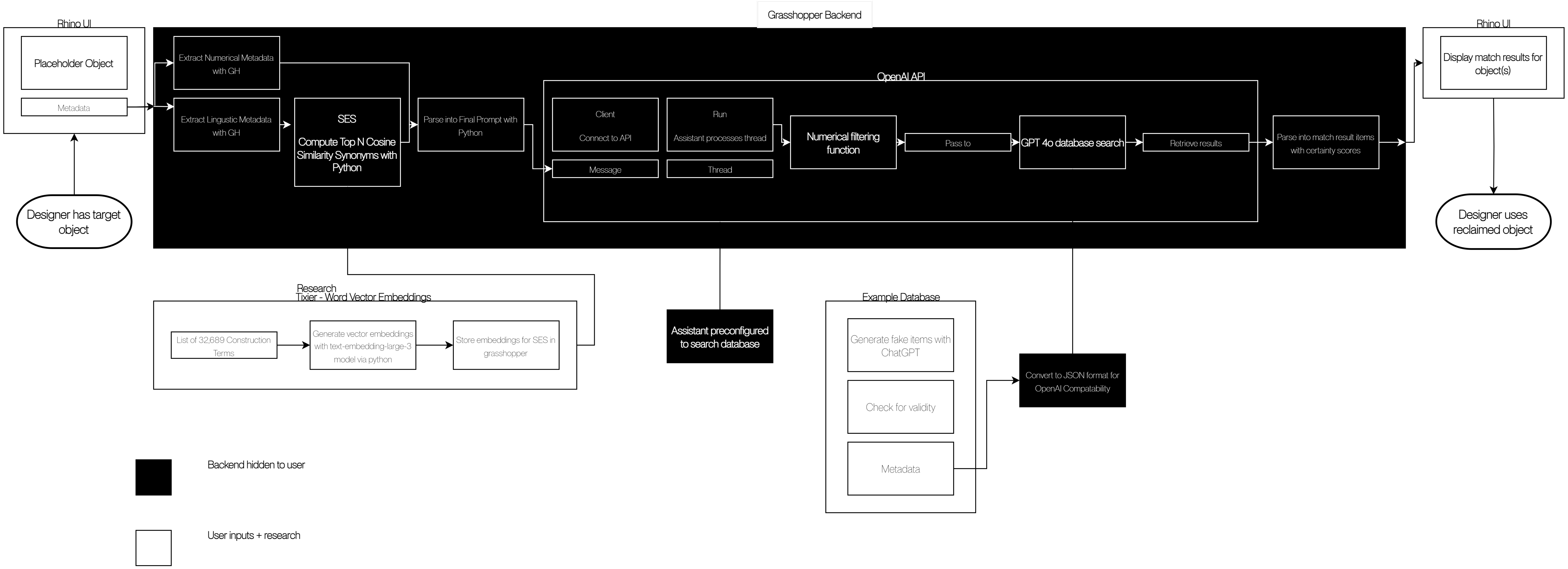


Figure 30 - Complete flow diagram of the computational tool. The structure was created in the early stages of research so components could be linked together efficiently.

