Toward a Design Space for Embedded Urban Data Visualizations

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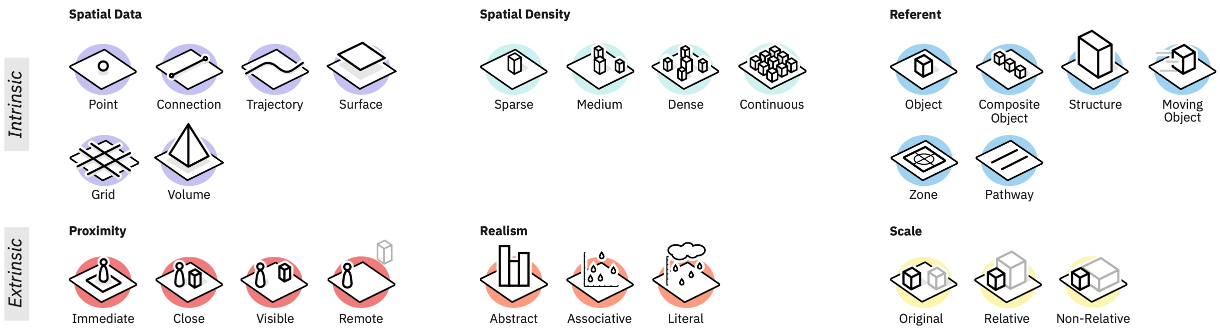

Figure 1: Overview of the design space dimensions. Intrinsic dimensions (top row) describe environmental and data characteristics; extrinsic dimensions (bottom row) reflect intentional choices in designing and situating embedded visualizations.

Abstract

We propose a design space for embedded data visualizations in urban environments, structured across multiple dimensions that articulate key contextual and representational characteristics. The design space is grounded in situated and immersive visualization theory, urban informatics, and co-creative ideation workshops. Its dimensions describe different aspects of how data visualizations relate to the physical urban environment and to the viewer. We illustrate the applicability of the design space using mappings to speculative embedded urban visualizations. This conceptual contribution is intended to support designers and researchers in structuring, analyzing, and generating embedded urban visualizations, and serves as a basis for future extensions.

Index Terms: Situated Visualization, Urban Data, Framework.

1 Introduction

As cities become increasingly data-rich, embedded data visualizations [30] offer new ways to engage with urban information in situ, making data visualization more ubiquitous [6]. Following Willett et al. [30], we use the term *embedded visualization* to refer to visual representations that are physically aligned with their real-world referents, distinct from *embedded views* in VR or 3D environments [10, 21, 22]. Advances in augmented reality (AR) technologies have made spatially registered visualizations in outdoor settings feasible [13]. While head-mounted displays have been used in some outdoor contexts, most practical applications rely on mobile AR for its low barrier to entry and broad accessibility [5]. Still, many existing examples focus on navigation, utilities [16] or entertainment (cf. [9]). Fewer works explore the use of embedded visualizations in public urban space. Research in immersive analytics [13], situated visualization [7], and cross-reality systems [3] shows how digital content can merge with the physical world, these approaches remain largely indoor or task-specific, leaving the spatial, social, and design complexities of urban outdoor settings underexplored, despite the rising importance for public engagement, planning, and mobility [29].

Existing frameworks organize visualization design by temporal [4], 3D urban data [21] or immersive dimensions [25], but none address embedded urban visualizations. Chen et al. [10] outline an immersive urban analytics design space, however explicitly exclude embedded visualizations. A recent taxonomy of AR visualization techniques touches on outdoor use yet focuses primarily on implementation and rendering [33]. As a result, designers and researchers lack a conceptual space to describe, compare, or guide embedded visualization in urban environments.

This paper proposes a multidimensional design space for embedded data visualization in urban settings. Our contributions are a) a structured design space, b) a discussion on composite and emergent dimension combinations, and c) a set of illustrate examples demonstrating its descriptive and generative value. Our design space constitutes a conceptual framework in early development. While not yet empirically validated, it offers a vocabulary and lens for analyzing and ideating embedded urban data visualizations.

