The application of GenAI to technical design in architecture and urbanism

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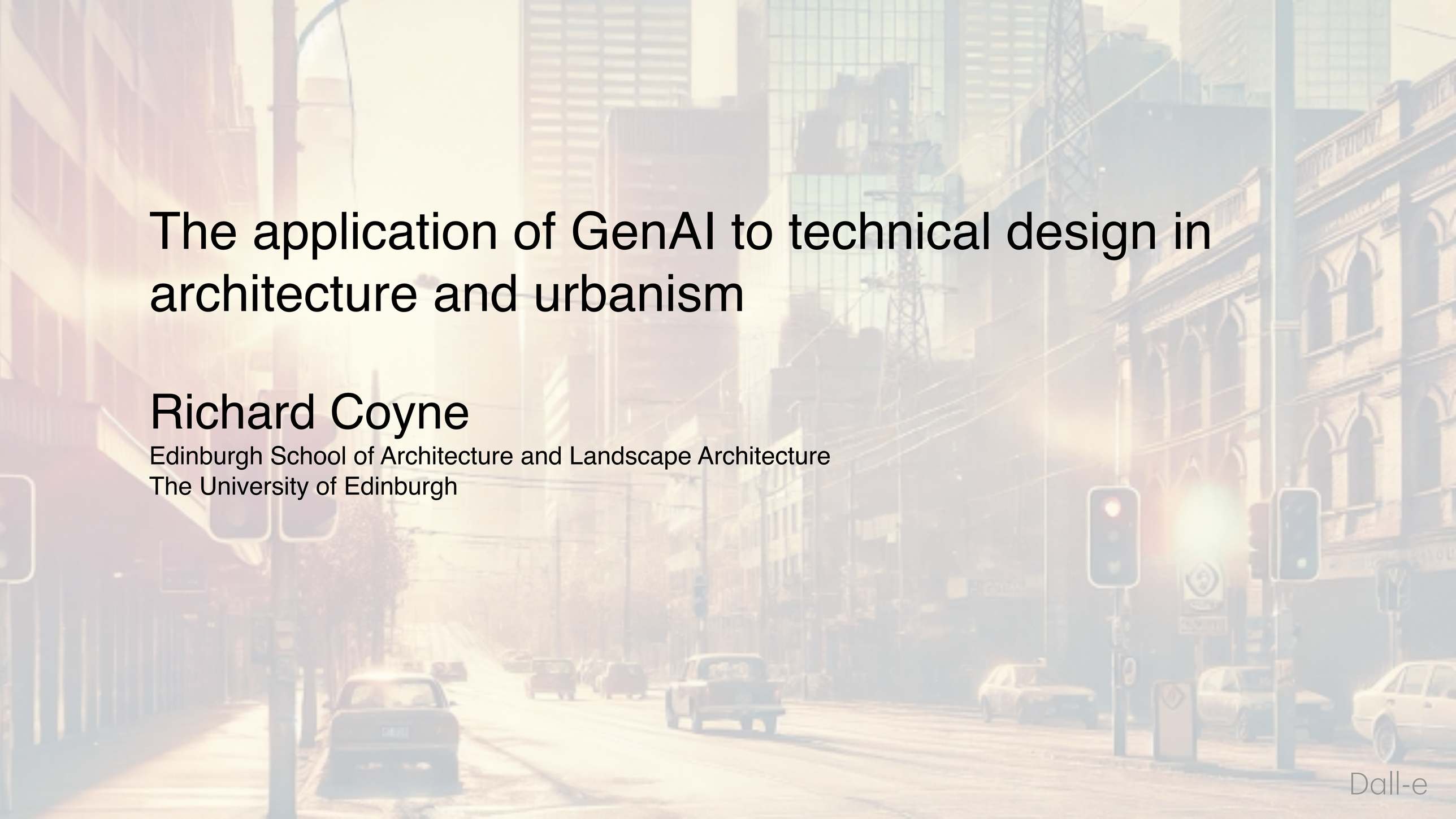


The application of GenAI to Technical Design

Slide 1: Personal Position on GenAI for Technical Design
Slide 2: Gaps in current GenAI technologies within your discipline or organisation
Slide 3: Future Roadmap for GenAI within your discipline or organisation

Personal position

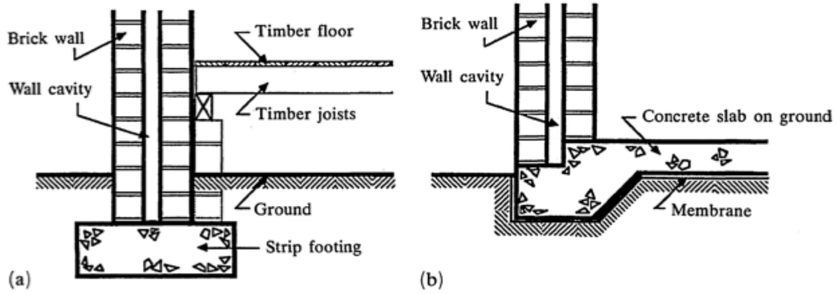


Figure 1. Examples of subfloor construction details: (a) raised timber floor and (b) concrete slab on ground.

