

MASTER'S THESIS

Making Urban Heat Big Data Meaningful for Climate Research

Thickening Big Data with Contextual Knowledge through Visualization

Virginia Pastore

MSc Design for Interaction
Delft University of Technology

GRADUATION COMMITTEE

Chair: Dr. Abhigyan Singh

Mentor: Mert Akay

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ABSTRACT

Urban heat is a growing concern for public health, energy demand and urban livability, yet the large-scale datasets used to monitor it remain “thin”: they show where a city is hot, but not how heat is experienced on a specific street. For non-expert users such as designers and architects, this makes the data hard to interpret and act on. This project asks how urban heat big data can be thickened with contextual knowledge through visualization, and made meaningful, meaning relevant, trustworthy and interpretable enough to support a judgment.

Following a Research through Design approach structured by the Double Diamond, the project combined a literature review on big data and data thickening with a review of eleven existing platforms and tools. None combined reliable heat data, situated experiential data and a visualization legible to non-experts. Fourteen ethnographic thermal comfort walks in Delft and Rome then captured the contextual factors that shape comfort at street level, and compared them with what existing platforms show. They were grouped into nine recurring themes, including surface heat, vegetation nuances, airflow, refuges and short-lived heat sources, none of which the platforms register. On the Delft route, each factor was further classified by its relation to the big data layer: adding nuance, hotter, cooler or temporary, with a fifth category, opportunity, marking where comfort could be improved.

These findings informed an interactive, map-based prototype that applies three established thickening strategies: onion-structured layering, ground-truthing and error-guided attention. A toggleable UHI effect layer sits beneath color-coded contextual points that are revealed through a hover-lens and open into street-level panoramas with participants’ quotes and photos. The prototype was refined over three evaluation rounds with six participants, including think-aloud sessions and structured user tests.

Non-expert users could explore and interpret the combined data without researcher mediation once the interface explained its own vocabulary, legend and layers. They recognized where their experience matched or contradicted the heat map, and examined the evidence behind each point themselves. An AI-generated interpretation feature, tested with two participants, did not clearly add value beyond its role in building the prototype: one participant doubted its claims and the other found it made the experience passive.

This project applies established big-thick data strategies to urban heat, a domain where, as far as the reviewed literature shows, they have not yet been used, and treats visualization as part of the thickening process itself. The evaluation suggests that thickened urban heat data becomes meaningful to non-experts when the visualization shows where thick data diverges from big data and lets users examine the evidence themselves. With a small sample, these findings are indications rather than validated principles. Future work should test crowdsourced contributions, keep thick data up to date as conditions change, and extend the prototype to other cities and languages.

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I started this graduation project wanting to bring my background as a visual designer into the field of interaction design. I did accomplish that, but somewhere along the way the subject itself took over. Urban heat, and the question of how to give big data back its context, turned into something I genuinely cared about, and that curiosity is what carried me through to the end, even in the more demanding moments.

My supervisors, Abhigyan Singh and Mert Akay, were a steady presence throughout this project. Their feedback consistently pushed me to go one step further and to work with precision and care, and they were generous with their time and attention at every stage. Leaving our meetings, I always had a clearer sense of where the project was going and a renewed sense of energy to carry the work forward on my own.

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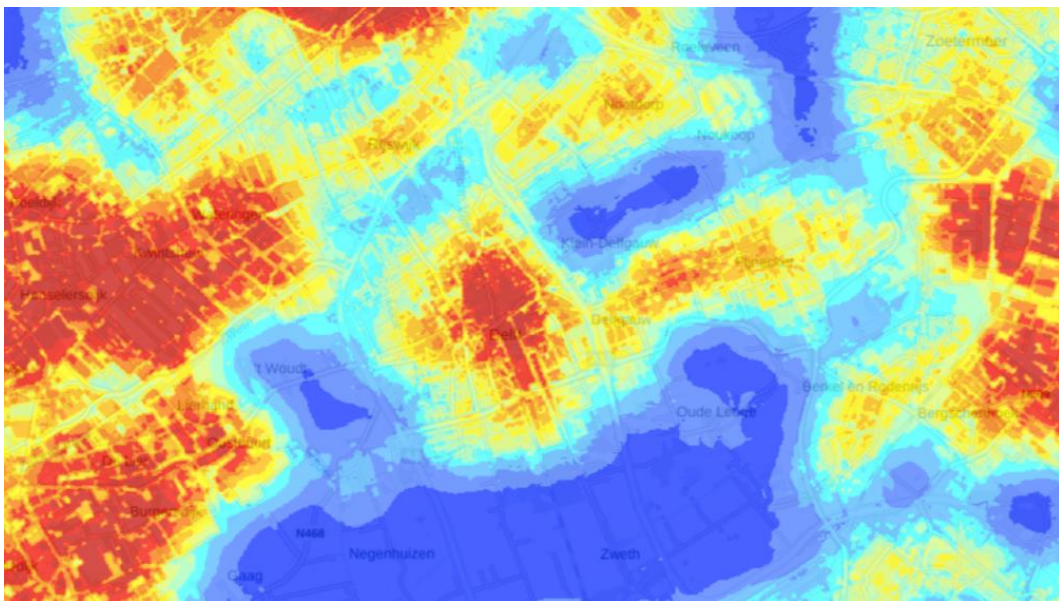
1. INTRODUCTION

1.1 Context

Cities are getting hotter. Climate change and ongoing urbanization are leading to an increase in both the frequency of extreme heat events and the number of people exposed to them, making **urban heat** an increasingly urgent concern for public health, energy demand, and urban livability (Fu et al., 2024; He et al., 2022; Nazarian et al., 2022). This heating, however, is not evenly distributed: urban heat is shaped by material choices, building density, vegetation cover, and the geometry of streets and squares, which means its effects vary sharply from one block to the next (Figure 1). Understanding this variation has become a central concern for climate research and for spatial disciplines that act on its findings, from urban planning to architecture and landscape design.

Figure 1

Atlas Leefomgeving, Urban Heat Island Effect over Delft area (Netherlands).



Note. Screenshot from Atlas Leefomgeving (n.d.), <https://www.atlasleefomgeving.nl>. Retrieved October 2026.

Over the past decade, the tools available to study urban heat have expanded considerably. Satellite imagery, distributed sensor networks, and geographic information systems now make it possible to observe temperature patterns at a resolution and scale that was previously not reachable, feeding into what has been described as a broader shift toward data-driven approaches to knowledge production (Kitchin, 2014). In principle, this abundance of data should make urban heat easier to understand and act on.

In practice, this is often not the case. Urban heat datasets are typically high-dimensional and heterogeneous, combining sources that differ in scale, format, and time resolution, and traditional analytical methods increasingly struggle to keep pace with this **complexity** (Wang, 2025). More data does not automatically produce a clearer picture; if anything, it can obscure it. Large volumes of data invite analysis without necessarily inviting reflection, and the enormous scale of available information can crowd out the slower work of **interpreting** what it actually means (Kitchin, 2014). The result is a familiar paradox in big data research: access to information has increased, while the ability to translate that information into understanding has not kept pace.

This project explores one direction for closing that gap: **data thickening**. Data thickening describes the process through which big data, which is wide but often “thin” because it lacks contextual depth, is brought together with “thick” data that captures the motivations, values, and lived experiences behind the numbers (Bornakke & Due, 2018; Mortati &

Cautela, 2025; Smith, 2018). For urban heat, the thin data are the large-scale satellite and sensor datasets described above, while the thick data are the **contextual factors** that shape how thermal comfort is actually experienced on a specific street, which existing urban heat platforms do not capture. Thickening alone, however, does not make data meaningful. How thickened data is visualized shapes whether people can read and understand it, and not only what the data contains (Shao et al., 2024; Schuster et al., 2024). This project therefore treats **visualization** as part of the thickening process itself, and explores how combining big and contextual data through visualization can make urban heat data **meaningful**, in the sense of being interpretable enough to support a judgment or a decision (Bhatia, 2014; Sharma et al., 2014).

The audience of this project are **non-expert users**: people in fields such as design, architecture, and urban planning who need to understand and act on urban heat data, for instance to decide what a temperature pattern means for a specific street or which intervention is worth pursuing, but who are not data specialists. Because urban heat is a problem that spans multiple disciplines (Kuznetsov & Tomitsch, 2018), this audience is poorly served by tools that assume technical fluency, and the literature shows that non-experts shown the same climate visualization often arrive at markedly different takeaway messages (Schuster et al., 2024). For this reason, the project focuses on making thickened urban heat data accessible to non-experts rather than on supporting technical analysis, and worked in the user research with master's students and PhD candidates at TU Delft who act as intermediary interpreters of such data (Section 3.2).

1.2 Problem Statement

This project is concerned with the gap between urban heat data and the understanding needed to act on it. That gap has three connected parts.

The first is that urban heat **big data** is **thin**. Existing platforms provide large-scale, quantitative data on temperature patterns, but they do not capture the contextual factors that shape how thermal comfort is actually experienced in a given urban area, and many of these are also temporary or situational rather than fixed properties of a place. The platform review conducted for this project showed that current platforms are generally strong on data access but weak on interpretation and context, and that none combines reliable big urban heat data, situated experiential data, and a visualization that makes the two readable together. Without this contextual depth, the data describes an abstract pattern of a location rather than the experience of a person at a specific moment and place.

The second is that thin data is not **meaningful** data. Meaningful data is data that is not only accurate and well-processed, but also relevant, trustworthy, and interpretable enough to support a decision (Bhatia, 2014; Sharma et al., 2014). Most current tools for working with urban heat data are built around analysis: they are designed to process, model, or visualize big data efficiently, rather than to support the interpretive work of making sense of what that data implies for a given site, decision, or design question. Thickening big data with contextual knowledge offers a way to address this, made effective through visualization, since how thickened data is visualized determines whether it can actually be read and understood. (Shao et al., 2024; Schuster et al., 2024).

The third is that this gap is especially limiting for **non-expert users**. Existing platforms tend to assume a level of technical fluency and familiarity with the data's provenance and limitations, that many of the people who need to use urban heat data do not have. For a non-expert who has to decide what a temperature pattern means for a specific street, or which intervention would be worth pursuing, a technically valid dataset is not enough, and non-experts shown the same climate visualization often arrive at markedly different takeaway messages (Schuster et al., 2024). Complexity is handled at the level of the dataset, but not at the level of the person trying to use it. As a result, insights generated from urban heat data often remain difficult to access or apply outside of a narrow technical audience.

This project takes as its starting point the gap between thin, high-dimensional urban heat data and the meaningful, contextualized understanding that non-expert users need in order to act on it.

1.3 Aim and Design goal

The aim of this project is to explore how urban heat big data can be **thickened with contextual knowledge** and made **meaningful through visualization** for non-expert users, in the context of climate research, and the design goal is to design and evaluate a visualization-based prototype that puts this into practice. Rather than proposing a new way of collecting urban heat data, the project takes existing big data as its starting point and operationalizes established thickening strategies (Section 2.3) through visualization, combining it with the contextual data collected during the user research activities. Climate research is the field the urban heat data belongs to, while the intended users are non-expert interpreters of this data, such as designers and architects (Section 3.2).

Within this project, thickening is what makes big data meaningful: the contextual data it adds provides the situated context that big data alone lacks (Sharma et al., 2014), and **visualization** is how that thickened data is brought to the non-expert user. As noted above, how data is visualized shapes how well people can extract meaning from it, and two further reasons make visualization the right means. It is the established way of communicating complex findings to varied audiences (Chi et al., 2016), which describes the position of a non-expert facing urban heat data. It is also a place where big and thick data can be brought together without being merged, as in Bornakke and Due's (2018) Big-Thick Blending, whose result presents quantitative data and thick findings in one visualization (Section 2.3). Existing urban heat platforms rarely do this: they visualize big data well but leave interpretation to the user, and the few that add situated data or narrative do not draw on the lived experience of their users (Section 4.1).

Generative AI is explored here as a supporting tool, for building the prototype and as a possible user-facing feature. Because AI-driven automation cannot fully replace human judgment when interpreting subjective factors (Rathod, 2023), it is not used in this project to decide what the data means, and its value as a feature is not assumed but tested by comparing two versions of the prototype during user evaluation (Section 5.2).

1.4 Research Question

This aim translates into the following research question:

How can urban heat big data be thickened with contextual knowledge and made meaningful through visualization for non-expert users?

This question is addressed through the following sub-questions:

- **SQ1:** What **contextual factors** shape how thermal comfort is perceived, and how are these currently addressed (or overlooked) by existing urban heat data platforms?
- **SQ2:** How can such contextual data be meaningfully integrated with quantitative urban heat data, i.e., how can **big urban heat data** be “**thickened**”?
- **SQ3:** How can **visualization** and **generative AI** support this integration process to produce outputs that convey both big and thick data in ways that support interpretation and decision-making for non-expert users?
- **SQ4:** How do non-expert users **interact** with and **evaluate** the prototype developed in this project, and what does this reveal about how big and thick data can be effectively visualized?

SQ1 is addressed through the literature review, the platform review, and the ethnographic user research conducted for this project; SQ2 is informed by the literature on data thickening together with the design directions that emerged from the user research; SQ3 guides the concept development and prototyping phase; and SQ4 is answered through user evaluation of the final prototype.