2 Methodology

We developed the design space through a four-step process combining theory, practice, and design exploration (see Fig. 2). We started by reviewing literature [7, 13, 20, 21, 25, 27, 30] and drew on informal input from experts in AR/VR, spatial planning, and urban informatics which helped us identify relevant design concepts. Next, we collected and analyzed examples of urban and situated data visualizations. Based on these, we generated early ideas for embedded visualizations. In an interdisciplinary workshop with 13 participants from urban planning, architecture, urban informatics, data visualization, and communication design, we analyzed concrete urban locations, identified main spatial functions, and designed speculative visualization scenarios using real-world data sources. These activities helped surface recurring spatial properties and informed early dimensions of the design space. We identified candidate dimensions from literature and adapted them in light of workshop insights and design sketches. Through discussion and synthesis, we selected, refined, and combined dimensions and attributes (detailed in Sec. 3.1). We then applied the dimensions to both existing examples and speculative concepts, iteratively refining the design space to ensure coverage and distinctiveness. These speculative exemplars (Sec. 4) serve to demonstrate the expressiveness and the practical utility of the design space.

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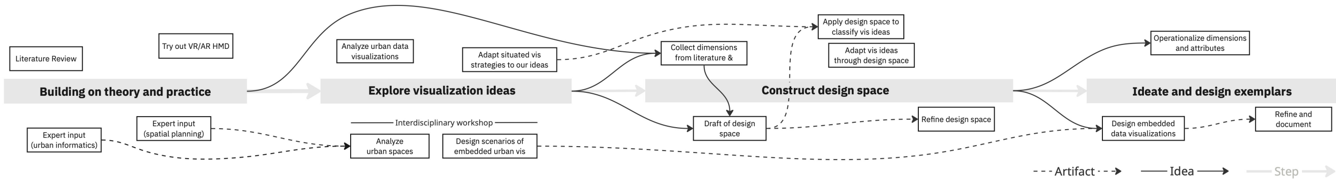

Figure 2: Process of creating the design space. Grounded in theory and practice, we explored early visualization concepts, synthesized and adapted dimensions, and finally, operationalized the design space through speculative exemplars to demonstrate expressiveness.

3 The Design Space

This design space structures key aspects of embedded data visualizations in urban environments. It supports analysis and creation by offering dimensions that describe spatial and visualization design characteristics. This aims to help explore possibilities and reason about embedded visualization strategies.

3.1 Dimensions

We organize the design space into two main categories (see Fig. 1): *Intrinsic dimensions* capture characteristics of the data and physical environment that are given or observed, such as spatial structure or referent type. *Extrinsic dimensions* reflect design decisions made when embedding visualizations into these contexts, including placement, visual realism, and scaling. In the following, we present three intrinsic and extrinsic dimensions each.

Spatial Data. Describes the spatial structure of the data, consisting of geographic coordinates in 2D (x, y) or 3D (x, y, z).

Point: A single georeferenced location. *Connection*: A link between two points without intermediate geometry. *Trajectory*: A sequence of points forming a path, typically used to represent flows or movement. *Surface*: A spatial extent, representing physical areas (e.g. parks, roofs), or abstract zones (e.g. administrative districts). *Volume*: A 3-dimensional region with internal variation, such as temperature fields or air quality zones. *Grid*: Raster data typically uniform with each cell having the same shape and size.

While spatial relevance is a defining characteristic of situated and embedded visualizations, prior work often distinguish only between abstract and spatial data (e.g. [8]). We employed traditional geospatial data classifications [2] to better capture the variety of spatial data types in embedded urban contexts.

Spatial Density. Describes the number and arrangement of data-referent locations in relation to a person interacting with an environment. It captures how densely data sources or their corresponding physical referents are distributed around the user, influencing attention, reachability, and interaction potential.