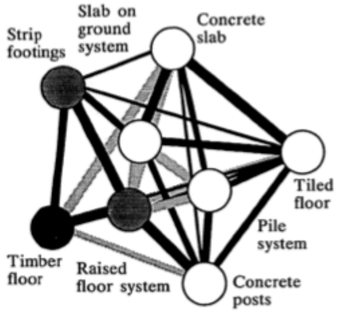


Figure 5. The results of a simulation exercise in which the 'timber floor' unit is clamped on.

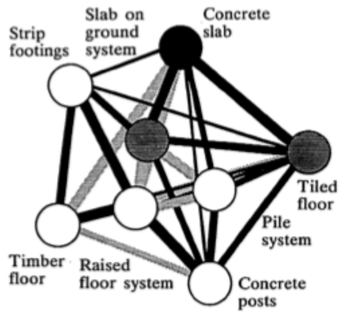


Figure 6. The result of clamping the 'concrete slab' unit.

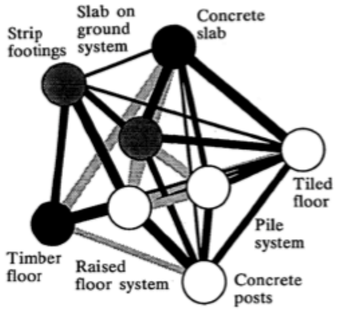


Figure 7. The result of clamping two units from different schemata.

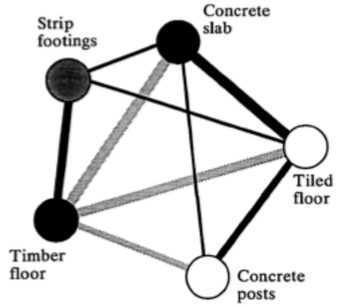


Figure 8. Removing the units pertaining to schema labels.

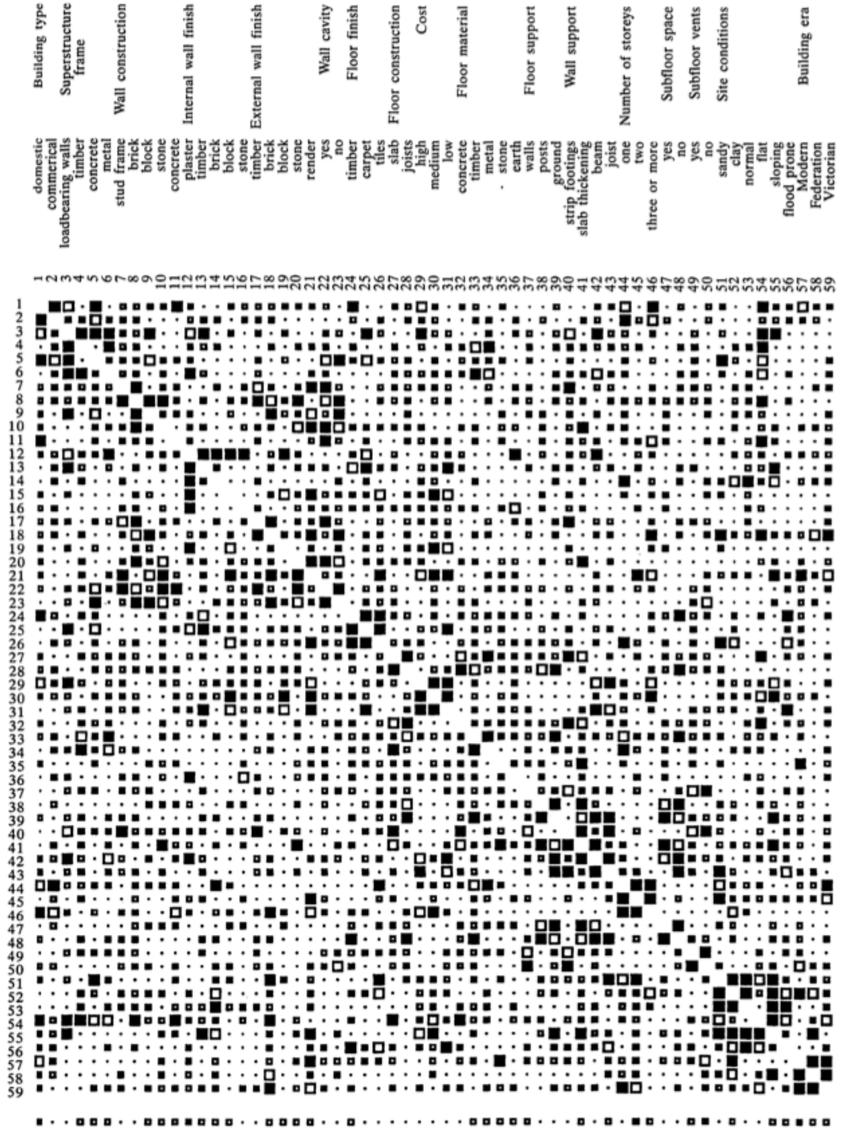
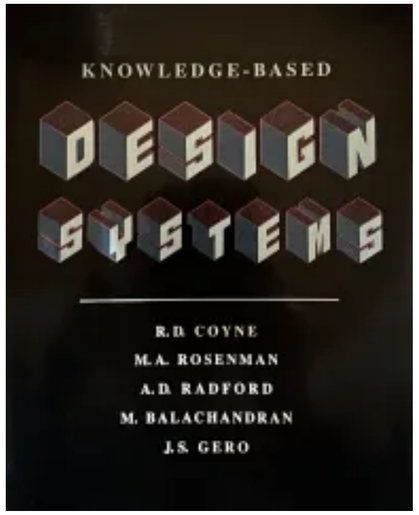