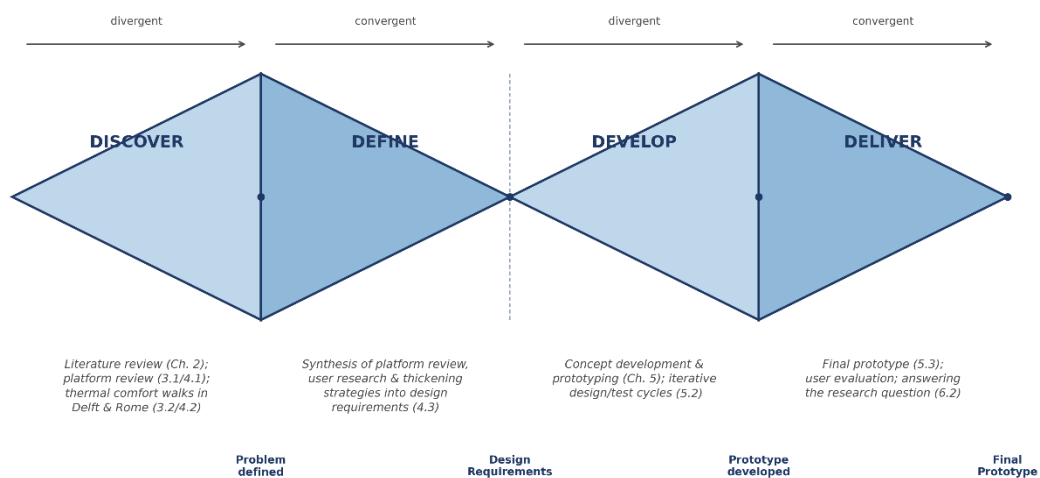
1.5 Research Approach

To answer this research question, the project follows a **Research through Design (RtD)** approach, in which designing is treated not only as a means of producing a solution, but as a way of generating knowledge about the problem itself (Zimmerman et al., 2007). Because the contextual factors that shape how thermal comfort is experienced at street level are not captured by existing urban heat platforms, and the ways in which they could be used to thicken big urban heat data have not yet been examined, this project treats discovery as an active, iterative process rather than a fixed starting point derived from the literature alone, and the same applies to the final prototype, which emerges through iterative cycles of design, testing, and refinement rather than being specified in advance.

Within this RtD paradigm, the project was organized using the **Double Diamond framework**, which describes a design process through four phases: Discover, Define, Develop and Deliver. Each diamond combines *divergence*, through which the inquiry expands, with *convergence*, through which its focus narrows. The framework allows moving back and forth between phases, rather than following them strictly in order, as research and testing refine the questions being asked. (Design Council, n.d.). The first diamond covers the problem space: a Discover phase, comprising the literature review (Chapter 2), the platform review (Section 3.1), and the ethnographic thermal comfort walks in Delft and Rome (Section 3.2), followed by a Define phase in which these three strands are synthesized into a bounded set of design requirements (Section 4.3). The second diamond covers the solution space: a Develop phase of concept development and iterative prototyping, including the branch comparing a version of the prototype with and without a generative AI feature (Section 5.2), followed by a Deliver phase in which the prototype is finalized and evaluated with users, closing the loop back to the research question (Section 6.2). Figure 2 summarizes this structure.

Figure 2

The Discover, Define, Develop and Deliver phases of the Double Diamond, applied to this project's research and design process.



Note. Adapted from Design Council (n.d.).

The research is structured around two complementary strands, informed by the literature review in Chapter 2. The first is a review of existing platforms and tools, ranging from urban heat and climate data platforms to tools for interactive visualization and AI-supported generation of visual output, to establish what is available and where its limitations lie (Section 3.1). The second is ethnographic user research in Delft (NL) and Rome (IT), aimed at uncovering the contextual factors that shape how thermal comfort is experienced and that are missing from the “thin” data provided by platforms such as the Atlas Leefomgeving (Section 3.2). These two strands correspond to SQ1 and SQ2.

Together with the thickening strategies from the literature review (Section 2.3), they are used to derive a set of design requirements (Section 4.3), which inform the concept development and prototyping in Chapter 5. In line with the RtD approach, the resulting prototype is then evaluated with users (Section 5.2), which both tests the design and generates further knowledge about the problem.

1.6 Structure of the Report

The remainder of this report follows the Discover-Define-Develop-Deliver structure introduced above. *Chapter 2* opens the Discover phase with a review of relevant literature, first establishing what urban heat is and what challenges it involves, then situating this within the broader use of big data in climate and urban environmental research, before introducing data thickening as the theoretical framing used throughout the project. *Chapter 3* continues the Discover phase with a review of existing platforms and the ethnographic user research conducted to understand the contextual factors relevant to thickening this data. *Chapter 4* closes the first diamond's Define phase: it presents the findings from this research and translates them into a set of design requirements. *Chapter 5* covers the second diamond's Develop and Deliver phases, from concept development and prototyping to the final prototype and its evaluation. *Chapter 6* discusses the findings in relation to the research question, the project's contribution to research, and its limitations. *Chapter 7* concludes the report with a reflection on future work and on the graduation project as a whole.

2. LITERATURE REVIEW

2.1 What is urban heat and why is it challenging?

Urban heat refers to the higher temperatures experienced in cities compared with surrounding rural areas, typically ranging from 1–2°C globally but exceeding 7°C in some locations (Corrado et al. 2025). This phenomenon results from the interaction of impervious surfaces, vegetation loss, anthropogenic heat from buildings and transport, rapid urbanization, and urban geometry that traps heat and restricts airflow (Corrado et al., 2025; He et al., 2022; Imran et al., 2021; Nazarian et al., 2022; Tyagi et al., 2021). Urban heat varies across climates, spatial scales, and time of day, with both regional climate and urban form influencing its intensity (Corrado et al., 2025; He et al., 2022; Zhao et al., 2014). While Urban Heat Island (UHI) intensity measures urban-rural temperature differences (Corrado et al., 2025), absolute urban temperatures are often more relevant for understanding human thermal comfort and health impacts (Nazarian et al., 2022).

How people experience these absolute temperatures is usually studied through the concept of **thermal comfort**, most commonly defined as “that condition of mind that expresses satisfaction with the thermal environment” (ANSI/ASHRAE, 2017), a definition originally developed for indoor environments but widely extended, with adaptation, to outdoor and urban settings. Outdoor thermal comfort, however, is inherently more dynamic than its indoor counterpart: pedestrians move continuously through changing microclimatic conditions, so a single person’s comfort state can shift markedly within one walk depending on shade, wind exposure, and urban geometry (Vasilikou & Nikolopoulou, 2020). It is precisely this contextualized understanding of thermal comfort (linked to the specific conditions of a given street rather than to a single average value) that forms the basis of the ethnographic walks on thermal comfort conducted as part of this research (Section 3.2).

Beyond this individual, situated experience, urban heat also produces consequences at a much larger scale, extending across environmental, social, and economic systems. Heat increases mortality and morbidity, disproportionately affecting vulnerable groups such as elderly people, low-income communities, and outdoor workers (Corrado et al., 2025; Imran et al., 2021; Kuznetsov & Tomitsch, 2018; Nazarian et al., 2022). It also raises cooling energy demand, contributes to annual productivity losses of approximately \$6 billion, increases pressure on infrastructure and electricity grids, and reinforces existing socio-economic inequalities (Corrado et al., 2025; Fu et al., 2024; He et al., 2022; Kuznetsov & Tomitsch, 2018; Nazarian et al., 2022).

The literature consistently describes urban heat as a “**wicked problem**” because it emerges from complex interactions across multiple disciplines and scales, making it difficult to address through isolated technical solutions (Kuznetsov & Tomitsch, 2018). Current challenges include modelling biases, limited observational and multidisciplinary data, difficulties integrating models across scales, and the lack of standardized methods and quantitative attribution of UHI drivers (Corrado et al., 2025; Dey & Joshi, 2022; Imran et al., 2021; Keith et al., 2020; Zhao et al., 2014). Institutional barriers such as fragmented governance, inconsistent policy frameworks, limited heat mitigation plans, and competing stakeholder priorities further hinder effective implementation (He et al., 2022; Keith et al., 2020; Kuznetsov & Tomitsch, 2018; Memon et al., 2008; Nazarian et al., 2022). As a result, addressing urban heat requires approaches that bring together technology, equitable design solutions, collaboration across different disciplines, and governance that helps coordinate actions across different systems (Imran et al., 2021; Keith et al., 2020; Kuznetsov & Tomitsch, 2018; Nazarian et al., 2022).

2.2 Big Data in Climate and Urban Research

Big data in climate and urban environmental research is commonly described through four characteristics: volume, velocity, variety, and veracity (Sun & Scanlon 2019). How much weight each of these gets depends on the field: remote sensing researchers tend to focus on volume and technical specifications, while urban researchers are more interested in spatial-temporal patterns and human behavior. Common data sources include satellite imagery, environmental sensor networks, mobile and GPS data, social media, and IoT infrastructure, with human behavior data being especially prominent in urban sustainability research.

Despite its potential, using big data effectively comes with several challenges. On a technical level, integrating different data sources is difficult due to their heterogeneity, inconsistent quality, and limited infrastructure to support them (Chi et al., 2016; Huang & Wang, 2020; Rathod, 2023; Sun & Scanlon, 2019). Analyzing this data is also demanding, requiring significant computational resources (Chi et al., 2016; Montillet et al., 2024; Wu et al., 2024) and struggling with real-time processing (Chi et al., 2016; Rathod, 2023; Sun & Scanlon, 2019). But perhaps the most pressing challenges arise once the data needs to be interpreted: big data analyses tend to reveal correlations rather than causal relationships (Chi et al., 2016; Sun & Scanlon, 2019), rely on models that are hard to interpret (Huang & Wang, 2020; Sun & Scanlon, 2019), and often struggle to translate technical results into insights that are actually useful for decision-makers (Chi et al., 2016; Huang & Wang, 2020; Sun & Scanlon, 2019).

These interpretation challenges often come back to the same underlying issue: large-scale datasets are good at capturing patterns, but say little about the context behind them. The following sections take a closer look at what big data entails, the challenges it presents, and what it means for such data to be genuinely meaningful and usable in practice.

Characteristics of reviewed studies

This section of the review included ten studies published between 2016 and 2024. Together, they covered a range of study types and application domains, summarized in Table 1.

Table 1.

Overview of the ten reviewed studies, including study type, geographic context, primary application domain, and research focus.

Study	Type of study	Geographic context	Primary application domain	Research focus
Sun & Scanlon, 2019	Systematic review	Global	Environment and water management	Disaster management, precision agriculture, smart farming
Chi et al., 2016	Conceptual	Global	Climate research and urban environmental research	Food security, crop assessment, disaster management, urban planning, sustainability
Kong et al., 2020	Conceptual	Global	Urban environmental research	Urban sustainability, mobility, land use, and planning
Huang & Wang, 2020	Systematic review	China	Urban environmental research and environmental sustainability	Urban vibrancy, polycentric urban structures, air pollution (PM2.5 exposure), land-use mapping

Rathod, 2023	Mixed methods (Conceptual, Empirical)	USA	Urban environmental research	Traffic congestion, air and noise pollution, rising carbon emissions, urban development projects
Ang & Seng, 2016	Systematic review	Global	Urban environmental research	Air pollution monitoring, assistive living, disaster management systems, intelligent transportation
Montillet et al., 2024	Systematic review	Global	Climate research and urban environmental research	Urban heat islands, droughts, floods, cyclones-induced storm surges, ice mass balance, sea-level rise
Wu et al., 2024	Systematic review	Global	Urban environmental research	City management and navigation aids network performance
Lokers et al., 2016	Mixed methods (Conceptual, Empirical)	Europe	Agro-environmental research	Agro-environmental modelling
Sorokine et al., 2016	Conceptual	USA	Urban environmental research and climate research	Urban areas' impact on environment and climate change's impact on urban areas

All studies addressed big data applications in environmental contexts, though with different emphases. Two studies explicitly mentioned urban heat islands (Montillet et al., 2024; Sorokine et al., 2016), while others focused on related phenomena such as air pollution (Ang & Seng, 2016; Huang & Wang, 2020; Rathod, 2023), sustainability (Chi et al., 2016; Huang & Wang, 2020; Kong et al., 2020), and disaster management (Ang & Seng, 2016; Chi et al., 2016; Sun & Scanlon, 2019). Most studies focused on the city level (Ang & Seng, 2016; Huang & Wang, 2020; Kong et al., 2020; Rathod, 2023; Sorokine et al., 2016; Wu et al., 2024), with some also addressing broader scales, including global (Chi et al., 2016; Sun & Scanlon, 2019) and European-level applications (Lokers et al., 2016).

Big data definitions and characteristics

Across the reviewed studies, definitions of big data varied, but most drew on the traditional “V” characteristics: volume, velocity, variety, veracity, and value (Sun & Scanlon, 2019). Kong et al. (2020) did not settle on a single definition, noting that definitions differ across the field. The most complete came from Sun and Scanlon (2019), who described big data as information assets marked by high volume, velocity, variety, and veracity, with value, high dimensionality, complexity, and uncertainty also playing a role, and who noted that data only counts as “big” once it exceeds what traditional IT infrastructure can handle. For spatial data, Huang and Wang (2020) offered a similar definition: data exceeding the capacity of standard data management tools and used computationally to uncover patterns in human behavior. Chi et al. (2016) described big data in remote sensing through the “3Vs” of volume, variety (multisource, multitemporal, multiresolution), and velocity. Other studies defined it more narrowly, around volume and velocity (Montillet et al., 2024), volume, variety, and value (Ang & Seng, 2016), volume and complexity (Sorokine et al., 2016), or variety and veracity (Lokers et al., 2016). Taken together, these definitions show that while the core “V” characteristics are widely used as a starting point, how they are combined and prioritized depends strongly on the research context and application.