Sparse: A single data point is near-by and visible or within reach. *Medium*: One data point is within reach, with others dispersed in the greater vicinity. *Dense*: Multiple data points are in vicinity and within reach. *Continuous*: A grid where data points are uniformly distributed, surrounding the person.

Spatial Density is related to but distinct from spatial distribution, which describes overall placement patterns such as clusters or uniformity, and from spatial granularity, which refers to resolution or sampling intervals. Instead, this dimension focuses on the local density of data in relation to the user's embodied perspective. A low density is easy to manage and interpret, while higher densities can constrain the available space for individual visualizations within the user's field of view. This highlights design challenges related to visibility, comparability, and cognitive load, especially when referents are spatially fixed and not user-adjustable [31, 20].

Referent. Describes the characteristics of the physical entity in the urban environment to which an embedded visualization is anchored. Referents influence how data is situated, perceived, and interpreted.

Object: Singular, small to medium-sized items like benches, trees, or trash cans that serve as localized points of reference. *Composite Object*: Grouped or repetitive elements like bike racks, or floor tiles, where individual components can represent distinct attributes or act as reference for visual repetition (such as mapping days on a temporal axis). *Structure*: Large, static physical entities such as buildings, bridges, or façades that provide prominent, fixed surfaces or landmarks. *Zone*: Defined spatial areas like parks, or squares that act as broad, multi-faceted reference spaces. *Pathway*: Linear elements such as streets, sidewalks, or rivers that connect locations and guide movement. *Moving Object*: Mobile entities that serve as dynamic, transient reference points like cars, trams, or other people.

Prior work in immersive analytics identified objects or tables as common anchors for indoor use [25], while urban visualizations distinguishes buildings, streets, and natural features as common physical data entities [21]. We built on these by combining discrete objects with the larger spaces they inhabit, treating both as potential referents, aiming to align with perspectives that emphasize the diverse sociocultural meanings of a place [7].

Proximity. Describes the physical relationship between the referent and the viewer.

Immediate: The viewer is directly in physical contact with, or standing on or in, the referent. *Close*: The referent is close enough to be touched or easily navigated around to change perspective; within arm's length. *Visible*: The referent is in sight but not immediately reachable; may require the viewer to look in a specific direction. *Remote*: The referent is out of sight, distant and disconnected from the user's current position.

While proximity has been discussed in situated visualization—primarily in terms of interaction triggers [32, 27]—it is typically defined between the viewer and the system, not the referent. Researchers distinguishing situated and embedded visualizations have used proximity to describe the data–referent relationship [7], but do not account for the viewer's position. Our framing draws from proxemic interaction theory [15], which models distance through discrete zones, and adapts it to describe how physically close the viewer is to the referent within an urban context.

Realism. Describes the level of visual resemblance between the data representation and the real-world phenomenon or object it refers to.

Abstract: Traditional visualization marks such as bubbles, areas, or geometric shapes that bear no visual similarity to the real-world. *Associative*: A symbolic or metaphorical representation that suggests the real-world phenomenon through visual cues or thematic resemblance. *Literal*: Realistic or natural representation that visually mimics real-world elements, such as flooding simulations, or 3D models of buildings.

This dimension adapts the Design Metaphor continuum from data physicalization [12], focusing on how closely representations resemble real-world phenomena. In the context of embedded urban visualization, realism influences legibility, familiarity, and how intuitively users relate data to their surroundings.