Figure 21. The weights and thresholds set up by the system after learning from the training set of figure 20. A large white square indicates a strong positive association between features. A black square indicates a negative association (inhibition). The row of smaller squares at the bottom of the matrix indicates threshold values of units. Again, white is positive and black is negative.



Coyne, R.D., M.A. Rosenman, A.D. Radford, M. Balachandran and J.S. Gero (1990). Knowledge-Based Design Systems, Addison-Wesley, Reading, Massachusetts, 567 pages.

Coyne, Richard. "Modelling the emergence of design descriptions across schemata." *Environment and Planning B: Planning and Design* 18 (1991): 427-458.

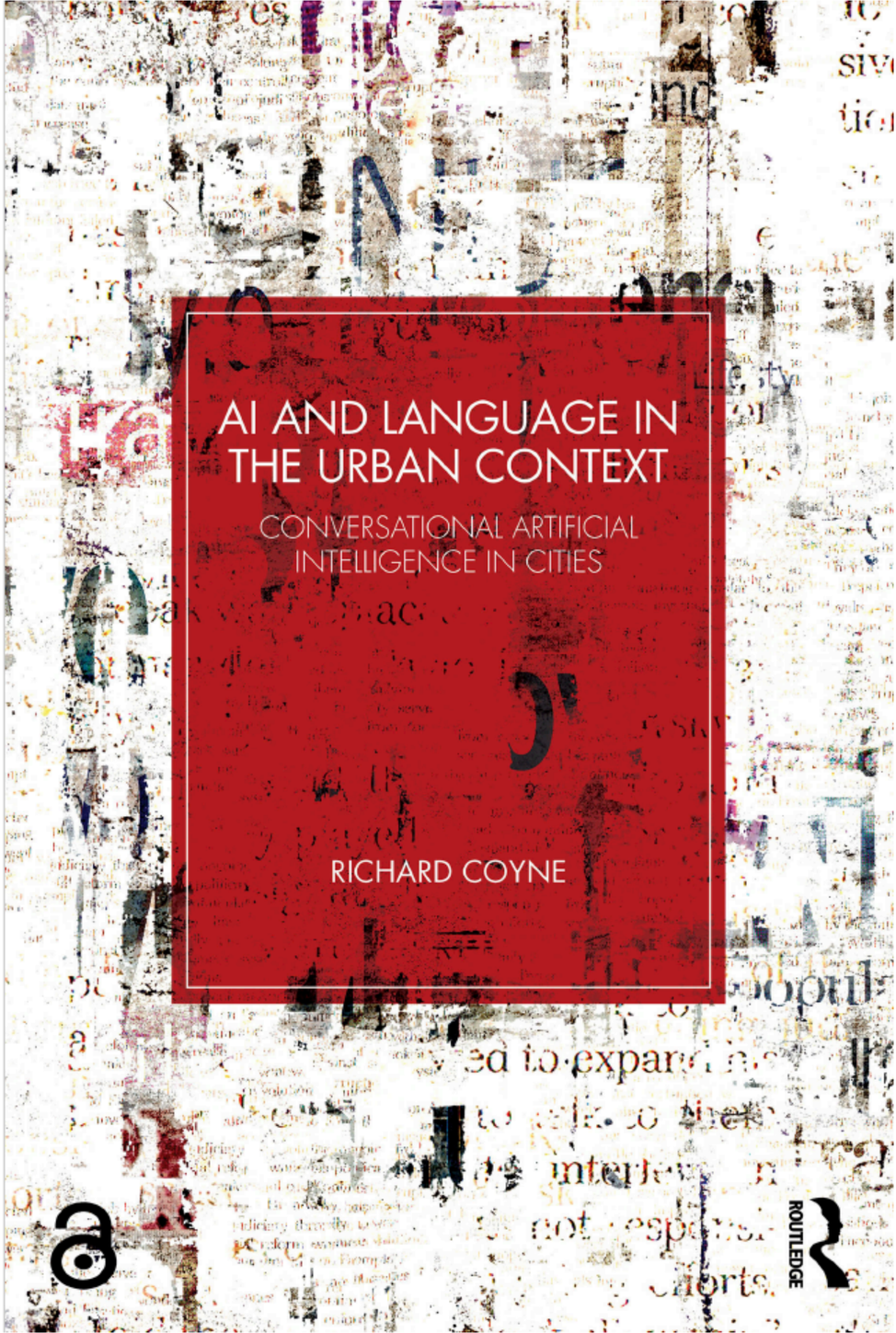
AI and language in the urban context

Conversational AI in cities

Richard Coyne

Coyne, Richard. *AI and Language in the Urban Context: Conversational Artificial Intelligence in Cities*. London: Routledge, 2025.

https://www.routledge.com/AI-and-Language-in-the-Urban-Context-Conversational-Artificial-Intelligence-in-Cities/Coyne/p/book/9781032879901?srsltid=AfmBOoptj3CZHDsHv6T8pIJhOenM0iQxT23Q7_q7JpD4aovR6tOYIGJ8