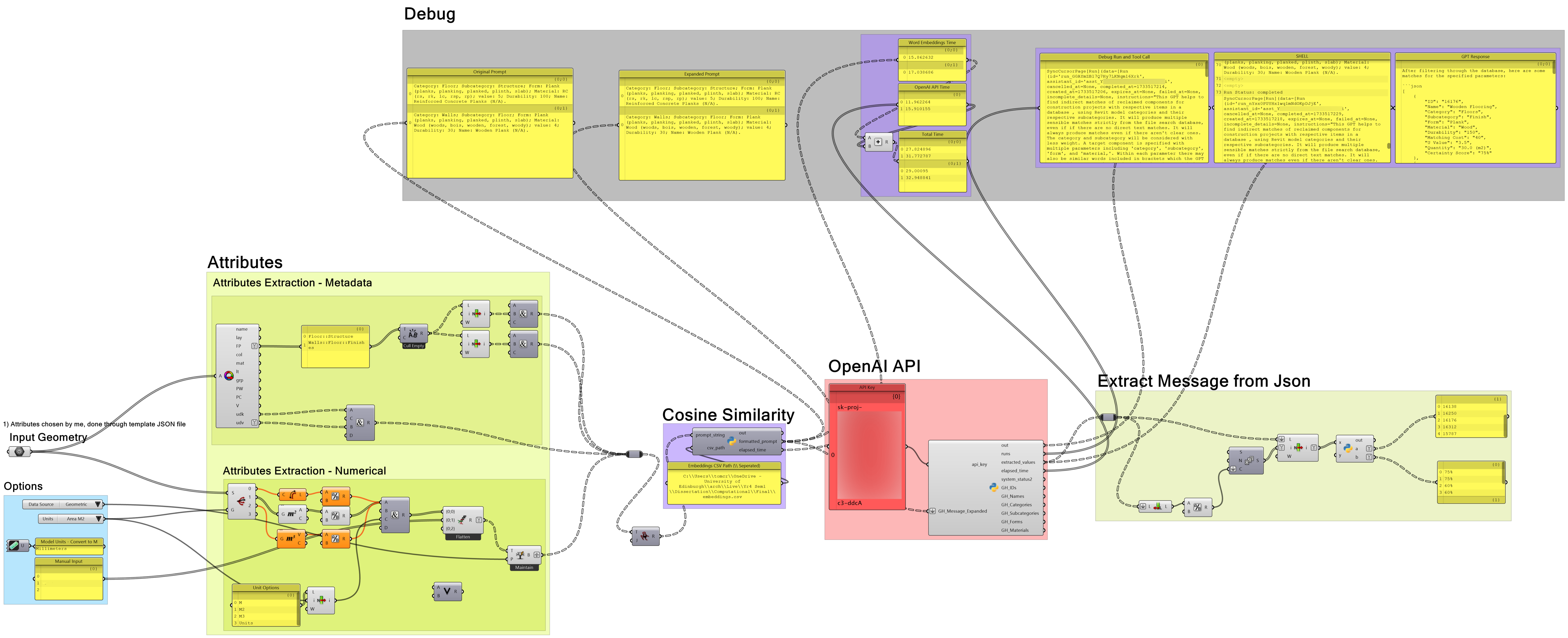


Figure 31 - Overview of Grasshopper as a user would see. Users can choose input units to be calculated automatically or can manually specify values

4 - RESULTS & DISCUSSION

TESTING FRAMEWORK

EXTERNAL COMPARISON

Testing Framework

Evaluating the tool in a scientific sense allows us to prove or disprove to a limited extent, AI's potential to integrate a reuse workflow into Rhino. These results do not statistically predict the uptake of the tool at scale in terms of designer behaviour. They do however, represent the versatility and potency of AI in language understanding in this reuse context.

Direct Reuse
Reuse which makes reuse of components as they were originally intended

Indirect Reuse
Reuse which reinterprets objects to use them for a function originally unintended

To rank the effectiveness of matches to a given target, ChatGPT's certainty score was considered alongside a human ranking. The human ranking was performed blindly (to avoid bias) by myself and another architecture student who both had reasonable construction knowledge of reclaimed components. For the tool's function, data was categorised into direct and indirect reuse. Searching for direct results was an interesting problem relying on our ability to find objects matching our language. Indirect reuse however was the more interesting field because it challenged the LLM to understand how a physical form might be relevant to different uses. To measure the efficacy of SES, the tool's configuration was separated into (1) pure use of ChatGPT for matching and (2) Combination of the former with the module for SES. Thus, comparison is possible for two different tool configurations (SES vs. no SES) for both indirect and direct searching.