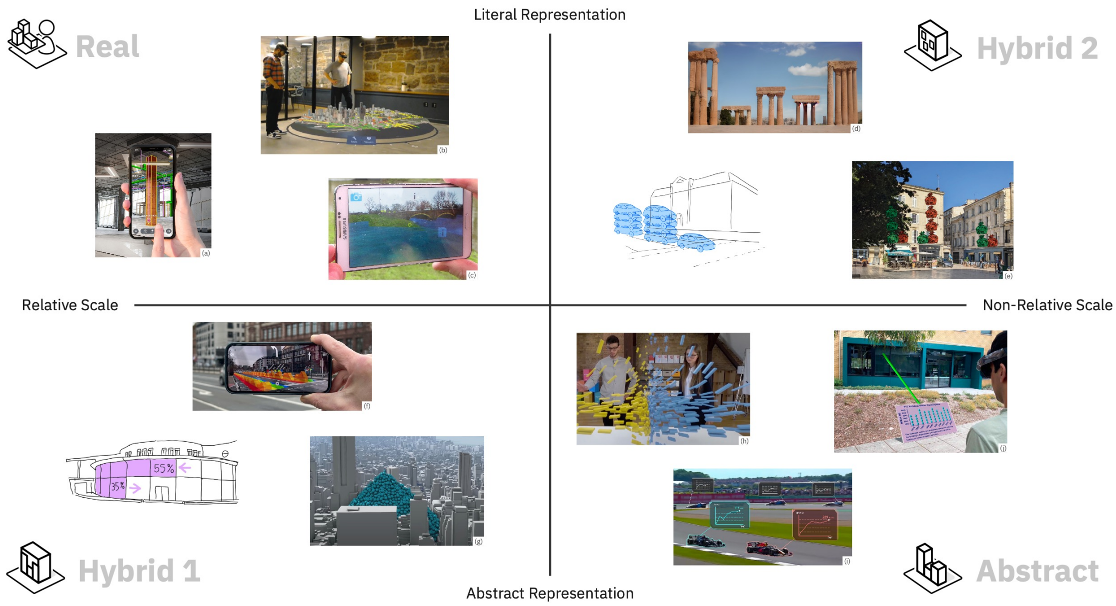

Figure 3: Emergent space of Visualization Appearances combining the dimensions Scale and Realism, resulting in the four quadrants Real, Abstract, Hybrid 1 and Hybrid 2, with examples in each area.

Scale. Describes the scale of the visualization in relation to the referent, semantically to the real-world phenomenon or object.

Original: Uses the same size as the referent. This is a specific case of Relative with a 1:1 scale. *Relative*: Uses a scale relative to the dimensions of the referent, e.g. smaller to get an overview, or larger to see details. *Non-Relative*: Uses an artificial scale, fully independent of the referent.

3.2 Emergent Spaces

Beyond treating dimensions in isolation, we also explore how their combination can reveal richer design patterns. As an example, we look at the visual characteristics of embedded representations.

Saffo et al. categorize data visualizations in immersive analytics as either Natural, such as volumetric brain rendering, or Abstract, as seen in traditional information visualization [25]. While they acknowledge that Natural representations can be scaled to real-world size, they do not consider this a defining characteristic. Shin et al. introduce a similar distinction when discussing visual expressions used for situated analytics [27]. Their Physical category is narrower, requiring that spatial data is shown in their real-world dimensions. Saffo et al. further argue that abstract representations lack an inherent real-world reference for scale. However, this perspective overlooks hybrid approaches that integrate abstract visualizations with meaningful physical references. Nagel et al. [23] propose Spatial Proportions as a subclass that combines abstract visualization methods with real-world measurements. They demonstrate this by scaling 3D stacked area charts to match the streets they represent, thereby aligning an abstract representation (traffic data) with a spatial reference (street width). Notably, this scaling does not encode data but instead serves as an anchor, reinforcing the link between the visualization and its physical context.

To systematically explore this area, we combine Realism and Scale to form a two-dimensional space (Fig. 3). Here, we treat both dimensions as discrete variables with two values each. We merge *Original* into *Relative*, as 1:1 scale can be considered a specific case of relative scaling, and omit the middle category *Associative* from the Realism dimension to simplify the space. The resulting combination defines a new meta-dimension with four distinct categories.

Visualization Appearance. Describes the relation between the virtual representation of data and the real-world phenomenon it represents.