A gap for architecture, engineering and construction

Deploy LLM conversational and retrieval-augmented generation capabilities but also

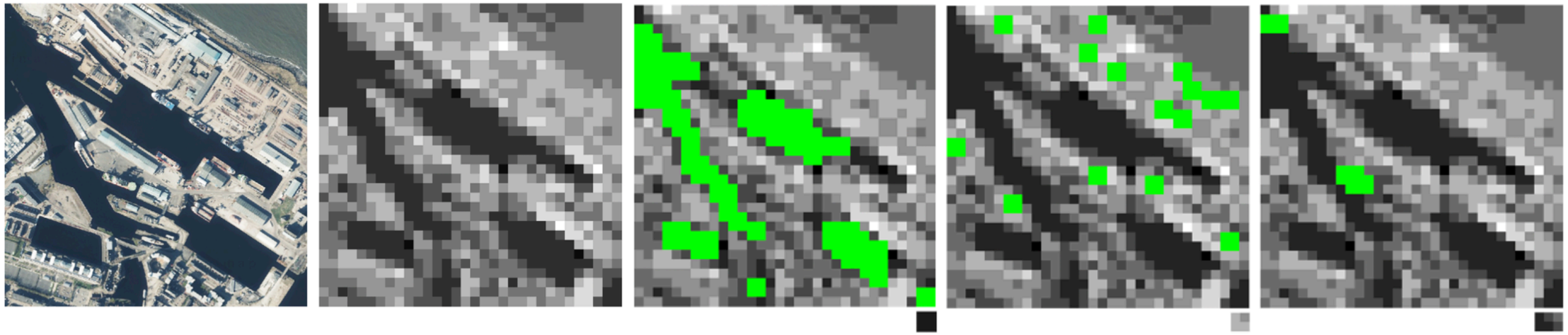
- Bypass language (i.e. linguistic tokens) and work directly with spatial (architectural) tokens: e.g. landmarks, mapped data, building components, events, actions, social memes, ...
- Deploy GPT (generative pre-trained transformer) core functions (semantic, positional and attentional encoding) to generate and tune design actions.
- Applications: planning sequences, processes, instructions, paths, explanations, retrieval, agents ...

Core functions of LLMs, and their urban correlates

Generative Pre-trained Transformers (GPT)

1. Prediction
2. Patterns
3. Corpus (300 billion words +)
4. Tokens (~ 100,000)
5. Semantic relationships (1,536 vector dimensions)
6. Context window (up to 128,000 tokens / 96,000 words)
7. Position
8. Attention (multi-head)
9. Tuning (supervised training)

Tokenisation



Landmarks as tokens

Figure 7.2 Map of a heritage neighbourhood of single to five storey mixed use development. Shaded areas are green spaces.

Source: Author.