Types and sources of big data

The reviewed studies drew on a wide range of big data sources for climate and urban environmental research, though few addressed urban heat specifically. Remote sensing and satellite imagery are prominent, with multiple studies drawing on platforms such as MODIS, Landsat, and Sentinel, alongside high-resolution commercial sensors (Chi et al., 2016; Huang & Wang, 2020; Rathod, 2023; Sun & Scanlon, 2019). These are often complemented by ground-based sensor networks, including air quality monitors, weather stations, and low-cost devices such as PurpleAir and Aeroqual systems, highlighting the growing role of distributed sensing technologies (Ang & Seng, 2016; Huang & Wang, 2020; Rathod, 2023; Sun & Scanlon, 2019).

In parallel, mobile and human-generated data sources are increasingly integrated, including cellular signaling, GPS tracking, and smartphone-derived data (Huang & Wang, 2020; Rathod, 2023). Social media and crowdsourced datasets also feature prominently, supporting applications such as flood detection, behavioral analysis, and data labelling (Chi et al., 2016; Huang & Wang, 2020; Rathod, 2023; Sun & Scanlon, 2019). Additional inputs include IoT and smart-city infrastructure data, GIS datasets, meteorological station records, and government or administrative data such as census information and service complaints (Chi et al., 2016; Huang & Wang, 2020; Rathod, 2023).

Across the literature, human behavior data emerges as the most frequently utilized big data type (Kong et al., 2020), and many studies emphasize the integration of structured data with unstructured data, such as sensors and imagery alongside social media text (Chi et al., 2016; Huang & Wang, 2020; Rathod, 2023; Sun & Scanlon, 2019).

Data integration challenges

Nearly every reviewed study reported integration challenges, spanning technical, methodological, and organizational dimensions. Data heterogeneity stands out as the most common issue. Sun and Scanlon (2019), for example, found that the wide variety of data types adds considerable complexity to processing pipelines, requiring extensive standardization and data modelling. Huang and Wang (2020) take this further, identifying specific dimensions along which data differ, such as source, structure, format, scale, and resolution, and arguing that reconciling these varying spatiotemporal units requires dedicated measures. This broader concern with compatibility and standardization comes up in six of the reviewed studies: beyond the issues already raised by Sun and Scanlon (2019) and Huang and Wang (2020), other authors point to inconsistent definitions of big data itself (Kong et al., 2020), the difficulty of combining multisource and multiresolution data (Chi et al., 2016), integration processes that remain manual, inefficient, and error-prone (Rathod, 2023), and data that stays scattered rather than unified (Sorokine et al., 2016).

These heterogeneity issues are closely tied to questions of data quality and reliability, raised as a concern in three studies (Chi et al., 2016; Huang & Wang, 2020; Sun & Scanlon, 2019). Data cleansing, for instance, is a major hurdle, made worse by a scarcity of labelled datasets and a mismatch between how quickly data is generated versus processed (Sun & Scanlon, 2019). Huang and Wang (2020) approach the quality problem differently, pointing to representativeness, coverage bias, and measurement accuracy as persistent concerns when combining multiple sources, while Chi et al. (2016) add that the integration process itself tends to amplify noise and measurement error already present in the underlying datasets. A related but separate difficulty, reported in four studies, concerns aligning data temporally and spatially: this includes the need for (dis)aggregation measures to reconcile differing spatial scales (Huang & Wang, 2020), bottlenecks in real-time processing (Sun & Scanlon, 2019), the challenge of managing multitemporal and multiresolution data (Chi et al., 2016), and difficulty correlating real-time sensor data with historical records (Rathod, 2023).

Underlying many of these issues are limitations in technical infrastructure, identified in three studies. Bottlenecks in data transmission and the lack of scalable analytics platforms are one example (Sun & Scanlon, 2019), a constraint that Rathod (2023) measures directly, reporting latency of 9 to 12 seconds in geospatial query processing. Huang and Wang (2020) similarly stress that handling incomplete or inconsistent sensor data requires advanced data fusion processes that current infrastructure often lacks.

Finally, three studies point to interoperability challenges, meaning problems that arise when different data sources or systems struggle to work together (Chi et al., 2016; Lokers et al., 2016; Sun & Scanlon, 2019). These issues are not purely technical but also involve organizational and human factors, and they are a problem of **meaning** as much as of compatibility: for data from different sources to be combined, they need to be not only readable by the same system but also understood in the same way and trusted by those who use them. Sun and Scanlon (2019) note that data silos persist largely because of acquisition costs and a lack of incentive to share data, calling for improved data governance and sociotechnical infrastructure to address this. Lokers et al. (2016) frame the problem in more relational terms, arguing that building trust between data providers and users remains a persistent obstacle in interdisciplinary research. Chi et al. (2016), meanwhile, highlight a more technical side of the same issue: algorithms often need to be adjusted to work properly in new computing environments, which adds another layer of complexity to integration efforts. Together with the inconsistent definitions of big data (Kong et al., 2020) and the differences in source, structure, and scale noted above (Huang & Wang, 2020), these findings suggest that combining data is not only a matter of making systems compatible, but also of establishing what the data represent and whether they can be trusted, a question that technical solutions alone do not resolve. This concern returns in the literature on data thickening, which notes that big data, collected as a side effect of other processes, often does not clearly document what it measures (Bjerre-Nielsen & Glavind, 2022; Section 2.3).

Data analysis challenges

Processing and analyzing big data brought further difficulties, related to computing power, methods, and practical use. The amount of computing power needed was reported in three studies, at different scales. Chi et al. (2016) point to the difficulty of combining different types of computing resources and note that parallel processing uses a lot of energy. Wu et al. (2024) show a similar trade-off: the more detailed a geospatial analysis, the more computing power and energy it needs. Montillet et al. (2024) add that processing speed is especially critical for applications that need fast results, such as geohazard warning systems.

Closely related are storage and data management difficulties, reported in three studies. Sun and Scanlon (2019) note that “data lakes” (repositories that store raw data in its original format) hold many data types but become more complex, costly, and slower as data grows. Chi et al. (2016) point to challenges in accessing and delivering large volumes of data, while Sorokine et al. (2016) observe that environmental data tends to stay spread across different sources, which makes it harder to manage.

Limitations in current algorithms, also reported in three studies, affect several parts of the analysis process. Chi et al. (2016) found it difficult to adapt existing algorithms to run across multiple systems at once (parallelization). Huang and Wang (2020) note that standard analytical methods struggle with the complexity of big spatial data, since spatial patterns often don’t follow simple relationships. Rathod (2023) adds that current AI models struggle with feedback in languages other than English and with nuanced cultural context.

Real-time processing constraints, reported in three studies, consistently slowed systems down. As noted in the previous section, Rathod (2023) measured a delay of 9 to 12 seconds when processing geospatial queries, in line with Chi et al.’s (2016) call for platforms that analyze real-time and stored data together. Sun and Scanlon (2019) trace this delay back to data transmission bottlenecks, a key barrier to processing large-scale Earth observation data in real time.

Beyond these technical limits, five studies reported broader challenges related to methods and statistics. As noted in the previous section, Sun and Scanlon (2019) identify a lack of labelled datasets and a mismatch between how fast data is collected and how fast it can be processed. Lokers et al. (2016) find that variety and veracity remain the most persistent issues in data-intensive agro-environmental research, and Montillet et al. (2024) argue that big data differs enough from traditional datasets that new methods are needed to handle and interpret it. Other studies point to related gaps in software tools, including tools for visualizing and summarizing results (Sorokine et al., 2016), new computational and statistical approaches (Chi et al., 2016), and limited understanding of how deep learning models work internally (Sun & Scanlon, 2019).

Data interpretation challenges

Beyond technical processing, the studies highlighted considerable challenges in making sense of big data results and translating them into useful knowledge for environmental research and policy. Uncertainty quantification and error propagation, meaning how errors and unreliability in the data can build up and distort results, emerged as a recurring concern. Several issues raised earlier, such as representativeness and coverage bias (Huang & Wang, 2020), noise and measurement error (Chi et al., 2016), and difficulty correlating real-time sensor data with historical records (Rathod, 2023), resurface here as sources of uncertainty, alongside concerns about data quality and secure handling (Sun & Scanlon, 2019) and the way performance parameters vary depending on location (Wu et al., 2024).

Closely tied to this is the challenge of validation and verification, reported in three studies, particularly in situations where there was no reliable “ground truth” (real-world confirmed data) to check results against. Huang and Wang (2020) note that standard statistical checks are hard to apply to big spatial data when ground truth is missing, a problem that Sun and Scanlon (2019) trace back to the shortage of labelled datasets noted earlier. Chi et al. (2016) point to the buildup of noise, spurious correlation, and measurement error as a further complication when verifying results.

These uncertainty and validation issues feed into a broader concern with trust and reliability in automated analysis, identified as a critical challenge in three studies. Sun and Scanlon (2019) observe that big data analytics currently focus more on identifying associations than on explaining causes, and argue for approaches that remain interpretable to humans rather than relying purely on automated “black box” models, meaning models whose internal reasoning cannot easily be understood. This is not a simple fix, however, since Huang and Wang (2020) note that the complex, non-linear structure of big spatial data tends to require exactly this kind of harder-to-interpret model. Rathod (2023) brings this concern into a more practical setting, finding that AI-driven automation cannot fully replace human judgment, especially when interpreting subjective factors such as aesthetic compatibility or local cultural nuance.

This difficulty in trusting automated outputs is closely linked to another challenge, discussed in three studies: telling correlation apart from causation. Given the focus on association noted above, Sun and Scanlon (2019) identify better causal inference (methods that can show what actually causes what, not just what tends to occur together) as a key future need. Chi et al. (2016) add that combining data from sources with very different characteristics makes it even harder to establish real causal relationships in the first place. Rathod (2023) gives a concrete example of this problem, returning to the cultural limits noted earlier: qualitative aspects such as community character still need to be manually assessed, since AI models struggle to capture nuanced cultural values.

Even once these analytical challenges are addressed, turning technical results into actionable insight remained difficult in three studies, requiring researchers to bridge several gaps at once. Sun and Scanlon (2019) point to a significant lag between drawing meaning from data and actually acting on it, while Huang and Wang (2020) frame the core challenge as turning large volumes of data into genuinely valuable insight, rather than just processing them. Chi et al. (2016) add that part of this challenge lies in identifying the right data to use and deploying it effectively for decision-making.

Closely related is the difficulty of communicating findings to diverse stakeholders, reported in three studies. Rathod (2023) found that the language limitation of AI models noted earlier also had a practical cost: excluding non-English community feedback limited stakeholder engagement. Sun and Scanlon (2019) suggest that this gap could be addressed through the improved data governance and sociotechnical infrastructure mentioned earlier. Chi et al. (2016), meanwhile, emphasize that visualization plays a crucial role in communicating complex findings to these varied audiences.

Solutions and recommendations

The reviewed studies proposed technical, methodological, and institutional solutions to the challenges identified above, though few combined all three into a single framework. Technical solutions came first, centered on scalable computing platforms and specialized tools. Sun and Scanlon (2019) pointed to platforms such as Hadoop, Spark, and Google Earth Engine, Rathod (2023) proposed a layered system combining Kafka, Spark, and dual storage through Delta Lake and MongoDB, and Wu et al. (2024) advocated for more efficient geospatial indexing through H3. Three studies took this further, embedding these tools into broader frameworks or workflows, such as Rathod's (2023) four-phase methodology, Chi et al.'s (2016) "trinity concept" linking data ownership, methods, and applications, and Sorokine et al.'s (2016) UrbIS architecture.

These technical foundations, however, were repeatedly described as insufficient on their own. Three studies called for integration and collaboration strategies to address organizational barriers: Sun and Scanlon (2019) and Chi et al. (2016) both stressed the importance of collaboration between data scientists, domain experts, and institutions, while Rathod (2023) proposed federated learning, a method that allows models to be trained across multiple cities without needing to centralize their data, as a way to support this kind of collaboration. Beyond this, three studies recommended methodological improvements that move explicitly beyond purely data-driven approaches. Sun and Scanlon (2019) called for hybrid models that combine machine learning with physics-based reasoning, Huang and Wang (2020) recommended fusing multiple data sources for richer analysis, and Chi et al. (2016) stressed the need to build domain knowledge directly into the analytical process, rather than applying it only after results are produced. Three studies added policy and institutional recommendations, focused on building data science capacity and stronger governance structures (Lokers et al., 2016; Rathod, 2023; Sun & Scanlon, 2019).

Finally, looking ahead, two studies pointed to the same limitation: that current big data analytics remain restricted by their reliance on association rather than causation or context, as noted earlier in the discussion of interpretation challenges. Sun and Scanlon (2019) called explicitly for improved causal inference methods, while Huang and Wang (2020) called for stronger theoretical models to better support machine learning in spatial analytics.

Overall, these recommendations suggest that technical and methodological improvements, while necessary, are not enough on their own to fully resolve these challenges. This raises the question of what it actually means for big data to be useful and meaningful in practice, which the following section addresses before turning, in the next section, to the concept of thickening big data.

What does it mean for big data to be meaningful?

According to Sharma et al. (2014), making big data "**meaningful**" means turning raw accumulation into usable judgment. In this literature, that means preserving enough veracity and context that the data are accurate, relevant, and linkable, and then shaping the output so it can actually support a decision. Bhatia (2014) frames this in terms of the practical challenges of big data: even when systems successfully capture large volumes of information, the "presentation of the results and its interpretation by non-technical domain experts is crucial to extracting actionable knowledge" (p. 9). In other words, size and volume alone do not make data useful; without accuracy, context, and an interpretable output, big data remains little more than a large, noisy archive rather than a meaningful one.

Taken together, this literature suggests that "meaningful" big data has two defining features. First, it must be accurate, relevant, and contextualized, so that raw data turns into usable insight for decision-making (Sharma et al., 2014). Second, it must answer a question, be trusted, and be actionable, which also means it must be interpretable by non-experts (Bhatia, 2014). Yet even when these conditions are met, meaningful use of big data still depends on how well it reflects the complexity of the contexts it describes, a question the next section takes up directly.