30 target prompts were fed into the search tool in both configurations (1) and (2). The top three results were taken for each search prompt leaving 180 suggestions for manual scoring. A simple scoring system was used but extremely poor matches were not categorised as direct or indirect. (Figure 32)

Comparing ChatGPT's certainty with human scoring led to interesting conclusions. Whilst its effectiveness at matching overall, will be demonstrated, the GPT certainty had an extremely poor correlation with human scoring. (Figure 33) Thus, it was deemed an unreliable indicator and human scoring was used exclusively for validation. SES had little improvement on direct matches though, with 95% of matches ranked average or above, the tool was potent. (Figure 34)

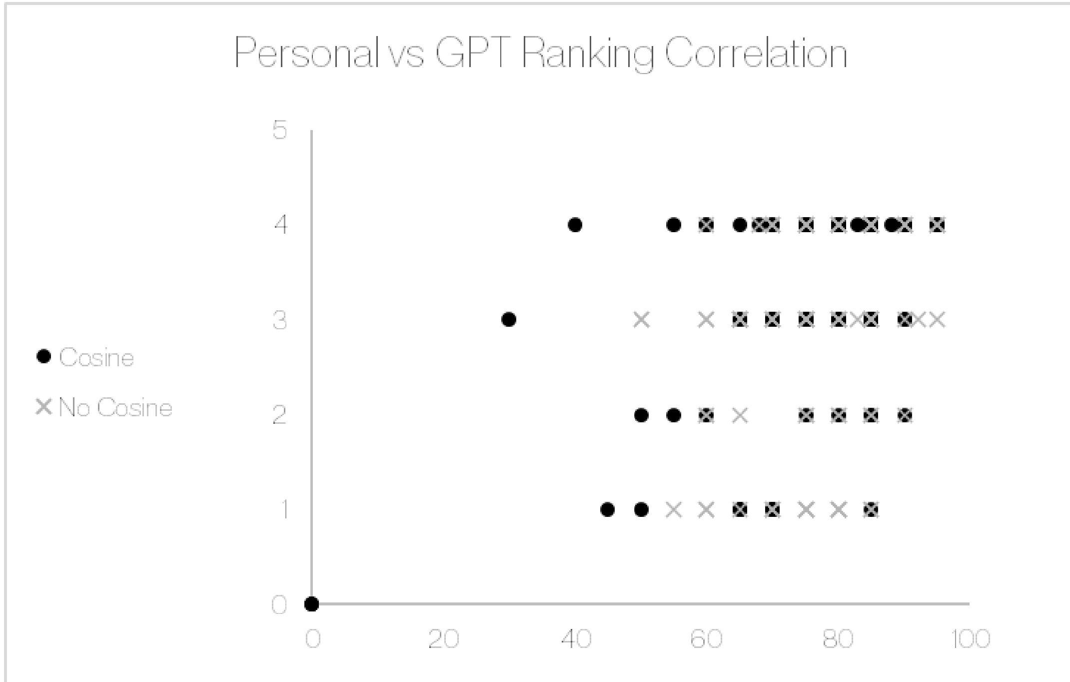


Figure 33 - A poor correlation is shown between GPT and personal rankings. For this reason the human-based rankings are considered only.

<table>
<tr><th></th><th>Infeasible</th><th>Unusual</th><th>Average</th><th>Excellent/ Exact</th></tr>
<tr><td>Direct</td><td rowspan="2">1</td><td rowspan="2">2</td><td rowspan="2">3</td><td rowspan="2">4</td></tr>
<tr><td>Indirect</td></tr>
</table>

Figure 32 - Human match scoring table for myself and the other validator.

For indirect matches, strikingly, SES increased the proportion of above-average results and reduced poor suggestions by 10% equally. (Figures 35 & 36) Undoubtedly, SES provided greater context of objects' form to the GPT giving it a better awareness of indirect results. Though attributing understanding to a model which simply recognises language patterns is misleading, the illusion of greater comprehension through richer description is created. As reviewers, the GPT's responses sometimes had an aura of creativity. The suggestion that, for a target of timber shading louvres, old floor boards might be used, was fascinating.