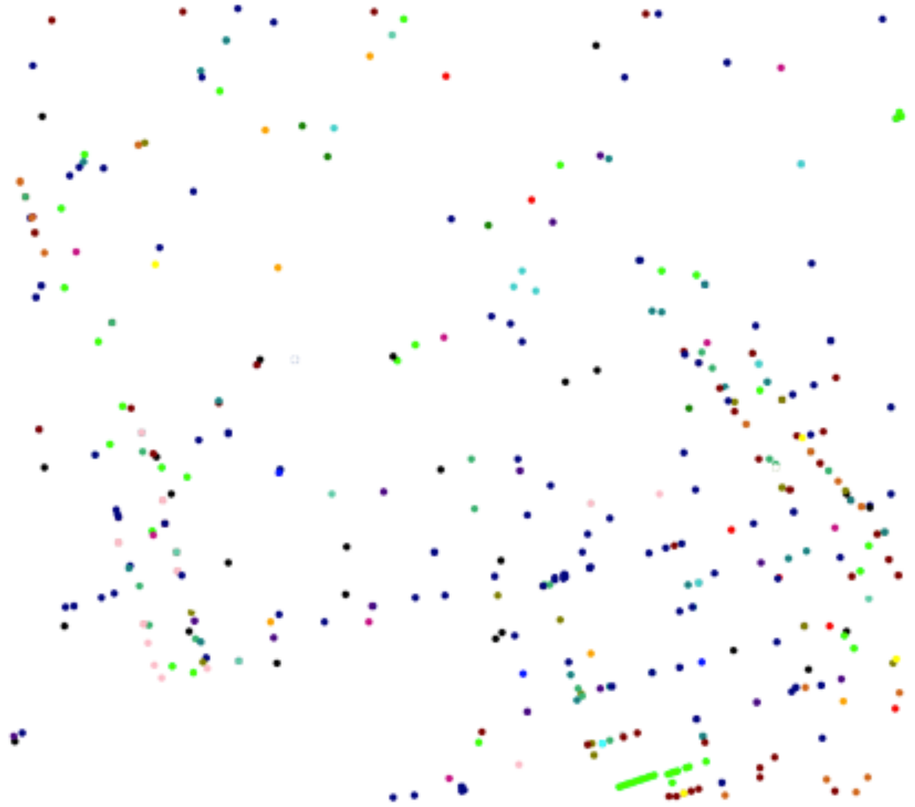


Figure 7.3 Map derived from data about Figure 7.2 of physical neighbourhood landmarks as data points shaded according to category of landmark: retail, community, park, business, public service, etc.

Source: Author.

Semantics and token proximity

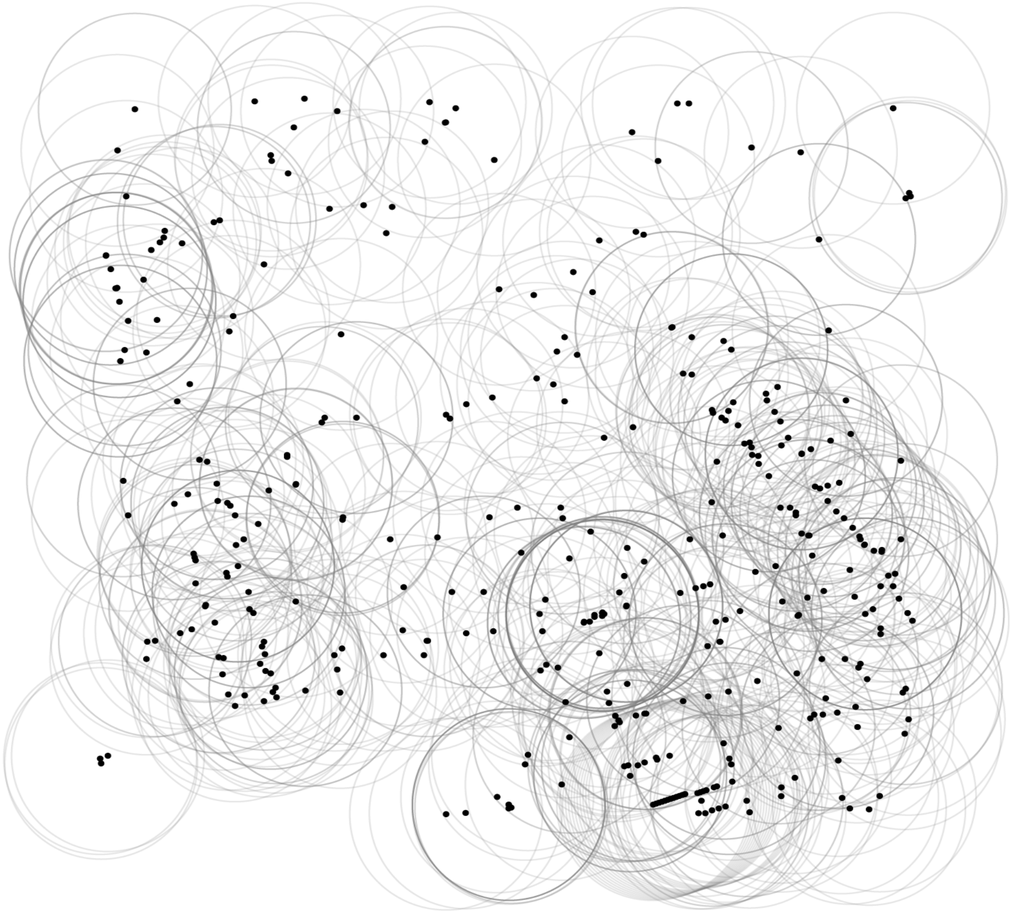


Figure 7.4 The data points of Figure 7.3 each shown with a circle of radius 100 metres to circumscribe neighbouring landmarks, thereby defining a context for each landmark.