Real (Literal—Relative): Includes scientific and geospatial visualizations, where data retains both its real-world form and a meaningful spatial scale. Examples include world-in-miniature models. This aligns with Willet et al's Facsimiles [30], and, when presented at a 1:1 scale, with Shin et al.'s Physical category [27].

Abstract (Abstract—Non-Relative): The conventional domain of information visualization, where abstract representations are detached from real-world spatial proportions. In immersive environments, these visualizations often appear as floating panels, making them non-diegetic overlays in AR/XR settings, even in the case of e.g. a 3D line chart atop a physical table. This relates to the Abstract categories of prior work [25, 27].

Hybrid 1 (Abstract—Relative): This quadrant includes abstract representations that adopt real-world scale references without encoding data directly within the spatial dimensions used for scaling. Importantly, abstract visualizations can be scaled relative to a physical object (e.g., to fit a table acting as a canvas), but to belong to this category, the scaling must relate to a semantically relevant referent. For example, the aforementioned street-scaled area charts [23], or CO_2 emission bubbles placed in NYC [24], which use the cityscape as spatial reference without the resulting shape (the pyramid in Fig. 3) reflecting any meaningful real-world object.

Hybrid 2 (Literal—Non-Relative): A relatively underexplored quadrant where visualizations maintain natural, recognizable forms but are scaled arbitrarily rather than being constrained by real-world proportions. Potential approaches include unit-based bar charts or visually transformed real-world objects used for data encodings. For instance, isotype pictorial plots where individual marks resemble real-world objects but are arranged according to abstract scaling principles, such as virtual trash bags stacked and anchored to buildings [17], or generative AI to morph architectural elements into data representations [19]. This *Hybrid 2* strategy could provide intuitive, real-world referents while maintaining the flexibility of abstract data representation.

Rather than treating it as a separate dimension, we framed Visualization Appearance as a composite space spanned by two di-

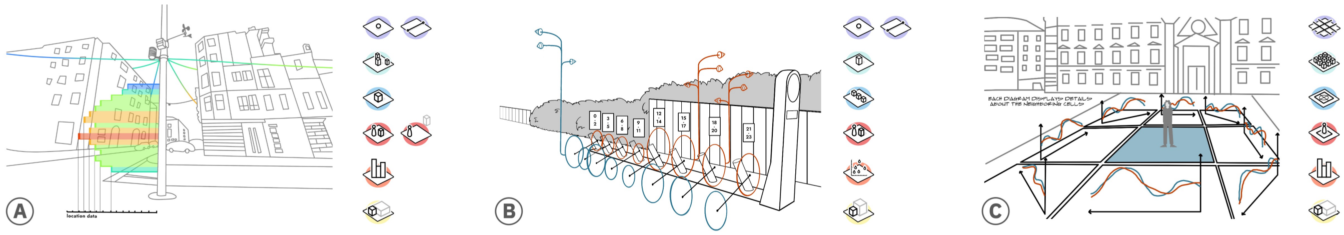

Figure 4: Three embedded urban visualization scenarios and their respective attributes from the design space. (A) A hyperlocal temperature curve on a sensor pole. (B) A visualization of rentals at a shared bike station. (C) Visualizations of a gridded climate model over time.

mensions. It illustrates how multiple elements of the design space can be brought together to reflect on conceptual distinctions and highlight underexplored design strategies.

4 Speculative Exemplars

To demonstrate the descriptive and generative potential of our design space, we developed three speculative visualizations (Fig. 4). Each project is set in a real-world scenario and was designed to explore different combinations of key dimensions.

The first concept anchors a virtual temperature curve to a pole-mounted sensor (A). The referent is the pole itself, offering the diagram to close viewers. The visualization itself is abstract, but scaled to the height of the pole for good visibility. Virtual lines show temperature difference to near-by sensors that are part of the network.

The second concept shows usage of a shared bike station, and uses a row of bike racks as a composite referent, with each rack representing a temporal unit (B). The wheels represent trips to and from that station, using an associative Realism. Additionally, arrows show trips to other places.