Shortcomings:

Even in its small scope, the tool's practical shortcomings are clear. An average compute time of 10s for SES and 7s for the GPT per search made for slow results. I propose future improvements either beyond my capability or timescale:

- Development of cleaner user interface accessible in Rhino or Revit directly. E.g. through the Grasshopper Player.
- Reconfiguration of Python to avoid unnecessary repetition of functions
- Connection of the OpenAI API to an actual reclamation database like materialreuseportal.com which aggregates many marketplaces.
- Computation of word embeddings in real-time within the OpenAI API. This would allow comparison of terminology which does not feature in the embeddings list generated.
- Use of complex geometric data to make better suggestions.
- Running SES with CUDA. By performing the search on the GPU the process could potentially be sped up by 100 times.[85]

External Comparison

There is an apparent absence both of use of semantic search for architectural reclamation and use of the OpenAI Assistants API within Grasshopper. Whilst in the methodological review, I explored semantic search beyond architecture, this provides a limited comparison benchmark for data validation. Therefore, I compared to one design-related study tackling semantic search. This used language prompts to suggest room geometries through an older version of the OpenAI API. Averaging its best results, the study showed a 56% correctness score for GPT responses to the prompt.[86] Equating this study's 'correct' score to my proportion of reasonable matches, it was clear that GPT 4o has significantly improved understanding