Source: Author.

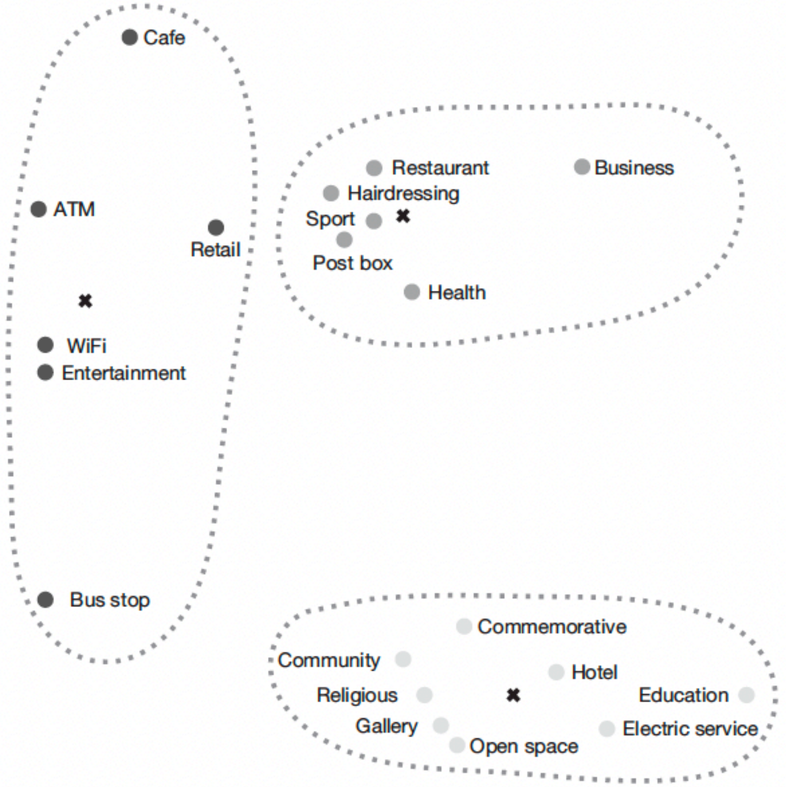


Figure 7.5 Relationships between feature tokens in the neighbourhood map based on their semantic embeddings. The horizontal and vertical axes represent the input values to the two hidden units that originate from each input node (i.e., each feature token). The diagram illustrates how a clustering algorithm (K-Means Clustering) has identified three distinct groupings of tokens, indicating that these tokens have similar or closely related semantic embeddings. The centroid of each cluster is marked with an "x," showing the central point around which each group of tokens is organised.

Source: Author.