2.3 Data Thickening

The notion of “thickening of big data” emerges as a critical response to the limitations of purely quantitative, large-scale datasets in capturing the complexity of human behavior and socio-cultural contexts (Bornakke & Due, 2018; Mortati & Cautela, 2025; Mortati et al., 2023; Smith, 2018). While big data provides extensive, high-volume insights into patterns, trends, and correlations, it is often characterized as “thin” due to its lack of contextual depth and meaning (Bornakke & Due, 2018; Mortati & Cautela, 2025). This limitation has led researchers to emphasize the importance of integrating qualitative, context-rich “thick data,” which captures the underlying nuances of motivations, values, and experiences of users. Smith (2018) emphasizes this distinction by arguing that smart city initiatives that rely too heavily on big data risk overlooking concrete realities, and that data has to be brought back into the social contexts it measures, through community involvement and context-sensitive use. Mortati and Cautela (2025) define “data thickening” as a mechanism through which designers actively bridge thin data and thick data, enabling a deeper exploration of problem spaces and fostering more meaningful solution generation. Rather than treating data types as separate, this approach emphasizes their complementarity, where big data contributes scalability and pattern recognition, while thick data provides interpretive richness and contextual grounding.

The process of thickening involves layering data with additional qualitative insights, metadata, and contextual interpretation (Mortati & Cautela, 2025), transforming raw datasets into knowledge systems that embed multiple dimensions of meaning and that Latzko-Toth et al. (2017, as cited in Mortati & Cautela, 2025, p. 3) describe as “onion-structured”. This aligns with broader interdisciplinary calls to “make big data thick and thick data big” (Adler-Nissen et al., 2021, p. 5), reflecting a convergence of data science, ethnography, and design cognition perspectives (Mortati & Cautela, 2025, p. 8). Mortati et al. (2023) further argue that such integration enhances innovation by enabling designers to move beyond surface-level observations and engage with the deeper drivers of user behavior. Importantly, this shift also reframes the role of data from a passive input to an active component of sense-making and creativity. Designers do not simply analyze data but interpret, contextualize, and recombine it to generate insights, highlighting the centrality of human cognition in data-driven processes (Mortati & Cautela, 2025).

Overall, this literature suggests that thickening offers a different way of working with big data. Instead of relying on quantitative data alone, it combines large-scale patterns with contextual depth, which can help people understand complex phenomena more fully. In design, this may lead to outcomes that better reflect the needs and circumstances of the people they are made for. Thickening can therefore be seen as more than a technical improvement: it is also a way of making data easier to interpret and more relevant to the people who use it, both in research and in practice.

Methodological Approaches to Thickening

Table 2 summarizes eight studies that are central to this project. The first three (Smith, 2018; Mortati & Cautela, 2025; Mortati et al., 2023) frame data thickening conceptually, as discussed above. The other five turn it into concrete practice, and they differ mainly in where the thickening happens. Albris et al. (2021) thicken data through follow-up interviews and structured fieldnotes. Adler-Nissen et al. (2021) describe a “**twin-move**,” returning to where the data was produced to recover context and using thick data to flag where the meaning of big data is unclear, while Munk et al. (2022) follow a model’s prediction errors to the parts of a dataset most worth closer human interpretation. Bornakke and Due (2018) propose “**Big-Thick Blending**,” which combines the insights of both data types without merging the datasets themselves, and Bjerre-Nielsen and Glavind (2022) argue that the strength of ethnography lies in supplying both “**ground truth**,” a direct, on-the-ground check of what big data is really capturing, and “**thick description**” in Geertz’s (1973) sense, the social meaning behind a data point rather than the data point itself. Across this literature, **ethnography** stands out as the most consistently proposed way to thicken big data.

Across these studies, the authors treat ethnography not as an optional qualitative supplement, but as a rigorous method that can genuinely improve quantitative research, precisely because, unlike big data, it was never designed as a side effect of something else, but built from the ground up to capture context and meaning. Taken together, they show that thickening is not one single technique but a family of strategies: adding context manually through fieldwork,

designing hybrid qualitative-quantitative tools, blending analytical and ethnographic insights, or using a model's own mistakes to flag where interpretation is needed. Section 6.1 returns to these sources in mapping each strategy onto a specific feature of this project's final prototype.

It is also worth noting that this part of the literature is concentrated almost entirely in social media analysis, international relations, and digital sociology or anthropology. There does not yet appear to be an established body of work that applies this “thickening” framework, or similar language, within climate research or urban heat island studies specifically. Related mixed-methods work does exist in these fields, for example studies that combine resident surveys or participant responses with sensor-based temperature measurements (Gallacher & Boehnke, 2025; Vasilikou & Nikolopoulou, 2020), or with remote sensing and household-level sensing (Hotterdam; Gemeente Rotterdam & TU Delft, 2022). However, it is rarely framed explicitly in terms of “big” versus “thick” data, or theorized as a thickening process in the way described above. This points to a gap in the reviewed literature, and positions the use of ethnographic methods to add context to big data on urban heat in this thesis as a new application of an established idea, in a field where it appears not to have been systematically explored.

Table 2.

Methodological approaches to thickening big data reviewed in this section, including each study's context and the specific mechanism through which data are thickened.

Source	Context	Method / approach	How data are thickened
Smith (2018). <i>Smart cities need thick data, not big data.</i>	Commentary (The Guardian blog) on smart cities, built around a case study of a citizen noise-monitoring project in Barcelona. Framing/context source.	Case-based commentary rather than a formal method. Residents used low-cost sensors to measure noise, compared readings with official guidelines and Council data, and discussed the results in workshops and a citizen assembly. Drawing on Geertz's “thick description,” it argues that data requires understanding the context in which it arises.	Sensor readings are combined with residents' lived experience, official data, health studies, and activities in the square. Collective data gathering turns noise from an individual complaint into a shared issue, giving the data social meaning. Context comes from community input and dialogue rather than more data, bringing it back into the social context it measures.
Mortati & Cautela (2025). <i>Data thickening: A new frontier in design cognition.</i>	Design research / design cognition.	Defines “data thickening” as the mechanism through which designers actively bridge thin/big data and thick/small data, enabling deeper exploration of problem spaces and more meaningful solution generation.	Layers data with additional qualitative insights, metadata, and contextual interpretation, transforming raw datasets into “ onion-structured ” knowledge systems that embed multiple dimensions of meaning; big data supplies scale and pattern recognition, thick data supplies interpretive richness and contextual grounding.
Mortati et al. (2023). <i>Data in design: How big data and thick data inform design thinking projects.</i>	Design thinking / innovation research.	Shows that integrating big and thick data enhances innovation by enabling designers to move beyond surface-level observations and engage with the deeper drivers of user behavior.	Reframes data from a passive input into an active component of sense-making and creativity: designers do not simply analyze data but interpret, contextualize , and recombine it to generate insight, placing human cognition at the center of the thickening process.

Source	Context	Method / approach	How data are thickened
Albris et al. (2021). <i>A view from anthropology: Should anthropologists fear the data machines?</i>	Computational anthropology.	Three concrete techniques: (1) combining social media data with follow-up interviews ; (2) logbook-style surveys mixing closed and open-ended questions; (3) writing fieldnotes in a structured, machine-readable format (e.g., XML tags for categories of information).	Follow-up interviews recover the context and intent behind quantitative patterns; logbook surveys produce datasets that are small but rich in detail over time (“thick” data even with few participants); structured fieldnotes let qualitative observations be processed computationally without losing depth of meaning.
Adler-Nissen et al. (2021). <i>Machine Anthropology: A View from International Relations</i> .	International relations / digital diplomacy.	Describes thickening as a “ twin-move ”: making big data thick, and making thick data big. (p.5)	Making big data thick means returning to where digital data was produced (e.g., interviews) to recover context the data alone cannot show; making thick data big means using quantitative checks not to confirm one “correct” interpretation, but to flag where meaning is unclear and worth closer qualitative attention.
Munk et al. (2022). <i>The Thick Machine: Anthropological AI between explanation and explication</i> .	Computational anthropology / AI-assisted analysis.	Rather than optimizing a machine learning model for maximum accuracy, treats its mistakes as a guide: social media comments a neural network fails to classify correctly are treated as signals of ambiguous, meaning-rich situations.	Uses the model’s prediction errors to point researchers toward the specific parts of the dataset most worth “thickening” through closer human/ qualitative interpretation , rather than thickening the dataset uniformly.
Bornakke & Due (2018). <i>Big-Thick Blending: A method for mixing analytical insights from big and thick data sources</i> .	Methodological article in sociology/digital methods (<i>Big Data & Society</i>), developed from two applied cases: a Danish optometrist chain’s in-store study and a Copenhagen bike-sign evaluation.	Proposes “ Big-Thick Blending ”: selectively combining big data and ethnographic insights into a blended space through a rapid, iterative, collaborative process, using four strategies: calibrating, contextualizing, adding the “why”, and behavioral scale	Big data is thickened through ethnographic observation, adding context to quantitative patterns, recalibrating inflated counts in the shop study and explaining route choices in the bike study. The result combines quantitative and thick findings in one visualization without merging the datasets.
Bjerre-Nielsen & Glavind (2022). <i>Ethnographic data in the age of big data: How to compare and combine</i> .	Comparative methodology: ethnography vs. big data (sociology).	Compares big and thick data along three dimensions: N (how many people observed), M (how much detail captured per unit), T (how much time is covered). Positions ethnography as supplying “ ground truth ” (a term borrowed from remote sensing, Hoffer 1972) and “ thick description ” in Geertz’s (1973) sense, both terms cited in Bjerre-Nielsen & Glavind, 2022.	Big data scores high on N and T but low on M (“exhaust data”); ethnography supplies the missing M, the depth of meaning per observation, and validates whether big data is measuring what researchers assume it measures (illustrated through the eye-twitch/wink example and the authors’ study of smartphone-use “contagion,” where sensor data detected the effect but not its underlying causes or timing).

Visualization as a Thickening Mechanism

Beyond the content that is added to big data, a separate strand of literature points to visualization itself as a determinant of whether data becomes usable at all. Shao et al. (2024) show, through a comparative study of over one hundred participants, that visualizations built around data storytelling elements measurably improve both the speed and the accuracy with which people retrieve key data points and grasp their main insight, compared with conventional charts, indicating that how data is presented shapes comprehension, not only what the data contains. This concern surfaces specifically in climate contexts as well. Schuster et al. (2024), based on interviews with both domain experts and lay audiences, find that non-expert viewers shown the same climate visualization frequently arrive at markedly different takeaway messages, and that experts tend to underestimate how much simplification a general audience actually needs to read a chart correctly.

This reinforces a point already raised in section 2.2: producing accurate, well-processed data is not sufficient for it to be meaningful, since meaning is also constructed at the point where data is seen and read, not only at the point where it is collected or thickened. For this project, this suggests that visualization cannot be treated as a neutral final step applied once thickening is complete, but should be understood as part of the thickening process itself, since the same combination of big and thick data can remain opaque or become interpretable depending on how it is visually constructed for a non-expert user.

Generative AI has begun to be applied to two sides of this visualization question: making climate information tangible, and producing visualizations. For the first, Schmidt et al. (2019) start from the difficulty people have in mentally simulating the complex and probabilistic effects of climate change and propose a tool that, given an address, generates an image of how a familiar location could look under a climate-related event. Their prototype uses Cycle-Consistent Adversarial Networks (CycleGANs) trained on images of houses before and after flooding, pairs the output with climate model projections to retain scientific credibility, and realistically flooded about 70% of 80 test images; it covers only flooding so far, and the authors note that it does not yet incorporate the physical variables of the climate model. Like the AI-generated imagery of Ongekend heet (Section 4.1), this suggests that generated visuals can make abstract climate information personally legible, here tied to a place rather than to a single fixed scenario. For the second, Dibia (2023) presents LIDA, aimed at users with limited visualization experience, in which large language models summarize a dataset, propose visualization goals, generate visualization code, and produce stylized infographics through natural language or direct manipulation; it was evaluated on reliability (3.5% of generated visualizations failed to compile) and automated quality scores rather than with users. Both works concern how visuals are produced rather than how thickened data is read, and both rely on models that generate the most probable rather than necessarily the correct output (Feuerriegel et al., 2024), echoing the concerns about automated interpretation raised in Section 2.2. Whether generative AI adds value to a visualization that combines big and thick urban heat data for non-expert users therefore remains open, and is what the comparison of two prototype versions in this project is designed to explore (Section 5.2).

2.4 Positioning the Research Gap

Remote sensing specialists tended to concentrate on volume and technical specifications, such as data scale in terabytes to exabytes (Chi et al., 2016), while urban researchers focused more on behavioral and spatial-temporal dimensions (Huang & Wang, 2020; Kong et al., 2020). Environmental water-management researchers offered the most comprehensive definition, spanning all of the traditional “V” characteristics (Sun & Scanlon, 2019), while agro-environmental specialists emphasized variety and veracity as most critical to their field (Lokers et al., 2016). This suggests that domain-appropriate characterizations are often more useful than a single universal definition. Integration challenges are reported in nine of the ten reviewed studies, although their severity varies: studies combining heterogeneous sources such as satellite imagery, sensors, social media, and administrative data (Chi et al., 2016; Huang & Wang, 2020; Rathod, 2023; Sun & Scanlon, 2019) report greater difficulties than those using more uniform datasets. Climate-focused studies (Montillet et al., 2024; Sorokine et al., 2016) further emphasize that big data’s characteristics require novel analytical methods due to spatial and temporal complexity.