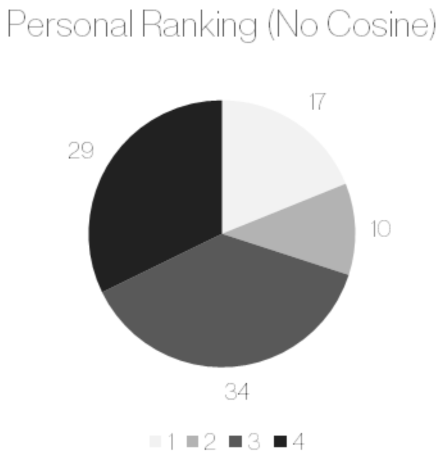


Figure 34 - Pie chart of rankings without SES

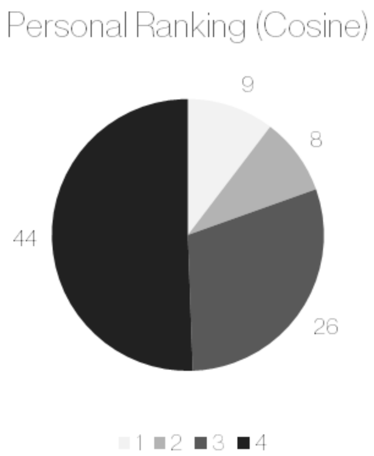


Figure 35 - Pie chart of rankings with SES

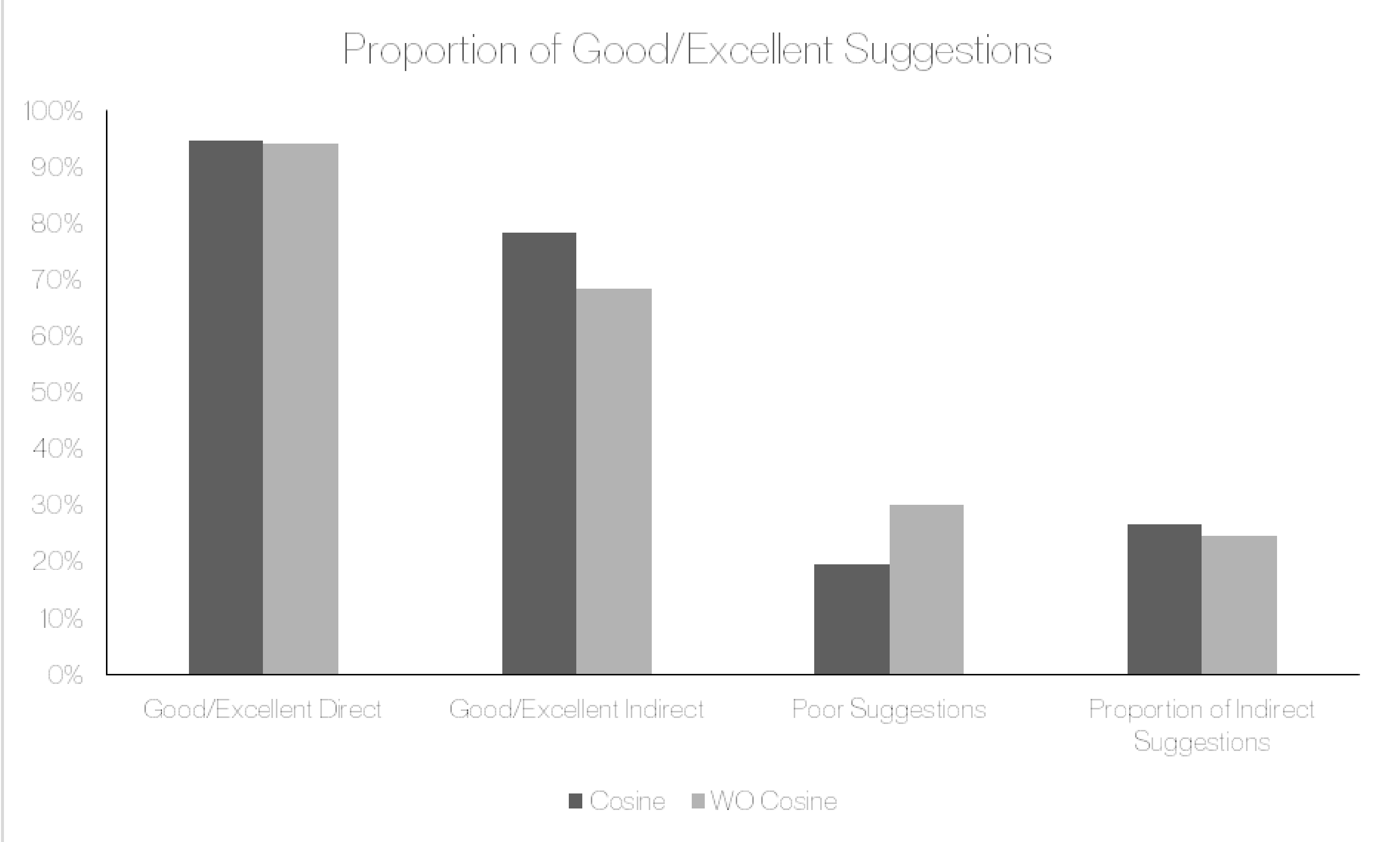


Figure 36 - Bar graph comparing suggestions with and without SES (cosine similarity) function

85 Veysov, 'Speeding up Word Distance Calculation 100x'.
86 Galanos, Liapis, and Yannakakis, 'Architext', 8.

Overview

The second section of the proposed approach demonstrates how AI can unravel the linguistic and technical complexities at the heart of architectural reuse. Through the development and testing of an AI-driven tool integrating semantic search and data filtering within Grasshopper, the research validates AI's capacity to automate the matching of reclaimed components with design requirements. The tool, leveraging OpenAI's GPT, proved effective in generating both direct and indirect reuse matches, overcoming the fragmented, manual nature of current processes. Further, the API is scalable being used across the world today. Although there is room for database integration, further speed and user interface improvements, the results are striking: AI can turn the chaos of swathes of reclaimed objects into actionable design insights. These findings reinforce AI's role as a practical enabler during the early stages of reuse, addressing key barriers by simplifying workflows and encouraging more intuitive exploration of reclaimed materials.

Though of course, this research does not take responsibility for the cryptic instrument, which is ChatGPT, the results are extremely promising. The fact that even a Python beginner such as I could set up a tool with the API begs the question: With such a low bar to accessibility, what could a competent software developer achieve? In fact, with no education in tools such as Grasshopper and Python during my degree, it was felt that my own architectural skillset to be the primary limitation. The pace of movement in the tools provided was astounding. In the 3 months of writing, OpenAI released an improved GPT (version 4o) and the Assistants API remained an incomplete Beta tool.

How can we make sure these platforms are integrated into architecture-specific applications rather than accessible only as general tools? These results expand evaluation of AI's varying scalability in the different stages of reuse. The use of LLMs is unique because it does not deliver entirely accurate results. Therefore, it is particularly suited to early design stages as a suggestive tool as designers can work with it creatively rather than relying entirely on it for sensitive tasks like the delivery of safety assessments.