Paths as sentences

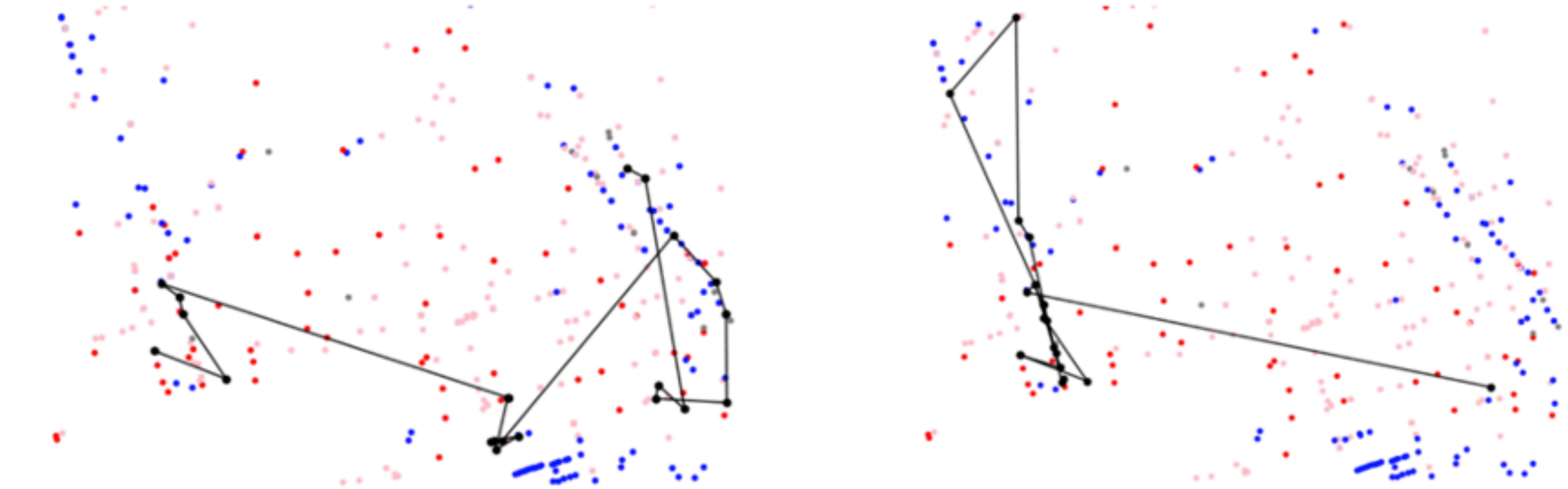


Figure 7.6 Neural network derived paths through the neighbourhood formed from processes analogous to the creation of sentences in an LLM. Segments of the paths follow obvious routes along commercial streets, and there are jumps. There is nothing in this simple model to preclude such discontinuities, nor about modes of transportation from one landmark to another.

Source: Author.

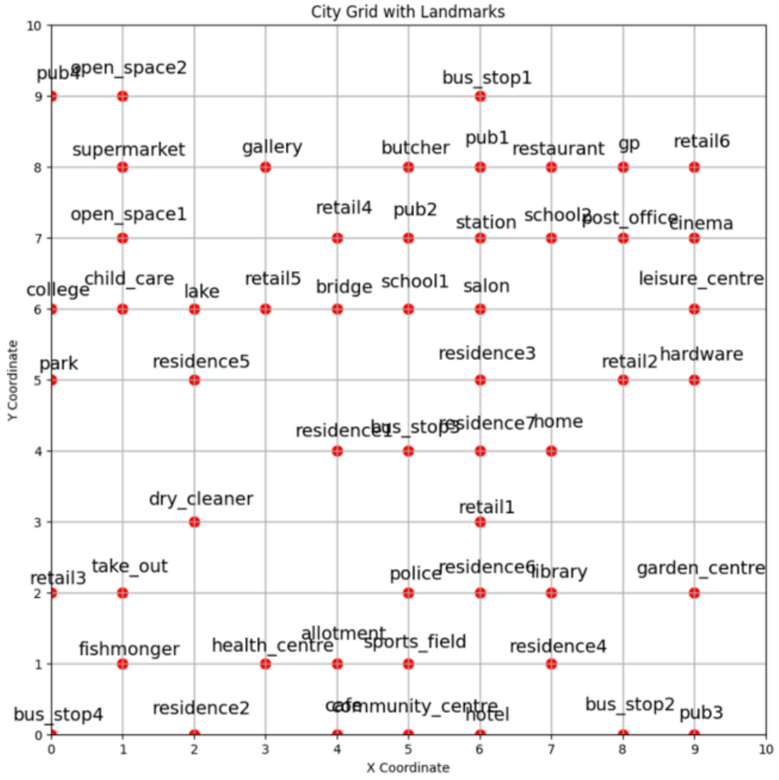


Figure 8.4 Arbitrary arrangement of neighbourhood landmarks on a grid generated by a program.

Source: Author.

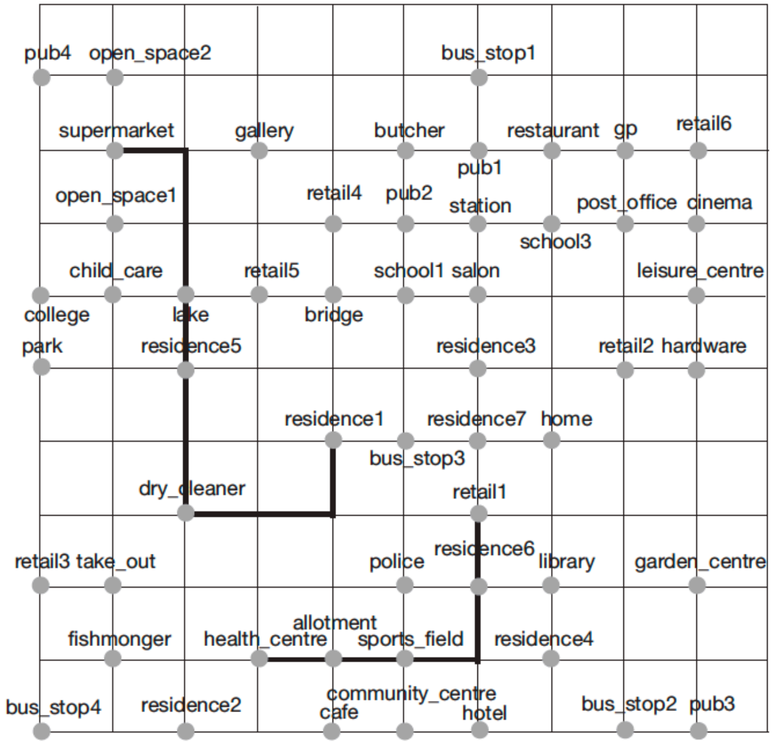


Figure 8.5 Two of the 500 paths generated by an algorithm to train the model.