Several studies show that platforms such as Apache Hadoop, Spark, and Google Earth Engine (Rathod, 2023; Sun & Scanlon, 2019), alongside methods like deep learning, data fusion, and hybrid machine learning and physics-based approaches (Huang & Wang, 2020; Kong et al., 2020; Sun & Scanlon, 2019), can address many technical barriers. Institutional challenges, however, remain persistent: data silos, low trust, and weak incentives for sharing continue despite technical advances (Chi et al., 2016; Lokers et al., 2016; Sun & Scanlon, 2019). Sun and Scanlon (2019) note that silos persist due to acquisition costs and limited incentives, while Lokers et al. (2016) highlight ongoing trust barriers. This indicates that technical solutions alone are insufficient without parallel progress in governance and incentives.

Even where these technical and institutional barriers are addressed, **interpretation** remains a key limitation (Chi et al., 2016; Huang & Wang, 2020; Kong et al., 2020; Rathod, 2023; Sun & Scanlon, 2019; Wu et al., 2024). Many methods prioritize association over causation (Sun & Scanlon, 2019), rely on limited interpretability (Huang & Wang, 2020), and struggle to produce actionable insights for decision-makers (Chi et al., 2016; Huang & Wang, 2020; Sun & Scanlon, 2019). Rathod (2023) shows that even advanced AI cannot replace human judgment in subjective urban planning contexts, highlighting a persistent tension between analytical sophistication and practical usability.

This persistent gap between technically valid analysis and practically useful interpretation is essentially what separates big data from **meaningful** big data, as defined earlier in this chapter: data that is not only accurate and well-processed, but relevant, trustworthy, and interpretable enough to actually support a decision (Bhatia, 2014; Sharma et al., 2014). Judged against these criteria, much of the reviewed literature shows that big data pipelines in climate and urban research are technically capable but still fall short on the interpretive side, precisely where meaningfulness is decided.

It is precisely this gap, between technically sophisticated analysis and meaningful, actionable interpretation, that the concept of “**thickening of big data**” responds to (Bornakke & Due, 2018; Mortati & Cautela, 2025; Mortati et al., 2023; Smith, 2018). While big data enables large-scale pattern recognition, it is often considered “**thin**” due to limited contextual depth. Researchers therefore stress the integration of qualitative “**thick data**” to capture meanings, motivations, and lived experiences. Smith (2018) argues that smart city initiatives relying heavily on big data risk overlooking lived realities, and that data has to be brought back into the social contexts it measures, through community involvement and context-sensitive use. In design research, Mortati and Cautela (2025) define “**data thickening**” as a process that bridges big or thin data with small or thick data to support deeper exploration and more meaningful solutions. This involves layering datasets with qualitative insights, metadata, and contextual interpretation, transforming raw data into knowledge systems that Latzko-Toth et al. (2017, as cited in Mortati & Cautela, 2025, p. 3) describe as “**onion-structured**.” Rather than treating data types as separate, this approach emphasizes complementarity, where big data supports scale and pattern detection while thick data provides interpretive depth. Mortati et al. (2023) further show that this integration enhances innovation by enabling designers to engage with deeper behavioral drivers and reposition data as an active element of sense-making rather than a passive input.

Yet thickening data conceptually is not, on its own, sufficient to close this gap: how that thickened data is subsequently **visualized** determines whether it actually reaches a non-expert user, since visualization choices have been shown to shape how well people comprehend data, not only what the data contains (Shao et al., 2024; Schuster et al., 2024).

Taken together, the literature suggests that the challenges facing big data in climate and urban environmental research are not purely technical, and cannot be resolved through technical innovation alone. Even as computational platforms and analytical methods continue to mature, the persistence of institutional barriers and interpretive limitations points to a more fundamental gap: the difficulty of translating large-scale, pattern-based data into meaningful, context-sensitive knowledge. Thickening offers one promising direction for closing this gap, suggesting that future research should prioritize **interpretability**, **actionability**, and the integration of qualitative depth alongside predictive performance, particularly in policy-relevant applications.

3. RESEARCH METHODS

This chapter covers the Discover phase of the project's Double Diamond process (Section 1.5), through which the two complementary strands of inquiry introduced there were carried out. The first, presented in Section 3.1, reviews existing platforms and tools for urban heat and climate data to establish what is already available and where current approaches fall short on interpretation and context. The second, presented in Section 3.2, describes the ethnographic user research conducted in Delft and Rome to surface the contextual factors that shape how thermal comfort is experienced at street level. Together, these two strands address SQ1 and SQ2.

3.1 Platform Review

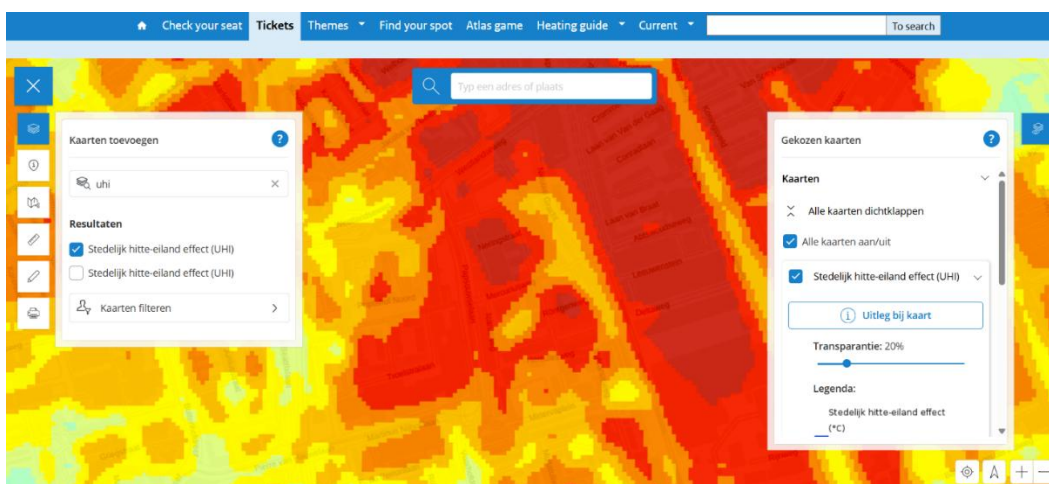
Atlas Leefomgeving

The Atlas Leefomgeving ("Atlas of the Living Environment") is an official Dutch government platform that makes environmental datasets publicly accessible through an interactive web map (Figure 3). It brings together information on topics such as urban heat, air quality, noise, green spaces, water, and energy, with the goal of making environmental data understandable and accessible to a broad audience. Users can search for a specific address and explore different map layers, including urban heat island intensity, heat maps, and shaded walking routes, allowing them to examine environmental conditions at different spatial scales.

The platform succeeds in making complex national datasets easy to access. Its interactive maps, layer based navigation, and simple search functionality lower the technical barrier to exploring environmental information without requiring GIS expertise. However, the platform is limited to the Netherlands and remains primarily analytical: its heat maps, for instance, are based on a single modelled hot summer day rather than continuous or real-time data. While it provides reliable and detailed quantitative data, it offers little support for interpreting what that data means in a real world context. Users are expected to draw their own conclusions from the visualizations, with no integration of lived experience, local observations, or contextual information that could explain why a location appears the way it does or how people experience it.

Figure 3

Atlas Leefomgeving, Urban Heat Island Effect Layer for the Delft Route



Note. Screenshot from Atlas Leefomgeving (n.d.), <https://www.atlasleefomgeving.nl>. Retrieved July 2026.

ShadeMap

ShadeMap is an interactive web platform that simulates sunlight and shadow for any location in the world based on a selected date and time (Figure 4). Using global terrain, building, and vegetation data together with solar position calculations, it allows users to explore how shadows move throughout the day and across different seasons. The platform is designed for a broad audience, including architects, urban planners, photographers, researchers, and members of the general public who need to understand how sunlight affects a particular place.

Compared with the Atlas Leefomgeving, ShadeMap provides a more interactive way of exploring environmental information. The possibility of selecting a specific hour and day allows users to relate the data to a real situation, making the visualizations more intuitive and personally relevant. This introduces a degree of contextualization by situating the data in time rather than presenting it as a static layer. However, the platform remains primarily analytical. It visualizes where shadows occur, but it does not explain how these conditions influence people's experiences, comfort, or decision making, nor does it incorporate qualitative observations or local knowledge.

Figure 4
ShadeMap, Shading Simulation for the Delft Route



Note. Screenshot from ShadeMap (n.d.), <https://shademap.app>. Retrieved July 2026.

Meteoblue Urban Heat Maps and Klimaateffectatlas

A similar analytical logic underlies two other government and commercially oriented mapping platforms reviewed for this project. Meteoblue's City Climate (Figure 5) provides hyperlocal, high resolution maps (down to 10 m, and locally 1 m) of urban air temperature, thermal comfort (PET), wind, and pluvial flood risk, combining large-scale weather forecasting models with satellite land cover data, and checking the results against a dense network of ground sensors. Its interface allows users to move a time slider between real time conditions and short term forecasts across toggleable layers, offering a finer spatial and temporal grain than the Atlas Leefomgeving, but without any built in explanation of what a given temperature or comfort value implies.

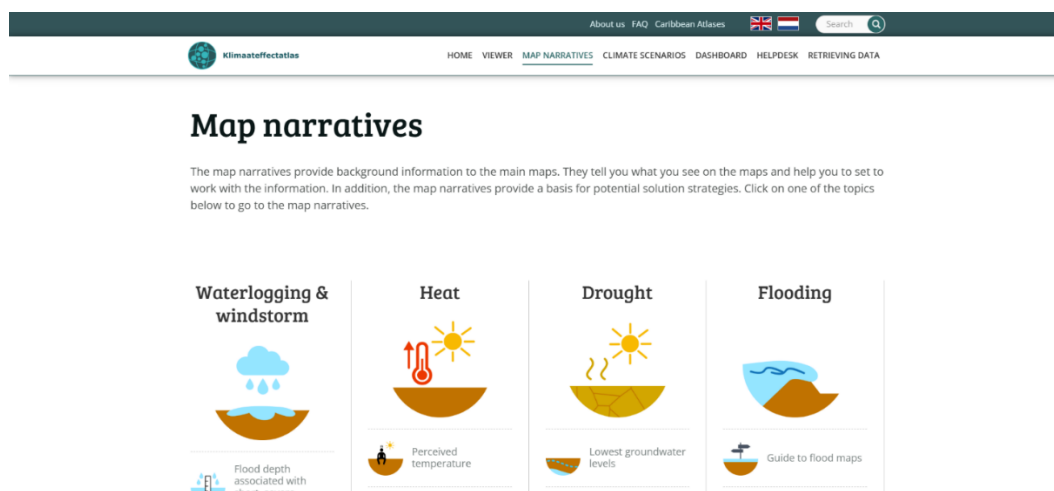
Klimaateffectatlas (Figure 6), a second Dutch government platform, covers flooding, waterlogging, drought, and heat using KNMI climate scenarios and modelled effect maps in a format comparable to the Atlas Leefomgeving. It goes one step further than either the Atlas or Meteoblue, however, by pairing its map layers with written "map narratives" that guide users on how to read specific maps, and a neighborhood level dashboard for comparing areas. Both platforms remain map first and layer based in their interaction design, and neither incorporates lived or experiential data alongside their quantitative layers.

Figure 5
Meteoblue City Climate, Urban Temperature Layer for Rome



Note. Screenshot from Meteoblue City Climate (n.d.), <https://www.meteoblue.com/en/weather/widget/setupheatmap>. Retrieved July 2026.

Figure 6
Klimaateffectatlas, Map Narratives



Note. Screenshot from Klimaateffectatlas (n.d.), <https://www.klimaateffectatlas.nl/en/map-narratives>. Retrieved July 2026.

Hotterdam

Hotterdam is an academic research project on Rotterdam's urban heat island rather than a live interactive platform, published as a report and atlas. It combines satellite imagery, GIS data, and modelled surface energy balance with resident health and census statistics, linking the two through hierarchical and multivariable regression to produce a "social heat map" that clusters physical heat exposure with social vulnerability indicators such as age, income, and health. A sub study, Sensing Hotterdam, additionally deployed low cost temperature loggers in roughly 1,000 homes and 300 public spaces over a summer, cross referenced with resident surveys and mortality data. This combination of remote sensing based big data with household level sensing and survey data distinguishes Hotterdam from the platforms discussed above, even though its output is delivered as a static report rather than an explorable tool.

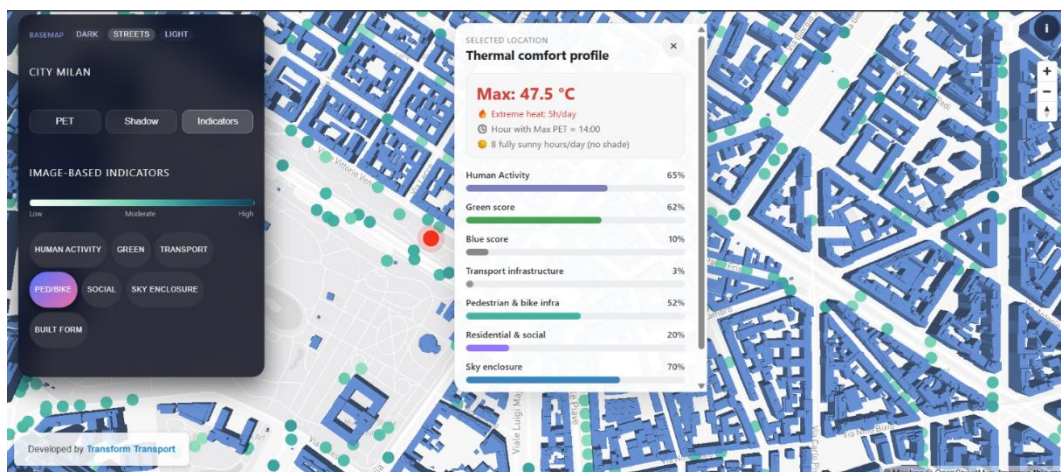
Transform Transport

Transform Transport is a research foundation publishing open studies on urban mobility and livable streets. Its most heat relevant study, “Seeing the Heat: Using Street-Level Imagery to Assess Outdoor Thermal Comfort in Urban Environments” (2026), estimates outdoor thermal comfort across Milan by combining microclimate modelling with street-level imagery and computer vision (Figure 7). The study follows a three-step process. First, it models expected outdoor temperature (PET) at different points across Milan using an established climate simulation tool. Second, it collects street-level photos from Google Street View every 20 meters along the city’s pedestrian streets, and uses computer vision to detect features in each photo, such as how much vegetation, sky, or building is visible, along with more subjective qualities like how safe or lively a street feels, while also accounting for how shadows and sunlight shift throughout the day. Third, it statistically compares these visual features against the modelled temperature values, and trains a machine learning model to predict how hot a street feels from its street-level images alone.