These findings directly echo the literature review's insights into the stages of reuse and the barriers at each. While the review positioned AI as a catalyst for technical processes like measuring and tracking, it also exposed how deep-rooted structural issues (regulatory inertia, lack of standardization, and economic disincentives) stall upscaling of reuse. The tool's outcomes validate this dual reality: AI spearheads reuse where data complexity is a consistent problem but remains constrained by a backdrop of cultural problems. The literature painted a clear picture—reuse struggles because the tools, workflows, and incentives don't align. This research takes a step forward by showing AI's potential to shift that balance, not as a standalone solution but as a means to bring reuse into the realm of mainstream possibility.

Figure 37 - Rubble from the Berlin Wall, perhaps no other rubble exists with as rich a story to tell.

5 - Conclusion

Perfection or Progress

Both tool and review, in unison, identify implications, applications, and limitations of AI as a catalyst to scaling up reuse. A commonality identified across all investigated stages of reuse (measuring, tracking, and designing) is the challenge of data complexity, which AI is uniquely positioned to address at scale. Perhaps this provides an incomplete answer to the hypothesis. The developed Grasshopper tool, a central outcome of this research, exemplifies how AI can streamline component matching, translating vast, datasets into actionable design insights with scalability. This practical application underscores AI's suggestive potential to simplify workflows and enable reclaimed materials to integrate seamlessly into architectural processes. This might be considered a narrow completion of the research objective. However, equally exposed were AI's limitations, it cannot act alone. The culture amongst industry, regulators and designers must consider reuse, beyond rhetoric, as a challenge worth addressing. These challenges are unique to each stage.

Personally, investigations into reuse were born out of the perceived misalignment between digital capabilities and design intentions. Patrick Schumacher professes that Parametricism is 'the only contemporary approach that can adequately address the challenges posed to architecture … by the Information Age.'[87] . Indeed, the adopted tools within practice are more parametric and data managing than ever, but they entirely overlook reuse. This age sees societies as more connected than ever. By extension, the tools distributed globally, may saturate designers with the same consumptive attitudes or antiquated approaches.

Recent history illustrates that advancements in technological tools, while enhancing productivity, have primarily demanded that designers produce ever-greater volumes of increasingly complex work. AI, with its capacity to radically reshape architectural practice—explored here through the lens of reuse—carries the potential for transformative change, though such a shift is unlikely to materialize without deliberate intervention. A critical understanding of AI's technical implementation and broader implications is therefore essential, not only to safeguard reuse from being sidelined but to ensure that tools are purposefully adapted to design from other industries. Many architecture courses teach us to challenge the assumptions in practice through rhetoric, but fail to equip designers with the foundational computational skills to do so.

87 Schumacher, Parametricism 2. 0, 10.

6 - Appendix

App. A – Method for calculating cosine simliarity

For search vector A, and a target vector B

$$cosine\ similarity = |A||B|cos\theta = \frac{A \cdot B}{|A||B|} = \frac{\sum_i^n A_i B_i}{\sqrt{\sum_i^n A_i^2}\sqrt{\sum_i^n B_i^2}}$$

To interpret the result (θ):

1: Perfect similarity (same direction).

0: No similarity (orthogonal vectors).

-1: Opposite directions (completely dissimilar).

Explaining the processes for multidimensional vectors is more complex and beyond scope.

App. B – API Functions provided by OpenAI

Object	What it represents
Assistant	Purpose-built AI that uses OpenAI's models and calls tools
Thread	A conversation session between an Assistant and a user. Threads store Messages and automatically handle truncation to fit content into a model's context.
Message	A message created by an Assistant or a user. Messages can include text, images, and other files. Messages stored as a list on the Thread.
Run	An invocation of an Assistant on a Thread. The Assistant uses its configuration and the Thread's Messages to perform tasks by calling models and tools. As part of a Run, the Assistant appends Messages to the Thread.
Run Step	A detailed list of steps the Assistant took as part of a Run. An Assistant can call tools or create Messages during its run. Examining Run Steps allows you to introspect how the Assistant is getting to its final results.

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