The third concept visualizes a gridded climate model across a city zone (C). The referent is a larger urban area, with the viewer being at immediate proximity, always standing on one of the grid tiles. Visualizations are abstract and use panels to allow comparing neighbouring cells.

These speculative exemplars explore diverse regions of the design space and different visualization idioms. The first two concepts intentionally combine multiple probes: (A) also incorporates virtual overhead lines connecting to remote sensor poles, while (B) visualizes both time and spatial flows. Designing and classifying these scenarios provided a first practical check on the space's expressiveness and structure. Through this process, we also identified recurring challenges, such as mapping time onto physical structures and supporting comparisons between near and distant referents, highlighting opportunities for further explorations.

5 Discussion

Extending the space. The six dimensions described above form a starting point for our design space, but they are not exhaustive. Rather than aiming for completeness, our goal was to establish a functional and generative foundation. We see this structure as open and extendable, and identify temporal aspects in particular as a natural direction for future expansion. Intrinsically, temporal situatedness describes how closely data aligns with the time of observation [28], ranging from historic to real-time to predictive data [26], while temporal scale and scope capture the granularity and extent of time data [1]. Extrinsically, temporal directionality reflects how embedding and viewpoint affect perceived time flow [23], and time mapping distinguishes between static and dynamic representations [1]. Together, these dimensions would allow exploring how temporal characteristics intersect with spatial embedding.

Intrinsic vs extrinsic. While the distinction between intrinsic and extrinsic dimensions provides a useful scaffolding, it is not absolute: Some dimensions involve both contextual constraints and situated design choices. For example, we position Referent as an intrinsic dimension. However, the difference between *Object* and *Composite Object*, though grounded in physical reality, reflects design-relevant interpretations. Additionally, while referents are often shaped by the existing environment, they are not necessarily beyond the designer's influence. As Lee et al. note [20], some environments can allow the adaptation or selection of referents. In urban contexts, newly planned spaces or temporary interventions may offer opportunities to influence physical referents. This suggests that the boundary between intrinsic and extrinsic dimensions should be interpreted relative to the specific design context and the degree of environmental agency available to the designer.

Representation agnostic. Embedded data visualization can come in various forms and shapes, ranging from low-tech solutions such as chalkboards [18], to media facades or interactive screens integrated into public spaces [11], to embedded physicalizations, that represent data as tangible artifacts [30], and increasingly through AR experiences. To reflect this diversity, our design space is intended to be representation-agnostic. None of the dimensions are directly tied to an embedding technology or specific medium. The design space aims to encourage broader exploration of how data can be meaningfully embedded in the urban environment.

From descriptive to prescriptive. Our design space offers a systematic way to describe embedded data visualizations in urban settings, aligned with existing visualization taxonomies. Its structure supports descriptive analysis by categorizing prior examples by their characteristics, and it enables generative exploration by recombining dimensions to explore new ideas, discuss trade-offs, and reveal gaps. Although currently descriptive, we see potential for prescriptive work, as well; for instance, through design patterns (cf. [20]), or guidelines (cf. [3]). One such opportunity emerged from our speculative exemplars is the challenge of integrating temporal visualizations into physical environments without causing visual clutter. Additional practical challenges include perspective foreshortening, which can hinder comparison between varying distances [5], environmental factors such as lighting and surface materials which could impact readability [14], or crowd density, which might influence suitable interaction modalities [32]. We are currently exploring strategies to address these in embedded urban visualizations.

6 Conclusion

We presented a design space for embedding data visualizations in urban environments, grounded in a structured synthesis of dimensions and attributes adapted from diverse visualization and urban design research. Alongside a discussion of emergent combinations and illustrative examples, the design space offers a descriptive and generative foundation for further exploration. As a conceptual framework in early development, it serves as a starting point for future empirical validation and refinement. We hope that this design space helps simplify the creation, analysis, and application of embedded urban data visualizations.

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Figure Credits

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