The study found a clear day/night divide in what drives thermal comfort. During the day, direct sun and shading dominate so strongly that visual features alone only weakly predict temperature, though accuracy improves substantially once shading over time is factored in. At night, conditions are far more stable, and the same visual features become much stronger predictors on their own. Notably, features usually assumed to reduce heat, such as vegetation and open sky, can increase daytime heat exposure while providing a cooling effect after dark. Results are presented both as an interactive online map of Milan and as the published research article containing the full analysis.

Figure 7

Transform Transport, Interactive Map of Modelled Outdoor Thermal Comfort across Milan



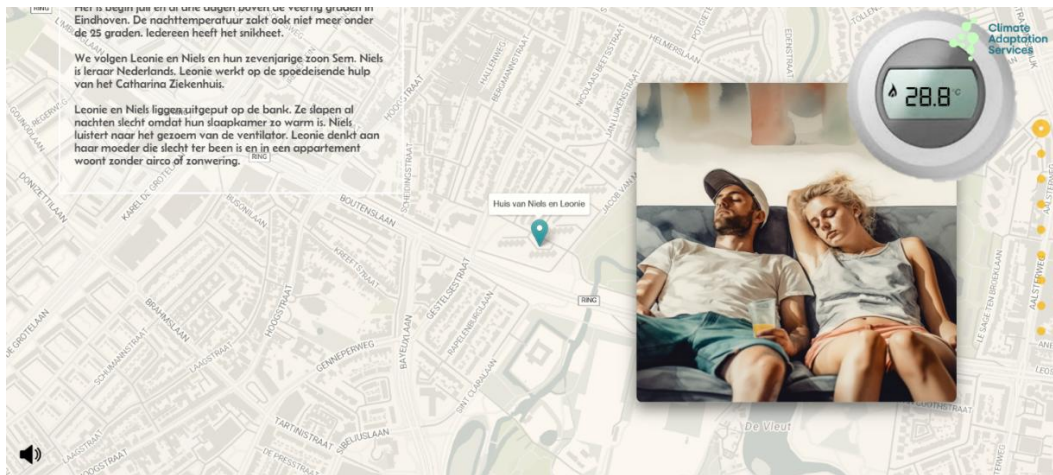
Note. Screenshot from Transform Transport (n.d.), “Seeing the Heat: Using Street-Level Imagery to Assess Outdoor Thermal Comfort in Urban Environments” <https://transformtransport.org/research/livable-streets/seeing-the-heat-using-street-level-imagery-to-assess-outdoor-thermal-comfort-in-urban-environments/>. Retrieved September 2026.

Ongekendheet.nl

Ongekendheet.nl takes a markedly different approach, built around storytelling rather than data exploration. Commissioned to make an extreme, currently “unprecedented” Dutch heat scenario (multiple consecutive days above 40°C) tangible to professionals and the public, it presents a scrollable multimedia “map story” following a fictional family in Eindhoven, combining narrative text, sound, dynamic charts, and AI generated imagery (Figure 8). The scenario itself is grounded in official KNMI climate projections and developed with input from climate adaptation experts, but delivered as a fixed, pre authored narrative that the user reads through rather than steers. Of all the platforms reviewed, this is the clearest example of a narrative driven approach to climate data, constructing a persona based account from projections rather than presenting the data on its own.

Figure 8

Ongekendheet.nl, Scrollable Map Story Following a Fictional Family in Eindhoven



Note. Screenshot from Ongekendheet.nl (n.d.), <https://www.ongekendheet.nl>. Retrieved July 2026.

RAWGraphs and Hugging Face

Two generic, non-heat-specific tools were also reviewed as precedents for the technical and interaction design components of the eventual prototype, rather than as urban heat platforms. RAWGraphs is a browser-based tool that lets users without coding or design skills turn tabular data into custom, exportable vector charts by uploading a dataset, selecting a chart layout, and mapping columns to visual variables. Hugging Face, by contrast, is a broad hosting platform for machine learning models and datasets, including generative text, image, and multimodal models, accessible through documentation and code or through ready-made interactive demos (“Spaces”) that require no coding. Neither tool is built around urban heat data or offers an interpretive or narrative layer: RAWGraphs handles the mechanics of turning data into a chart, while Hugging Face is infrastructure whose output depends on the model or Space used.

Claude

Claude is a general purpose conversational AI assistant, developed by Anthropic, capable of generating text and visual artifacts (such as SVG charts, diagrams, mind maps, and interactive HTML) directly from a natural language prompt rather than through manual charting or coding. Users describe what they want to see, optionally supplying their own data, and the assistant generates a corresponding text or visual that can be viewed inline, refined through further prompting, or downloaded. Anthropic also offers Claude Code, a coding-focused tool that allows users to build and iterate on software, including custom visualizations, directly through code. Because neither is built around a specific dataset or domain, they were included in the review as general purpose tools for producing text and visualizations through language and code, rather than through manual visualization tools.

Morphocode Explorer

Morphocode Explorer is a browser-based tool for urban analysis that allows users to examine site conditions and measure urban indicators directly on an interactive map, without requiring GIS software. It combines thematic layers such as land use, development intensity, transit networks, and demographic data with figure-ground diagrams and adjustable pedestrian sheds representing walking distances from a selected point. Users can select a location on the map and view charts summarizing its measurable characteristics (Figure 9). The platform is aimed at urban planners and designers, city agencies, real estate professionals, and mobility specialists rather than the general public. Unlike the other platforms reviewed, it was considered only for its interaction design and digital visualization approach, not for its relevance to urban heat data.

Figure 9
Morphocode Explorer, Hover Interaction Revealing Urban Indicators on the Map



Note. Screenshot from Morphocode (n.d.), <https://explorer.morphocode.com>. Retrieved October 2026.

3.2 User Research

While the platform review established what existing tools currently offer, and where they fall short in supporting interpretation, it does not on its own reveal what kind of contextual, experiential information would be needed to address that gap. To surface this, the project conducted **ethnographic user research** centered on a thermal comfort walk, an activity designed to capture how people actually experience heat while moving through a specific urban environment, and to compare these situated observations (*contextual factors*) against the “thin” data provided by existing platforms. The next section describes the selection of participants for this research, followed by the design and execution of the thermal comfort walk in its two research locations, Delft and Rome.

User Group Selection

The project was initially conceived with academic researchers working with urban heat and climate data in mind. This group was selected because they represent the primary users of the types of datasets and analytical platforms discussed in the literature review, and therefore offered the most direct perspective on the challenges of interpreting complex environmental data. However, early recruitment efforts (through an online survey) indicated that this audience was relatively small and difficult to access within the timeframe of the graduation project, making it unlikely that sufficient participants could be recruited for meaningful user research.

The intended users of the prototype were therefore defined as **non-expert** interpreters of urban heat data, such as designers, architects and planners, who need to understand and apply this data without expert-level technical knowledge. Climate research, as named in the project title, is the field the data and platforms belong to, not the group the prototype is designed for. To support the iterative nature of the Research through Design process, the user group was therefore refined to master’s students and PhD candidates at TU Delft from disciplines such as Design, Architecture, and Engineering. While these participants are generally not experts in climate data analysis, they have the potential to make use of spatial and environmental data to guide their design and project decisions. As intermediary interpreters of urban heat data, they provide a relevant perspective on how complex datasets can be translated into **meaningful** insights for users who need to understand and apply the information without requiring expert-level technical knowledge. This refinement maintained alignment with the research aim while enabling a broader and more accessible participant pool for the user research activities.

Thermal Comfort Walk

The thermal comfort walk is the ethnographic activity at the core of the user research. It builds on “thermal walks,” a method developed to study how pedestrians perceive thermal conditions while moving through a sequence of urban spaces (Vasilikou & Nikolopoulou, 2020). Thermal walks combine microclimatic monitoring with the responses of the people walking the route, who record their thermal sensation at set points. Their method responds to a limitation of outdoor comfort models based on thermal equilibrium, which leave out qualitative factors (demographic, contextual, and cognitive ones) that cannot be evaluated through a purely quantitative approach. In their walks in London and Rome, Vasilikou and Nikolopoulou found that pedestrians’ perception varied considerably along a route even where air temperature and humidity remained largely homogeneous. This is the same gap between measured conditions and lived experience that this project sets out to address, and that an ethnographic approach is well suited to explore.

More recently, Gallacher and Boehnke (2025) paired mobile meteorological measurements with questionnaires completed by pedestrians along a walking route in Dresden, to support urban planning. They argue that measurements alone fail to capture the nuances of thermal comfort, and that perceptions of comfort do not always align with quantitative measurements. They also suggest that short interviews and participatory methods could be used in future studies. Both studies rely mainly on instruments and questionnaires with predefined scales. This project instead adapts the walk into an ethnographic activity for collecting thick data: participants document, through notes and photos, the contextual factors that shape their experience along a short route, and these observations are then compared with the big data of existing urban heat platforms. As far as the reviewed literature shows, thermal walks have not previously been used in this way, as a means of collecting thick data to be compared with big data.

In this project, the thermal comfort walk was the main part of the user research activity. Participants individually walked an indicative route of less than 1 km, noting moments of thermal (dis)comfort along the way through written or audio notes and photos, and later discussing these observations with the researcher. The resulting thick data was then compared with the big data of existing platforms: the Atlas Leefomgeving in Delft, and Meteoblue and ShadeMap in Rome, where the Atlas does not provide coverage. The activity was conducted in two locations: at the TU Delft campus (Netherlands), with six participants, and in the Trieste neighborhood in Rome (Italy), with another six participants. In each location, the researcher also completed the walk herself as an autoethnographic walk, which is counted as part of the thick data set, giving seven walks per location and fourteen in total.

This set-up differs from the earlier studies in four ways. First, participants walked unaccompanied, while the researcher waited at the endpoint to avoid influencing their pace, route choices, or attention. In Gallacher and Boehnke (2025), by contrast, the researcher accompanied the participants while carrying the measuring device. Second, instead of stopping at predefined points, as in Vasilikou and Nikolopoulou (2020), participants followed an indicative route and noted moments of comfort or discomfort wherever they occurred. Third, the objective side of the comparison was not measured on site. Instead of collecting new measurements, the project takes the big data of existing platforms as its starting point and compares it afterward with the thick data from the walks. Fourth, the route is short, comparable to the 500 m routes of Vasilikou and Nikolopoulou and the roughly 800 m questionnaire route of Gallacher and Boehnke, who shortened their route after observing that accumulated heat stress made it difficult for participants to notice changes in their surroundings. The following subsections describe the participants involved and the procedure followed in each location.

PARTICIPANTS

In Delft, the researcher first completed the walk on the TU Delft campus herself, as an autoethnographic walk. It served as a pilot to get a first-hand sense of the route and refine the activity's setup ahead of the user sessions, and her observations were also included in the thick data set. Following this, six participants took part, all recruited from the campus population and belonging to the project's core target user group: master's students and PhD candidates from a range of design- and engineering-related backgrounds, including Design for Interaction, Strategic Product Design, Integrated Product Design, Architecture, and Applied Physics. All six participants were Italian. None of them reported previous experience working with urban heat data, and none had used the Atlas Leefomgeving platform. Participant sessions were conducted between 14 and 16 July 2026, at varying times of day (ranging from 12pm to 5pm) and under comparable summer conditions, with recorded temperatures between 26°C and 30°C. Four participants documented their walk through written notes, while two opted to record audio notes instead; all of them documented the walk with pictures (see Appendix B).

In Rome, the researcher again completed the walk herself first, ahead of recruiting participants, and included her observations in the thick data set. Six participants then took part, recruited through the researcher's personal network from outside the core user group, in order to broaden the research beyond design and architecture students and professionals. Their backgrounds spanned a markedly different set of professions, including a professional musician, a PhD candidate in Biotechnology, a master's student in Environmental Law, a general manager, a graduate student, and an officer in public administration. As in Delft, none of them reported previous experience working with urban heat data, nor with the platforms used to compare big and thick data. All Rome participants were Italian as well. Participant sessions were conducted between 4 and 6 August 2026, at varying times of day (ranging from 1pm to 4pm) and under considerably hotter conditions than in Delft, with recorded temperatures between 34°C and 37°C, reflecting peak summer heat in Rome. Four participants documented their walk through audio notes, while two opted for written notes instead; as in Delft, all participants documented the walk with pictures (see Appendix C).