Source: Author.

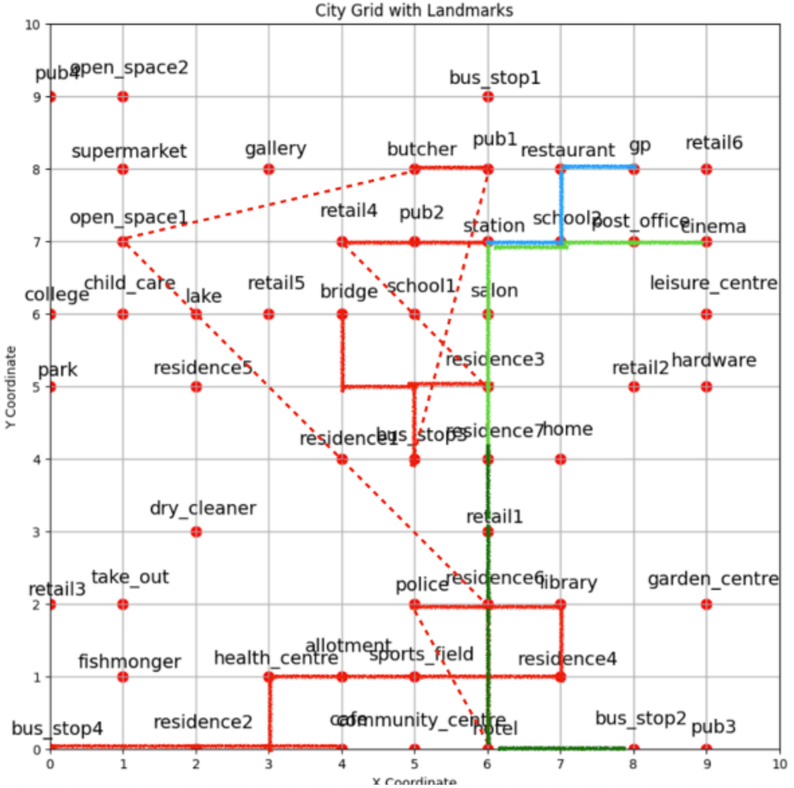
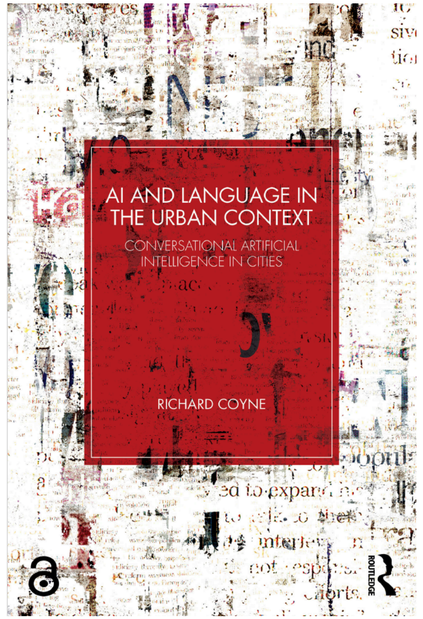


Figure 8.6 New paths generated by the trained model. The dashed lines show disconnects in some of the paths.

Source: Author.

Contents



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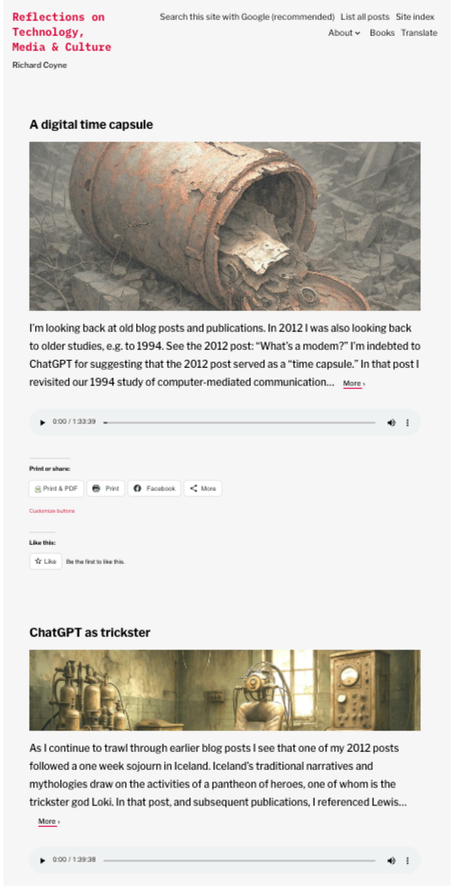

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