DELFT

The first thermal comfort walk activity was conducted on the TU Delft campus, along the route connecting the Faculty of Architecture and the Built Environment to the Faculty of Industrial Design Engineering (IDE). This route was selected because it is one that many students, particularly those in design- and architecture-related programs, already traverse regularly as part of their daily routine, which meant participants could draw on an existing, embodied familiarity with

the path rather than experiencing it for the first time. At the same time, the route offered considerable variation in urban form within a relatively short distance, alternating between tree-lined streets, open squares, parking areas, and building façades of different heights and materials. This combination of familiarity and micro-climatic variety made it a productive setting for surfacing the kind of contextual, situated observations this research was interested in.

Each session began at the Faculty of Architecture, where participants were given a printed map of the suggested route and briefed on the activity (Figure 10). The route was presented as indicative rather than fixed: participants were free to decide how to get from the Architecture to the Industrial Design Engineering building by taking the path they found most comfortable, so that their own route choices could in itself become part of the data. At any point along the way, participants were asked to mark the map with an X wherever they noticed a shift in temperature, a change in their thermal comfort, or simply something worth commenting on, capturing that moment through whichever method felt most natural to them: a written note, a short voice memo, and/or a photo.

Participants completed the walk unaccompanied, while the researcher waited at the endpoint, the IDE building, in order to avoid influencing their pace, route choices, or attention through her presence. Upon arrival, the participant and researcher met and went through the walk together retrospectively: the participant used their annotated map and photos as prompts to narrate their experience point by point, describing what they had noticed and why. This debrief conversation, grounded in the participant's own markers and images rather than in questions posed by the researcher, forms the primary data collected through this activity.

Immediately following this debrief, the researcher walked each participant through the Atlas Leefomgeving platform, showing them the route on the map, from the Faculty of Architecture and the Built Environment to IDE, displayed under three different filters: *Shade on Bike and Walking Paths*, *Urban Heat Island Effect*, and *Cooling Effect of Greenery and Water*. Together, the participant and researcher compared these filters against the data the participant had just collected during the walk, looking for consistent points of alignment or discrepancy between lived experience and the platform's "thin" data. The researcher and the participants then discussed together, in a semi-structured interview, possible methods for integrating the two types of data and making them communicate with each other.

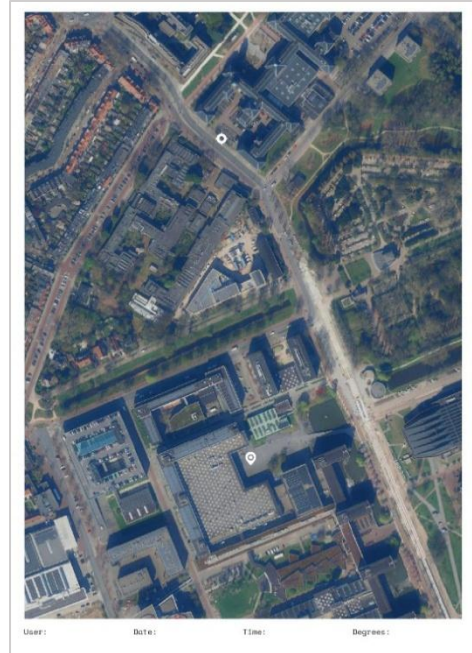
ROME

The thermal comfort walk in Rome was conducted in the Trieste neighborhood (*Quartiere Trieste*), the researcher's own area of residence and, not coincidentally, the area where all recruited participants have lived. The site was chosen deliberately to preserve symmetry with the Delft methodology: where the Delft route drew on participants' existing familiarity with a path they traverse as part of their daily study routine, the Rome route drew on participants' long-term familiarity with their home neighborhood. In both cases, participants were walking a route they knew well, rather than encountering it for the first time, allowing their observations to reflect an established, lived relationship with the space rather than a first impression. The choice was also a practical one: given the extreme heat conditions during the data collection period, asking participants to travel far from their homes to reach an unfamiliar location would have added an additional layer of discomfort unrelated to the activity itself.

As in Delft, the route offered considerable variation in urban form within a short distance: narrow, tree-lined side streets alternating with open, largely unshaded squares (e.g., Piazza Verbano), a wider tree-lined avenue (Corso Trieste), and proximity with built infrastructure, such as building entrance halls, a covered parking garage, a small indoor market, and a church, each producing a distinct and often abrupt microclimatic effect.

Figure 10

Printed route map given to participants in Delft.



Sessions followed the same procedure used in Delft. Each began with a briefing on the activity, and participants were given a printed map of the route (Figure 11). They were asked to mark the map wherever they noticed a shift in their thermal comfort, capturing that moment through a written note, a voice memo, and/or a photo.

As in Delft, participants walked unaccompanied while the researcher waited at the endpoint. They then narrated their experience point by point, using their annotated map and photos as prompts, and this debrief forms the primary data collected in Rome.

Immediately following the debrief, the researcher showed each participant screenshots of the equivalent platforms available for the Italian context. The Atlas Leefomgeving platform used in Delft could not be applied here, as it only provides coverage for the Netherlands; in its place, the researcher used Meteoblue's urban temperature maps for the Rome area, and ShadeMap's shading simulation for the same route, as the closest equivalents. Because the Rome participants were recruited from professional backgrounds outside academia and design research, and had more limited availability than the Delft group, this step was kept deliberately lighter than the full three-filter walkthrough conducted in Delft: rather than a guided, side-by-side comparison, participants were asked one or two open questions on whether the platform data matched what they had just experienced during the walk. This adaptation still captured participants' own sense of the gap between the platforms' "thin" data and their lived experience, while remaining feasible given the constraints of recruiting outside the researcher's immediate academic circle.

Figure 11

Printed route map given to participants in Rome.



Data Analysis

The data from the thermal comfort walks consisted of the participants' annotated maps, photos, written or audio notes, and the transcripts of the debrief and platform walkthrough conversations (Appendices B and C). Audio notes were sent by the participants to the researcher via WhatsApp, while the debrief conversations after the walks were recorded with the iPhone Voice Memos app. Both apps generate automatic transcripts. The recordings were then moved to the project folder and deleted from the original devices for privacy, in line with the informed consent agreement. The transcripts were translated from Italian into English with DeepL and edited for readability (Section 6.3).

The contextual factors presented in Section 4.2 were derived through an inductive grouping carried out by the researcher. All fourteen walks, including the researcher's own, were read in full, and every moment in which a participant described a change in thermal comfort, or something influencing it, was extracted together with the related photo and map marker (in Figma, where each walk was laid out on its own board). These extracts were then grouped by the type of factor they described, such as surfaces and materials, airflow, vegetation, or human heat sources. Groups were merged, split and renamed over until every extract fitted one theme, which resulted in the nine themes of Section 4.2. Themes were organized by content rather than by city, so that overlap and divergence between Delft and Rome could be compared. The platform walkthrough comments were analyzed separately. For each Delft participant, remarks were matched to the map layer they referred to (shade, urban heat island effect, cooling effect of greenery and water) and classified as alignment or discrepancy. The Rome comments, collected in a lighter format, were compared by recurring point. Participants' own suggestions for enriching the data (Opportunities for Data Thickening) were grouped by recurring idea.

The further classification of the Delft contextual factors for the prototype is described in Section 5.2.

4. RESULTS

4.1 Platform Review Findings

The platform review confirms the pattern already suggested by the literature review in Chapter 2: platforms that handle urban heat and related climate data as “big data” are, almost without exception, strong on data quality and access but weak on interpretation and context. The **Atlas Leefomgeving**, **ShadeMap**, and **Meteoblue’s City Climate** maps all present detailed, reliable, and in some cases very high-resolution quantitative layers, ranging from national UHI modelling to hyperlocal 10 m thermal comfort grids, through clean, map-first interfaces that require no GIS expertise to operate. None of the three, however, offers any built-in support for understanding what a given value means for a specific person, street, or decision. Users can see that a location is hotter or cooler, or more or less shaded, but are left to supply the interpretive step themselves. This limitation is not only interpretive but also one of missing context: even the most detailed of these platforms is built from satellite imagery, modelled surfaces, or fixed sensor readings, none of which can register the kind of temporary and nuanced human-scale detail that the thermal comfort walks surfaced, and these are precisely the moments that shape lived thermal comfort but never enter a dataset built from above. **Klimaateffectatlas** moves slightly beyond this baseline by pairing its maps with written “map narratives” and a comparison dashboard, but this amounts to guided reading rather than a constructed interpretation, and it still stops at describing what the data shows rather than what it means to act on. Across these four platforms, then, the review finds a consistent gap between data accessibility and data meaningfulness, echoing the distinction between “big” and “meaningful” data established in Section 2.2.

Two platforms in the review depart from this pattern by incorporating a second, more situated data source alongside the quantitative layer, though neither does so through an interpretive tool aimed at non-expert users. **Hotterdam** pairs remote sensing and modelled heat exposure with household-level temperature sensing and resident health and survey data, clustering the two into a “social heat map” that speaks to who is at risk and where, rather than only where temperatures are highest. **Transform Transport** takes a different, and for this project particularly relevant, route to the same kind of thickening: it shifts the viewpoint of the data itself, from the top-down, satellite-eye view that underlies most of the platforms reviewed here, to a pedestrian-eye view captured through street-level imagery. This shift is what allows the study to explain why a street feels hot or cool in terms of visible, human-scale features, such as shade, vegetation, and building coverage, rather than only reporting an abstract modelled PET value. Its finding that the same features (vegetation, open sky) can help or worsen thermal comfort depending on the time of day further shows the kind of nuance this pedestrian perspective can surface, nuance that a purely top-down, satellite-based reading of the city would likely flatten into a single, static value. Both **Hotterdam** and **Transform Transport** demonstrate that big urban heat data can be meaningfully combined with a more situated, human-scale data source, and both stop short of full narrative construction: **Hotterdam** is delivered as a static report and atlas, and **Transform Transport** as a research article with an interactive map, and in both cases the interpretive work is carried by the surrounding text rather than by the platform interface itself. Even so, both remain built from data that is fixed at the moment of collection, whether a household sensor reading or a street-level photograph, and so still cannot register the brief, situational moments that shaped thermal comfort during the walks, like a passing source of heat or cool air that exists only for a few seconds and leaves no lasting trace in the environment. They function as evidence that the underlying move, thickening big data with situated information, is feasible specifically for urban heat, and **Transform Transport’s** pedestrian-eye approach in particular offers a promising direction for how such thickening could be pursued in this project, even though neither platform captures this kind of transient detail or translates its approach into an interpretive tool aimed at non-expert users.

Ongekendheet.nl is the only platform reviewed that fully closes the gap between data and narrative, but it does so by removing the user’s own data from the process entirely. Its scrollable, multimedia story of a fictional family living through extreme heat is scientifically grounded in KNMI projections, yet it is fixed and pre-authored: every user encounters the same scenario, regardless of where they live or what conditions they want to understand. This confirms that narrative and AI-generated imagery can make an abstract climate projection feel personally and emotionally legible to a non-expert audience, which is precisely the “so what” layer missing from the purely analytical platforms

above. At the same time, it shows the limitation of the current approach: narrative quality here has been achieved at the cost of adaptability, since the platform was not designed to construct a narrative around a user's own site, measurements, or lived observations.

Morphocode Explorer was not reviewed as a heat data platform, since it does not present climate or thermal information, but was included to establish what is technically available for the interaction design side of this project, like the generic tools discussed below, which were reviewed for their technical potential rather than their heat data. In terms of interpretive depth, it follows the same pattern as the analytical platforms discussed earlier: it produces precise, comparable urban indicators, such as how mixed the land use is in an area or how much of it is built versus open space, but leaves all interpretation of what those indicators mean to the user, with no contextual layer built in. Its relevance to this project lies specifically in its hover interaction, which reveals big data about a location as the user moves the cursor across the map. This interaction directly informed the final prototype, which replicated a similar hover effect to reveal contextual factors on the map (Section 5.1).

The three generic tools reviewed, **Hugging Face**, **RAWGraphs**, and **Claude**, were not built specifically for urban heat data, but were included to establish what is technically available for the realization of the final prototype. Hugging Face confirms that a very wide range of generative models exists that could, in principle, support an AI-assisted narrative tool, but using them productively still requires technical setup or prompting skill. RAWGraphs confirms that turning a dataset into an exportable chart can be made accessible to non-experts through manual configuration. Its limitation is that it offers no customization options and no guidance on how the chart should be displayed to be more meaningful and understandable. General-purpose generative AI tools such as Claude were also briefly tested, to see whether a chat-based tool could support the kind of big-thick data integration this project is concerned with, rather than only generate a visual output from a prompt. In practice, this approach proved unreliable for anything beyond simple requests, and did not offer the structure or control needed to combine a quantitative dataset with contextual, thick data in a single interface. This ruled out a purely conversational tool as a way of handling that integration directly.

The review also shaped what role AI should not play in this project. Making data meaningful requires interpretation, and both the literature and the user research suggest that this should stay with people. Rathod (2023) found that AI-driven automation cannot fully replace human judgment when interpreting subjective factors, and Sun and Scanlon (2019) argue for approaches that remain interpretable to humans instead of relying on black box models (Section 2.2). The user research points the same way: one of the Delft participants (P4) questioned how much trust a person should place in an algorithm making thermally informed decisions on their behalf (Section 4.2). For these reasons, the project does not use AI to interpret the data or to decide what it means; generative AI is instead used as a tool for building the final prototype, not as the means by which the data is made meaningful. Whether an AI-supported feature could still add value for the user, beyond this development role, is not assumed. Two versions of the prototype, one with and one without such a feature, were presented during user evaluation (Section 5.2), so that its value could be judged from that testing.

Taken together, the eleven platforms and tools reviewed span the full range from purely analytical to story-based. Seven of them are urban heat or climate platforms, and none combines all three elements this project is concerned with: reliable big urban heat data, situated data, and a visualization that makes the combination legible and usable to a non-expert user. The analytical platforms (Atlas Leefomgeving, ShadeMap, Meteoblue, Klimaateffectatlas) supply the first element without the other two. Hotterdam and Transform Transport supply the first and a more situated second element, but not the third: Hotterdam is delivered as a static report and atlas, and Transform Transport's interactive map presents modelled values and image-based indicators without an interpretive layer aimed at non-experts. Ongekendheet.nl supplies the first and third, but without the second, since its story is pre-authored and not built around a user's own site or observations. Morphocode Explorer and the three generic tools were not assessed against these elements: they were reviewed only for what they offer to the technical, interaction and visualization side of the prototype, and none is connected to urban heat data or to situated, human-scale data. This positions the research gap identified in Section 2.4 concretely within the current platform landscape, and directly motivates the design requirements developed in Section 4.3.

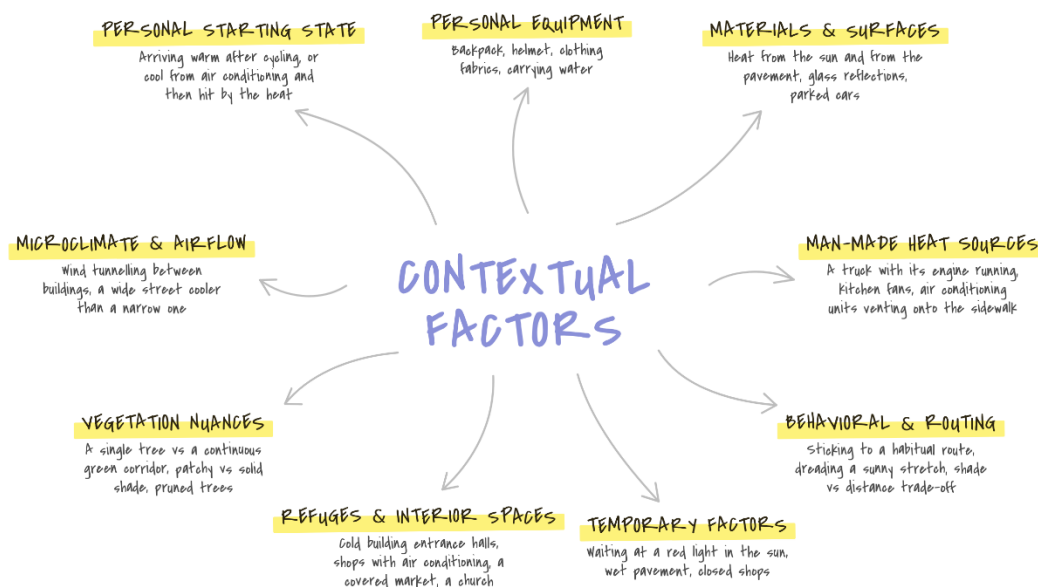
4.2 User Research Findings

Contextual Factors of Thermal Comfort

Across the fourteen thermal comfort walks conducted in Delft and Rome, a wide range of contextual factors emerged that shaped how participants experienced heat along an identical or near-identical route (Figure 12 summarizes these factors). The procedure used to derive these factors is described in Section 3.2 (Data Analysis). Many of these factors recurred independently in both cities, despite their very different climates and building typologies, suggesting that they are not incidental to one location but genuinely constitutive of how thermal comfort is experienced at street level. Others surfaced only in one city, pointing to context-specific nuances that a general model of urban heat would miss entirely. None of these factors, whether recurring or location-specific, is currently captured by the platforms reviewed in Section 3.1, all of which represent heat as a property of a location rather than of a moment, a body, or a decision. The factors below are organized thematically rather than by city, in order to make this pattern of overlap and divergence visible.

Figure 12

Overview of the nine contextual factors that shaped thermal comfort during the walks in Delft and Rome



Note. Own illustration, based on the thermal comfort walks.

Personal and physiological starting state

In both locations, participants' thermal state at the very start of the walk shaped their experience of the entire route, independent of the route itself. In Delft, participants who arrived by bike began the walk already warm, while others started from a neutral state, producing markedly different comfort readings of the same stretch of path (Delft, P1, P4, P6). The same pattern appeared in Rome in a sharper form: participants arriving by car with air conditioning or from an air-conditioned home began the walk cool, but experienced a more pronounced thermal shock upon starting it (Rome, P0, P7), while those arriving by scooter while wearing a helmet, or already sweating before leaving home, began hot (Rome, P8, P9). Several Rome participants also described peak summer heat as a constant, inescapable baseline unrelated to any specific location along the walk, rather than a condition tied to particular spots ("in summer there's never a moment when I'm not hot," P12). In Delft, a related but distinct factor was fatigue and monotony as a separate variable from temperature itself: long, straight stretches of the route were described as more uncomfortable even where they were partially shaded (Delft, P4).

Personal equipment and clothing

Clothing, equipment, and what participants happened to be carrying also shaped perceived heat independently of the ambient temperature. In Delft, this included the effect of wearing a backpack (Delft, P5); in Rome, participants specifically distinguished clothing materials, such as cotton compared with synthetic fabrics, as affecting comfort even under identical conditions (Rome, P10), and one participant described wearing a motorcycle helmet while waiting at a red light in full sun as substantially amplifying discomfort, an experience that occurred while arriving at the meeting point with the researcher (Rome, P9). Individual heat tolerance and prior acclimatization to the climate were also mentioned as shaping how the same objective temperature was experienced (Delft, P5). In Rome, carrying water was described not simply as hydration but as an active coping strategy deployed throughout the walk (Rome, P12).

Material and surface effects

Both cities showed a consistent “double exposure” effect, in which participants experienced heat both from direct sunlight and from heat radiating back up from hot pavement, independent of shade. In Delft, this was linked to concrete and asphalt surfaces, and additionally to windows and glass reflecting sunlight and amplifying heat locally, including from parked cars themselves acting as heat-absorbing and heat-reflecting mass in an open parking area (Delft, P0, P3). In Rome, the same underfoot effect was described directly (“the asphalt is boiling” P9), confirming that this is not specific to one material palette or climate but a general feature of paved urban surfaces exposed to direct sun.

Anthropogenic and man-made heat sources

A distinct category of localized, temporary heat sources tied to human activity rather than to the built environment or climate emerged in both cities. In Delft, one participant noted the intense heat while walking past a large truck parked with its engine running at the side of the road (Delft, P2). In Rome, this theme was considerably more developed: participants described restaurant and kitchen exhaust fans producing sudden, localized blasts of hot air strong enough to fill an entire section of street (Rome, P0, P10), and home air conditioning units exhausting hot air directly onto the sidewalk, in one case accompanied by an unpleasant smell that led the participant to cross the street entirely to avoid it, a multisensory rather than purely thermal discomfort (Rome, P10).

Microclimate and airflow

Wind and airflow, shaped by building geometry rather than by shade alone, were a recurring factor in both cities. In Delft, participants described wind tunneling between buildings that made certain shaded areas feel cooler than expected, as well as a lack of airflow in an enclosed square that participants attributed to the surrounding buildings’ geometry, and, conversely, greater perceived wind in more open areas without adjacent buildings (Delft, P0, P3, P4). In Rome, this translated into a comparison between street widths: a wider street (Corso Trieste) was consistently perceived as cooler than a narrower one (Via Chiana), independent of how much shade either provided (Rome, P7, P12). Rome participants additionally identified doorways and building entrance halls as acting as channels for cooler air reaching the street (Rome, P10, P11).

Vegetation nuances

In both cities, participants distinguished vegetation in ways more detailed than the binary “shaded or not” categories used by the reviewed platforms. In Delft, participants distinguished between a single isolated tree, described as negligible in effect or even, more strikingly, as “a vision in the desert” precisely because of its rarity, and a continuous corridor of vegetation, which had a substantial cooling effect; they also distinguished between patchy, broken shade and solid, continuous shade as producing different comfort outcomes even where a platform would classify both simply as shaded (Delft, P2, P3, P4, P6). In Rome, vegetation was additionally understood as a variable that changes over time and through human management: one participant noted that trees along the route appeared to have been recently pruned, visibly reducing the shade available compared to a few months earlier (Rome, P10), while another observed that flowerbeds had dried out and yellowed, no longer providing the cooling effect they previously had, framing vegetation health, not just vegetation presence, as relevant to comfort (Rome, P8). A further Rome participant described a sharp, binary experience between dense tree cover on one side of a street and none at all a block away, rather than a gradual transition (Rome, P9).

The single isolated tree in Delft, the one participants described as “a vision in the desert,” is also one of the clearest individual cases of the gap this project set out to address. The crossing between Michiel de Ruyterweg and Prins Bernhardlaan, where the tree stood during the walks, was not flagged as notable by any of the big data layers reviewed: their spatial resolution is too coarse to register the cooling effect of a single tree on a specific stretch of pavement. The relief it provided existed only in what participants expressed during the walk, invisible to the big data layer entirely (Delft, P1, P2). The case became more striking still after data collection ended: returning to the site after the summer, the researcher found that the tree had been removed. The prototype’s hover-lens for this point now shows a panoramic street view with no tree present, while the notes and images attached to it, collected only weeks earlier, describe the relief it once provided.

Refuges and interior spaces as cooling infrastructure

This theme emerged distinctly in Rome and was largely absent from the Delft data, plausibly reflecting differences in building typology and street-level commercial density between the two cities. Roman building entrance halls (atrii) were described independently during four walks as reliably cold shelters, especially when their doors were closed (Rome, P0, P8, P9, P12), and barred basement or cellar windows were noted as releasing a cool draft up to street level (Rome, P10, P12). Commercial spaces functioned similarly: a covered market full of refrigerators, ice, and ventilation acted as a passive cooling corridor even for participants who did not enter it (Rome, P8), and one participant described deliberately detouring into a shop with no intention of buying anything, purely to access air conditioning for a few minutes, describing the shock of stepping back outside as physically jarring (“hard to breathe,” Rome, P12). This behavior may also reflect an adaptation to the local climate: in a city that regularly experiences extended periods of extreme summer heat, briefly stepping into a shop purely to cool down appears to be a familiar, almost normalized coping strategy, whereas no equivalent behavior was observed or mentioned in Delft, where such heat is comparatively rare. Since all participants were Italian, this difference is less likely to reflect cultural background and more likely to reflect the heat conditions and built environment of each place, as well as participants’ everyday experience of living in each climate.

Temporary and contingent factors

Several factors emerged as tied to a specific, transient moment rather than to a fixed property of a location. In Delft, these included waiting for a traffic light to change while standing in direct sun, and a stretch of wet pavement that cooled a spot temporarily (Delft, P0, P5). The same red-light effect appeared independently in Rome (Rome, P9). Rome participants also described wet pavement, in this case from balconies being watered or from surfaces being washed down, as producing a similar temporary cooling effect, but explicitly framed this as a trade-off rather than a pure benefit, since it also increased humidity (Rome, P0, P7). A further contingent factor specific to Rome was the mismatch between a planned cooling strategy and unrelated schedules: one participant’s plan to cool down by stopping in shops failed because the shops happened to be closed during the midday hours of the walk (Rome, P10).

Behavioral and routing factors

Finally, in both cities, participants’ route and pace decisions were shaped by thermal considerations in ways that went beyond simply avoiding the sun. In Delft, several participants described sticking to a familiar route out of habit even when a cooler alternative existed, in one case explicitly unable to explain why (“I don’t know why, I always take this route,” P0, P4, P6), alongside anticipatory dread of an upcoming sunny stretch affecting mood and pace before it was even reached, and a strongly affective sense of relief on reaching shade (P4). In Rome, this extended to a heat-driven safety trade-off, where one participant crossed the street on a red light specifically because standing still in the sun felt worse than the small risk involved (P11), and to a conscious rejection of a known cooler route through a park because it added too much distance, an explicit shade-versus-distance trade-off (P9). Rome participants also described entering a church purely as thermal shelter, unrelated to any religious purpose, and staying on a particular side of the street specifically to end the walk near a gelato shop, turning the end of the walk into a planned heat-recovery ritual (Rome, P11). More generally, Rome participants described their route and pace decisions as improvised reactively in search of shade during the walk, rather than fixed in advance as a matter of habit, in contrast to the more habitual routing described in Delft (Rome, P7).

Platform Walkthrough: Delft

Following each thermal comfort walk in TU Delft campus, participants were shown the Atlas Leefomgeving platform and asked to compare three map layers, shade on bike and walking paths, urban heat island effect, and cooling effect of greenery and water, against what they had just experienced (analysis procedure in Section 3.2). Across the six Delft walkthroughs, a consistent pattern emerged: participants did not describe the platform's data as simply wrong, but as too general to capture the finer-grained, situated reality of their walk. Where the platform and lived experience aligned, it was generally on the more stable, slow-changing features of the environment; where they diverged, it was almost always around details that were highly localized, short-lived, or dependent on the specific time of day.

The **Shade on bike and walking paths** layer (Figure 13) produced the most direct comparisons, and the results were mixed. One participant found it broadly reliable, reasoning that shade “doesn’t change much over time,” and confirmed that the map’s indication of more shade on one side matched where they had walked (P4). This was the clearest case of alignment across all six interviews, and notably, it was justified by the participant themselves in terms of the feature’s relative temporal stability. Most other participants, however, described the shade layer as understating or misrepresenting what they had actually experienced. One participant reported that a stretch marked as having some shade on both sides had, in reality, no shade at all except for a single large tree (P1). Another described the alternation between sun and shade along the route as “a lot more detailed” than the map suggested, calling out a specific point marked as shaded where they had been “fully exposed,” and expressing uncertainty about whether the parking lot, the worst part of their walk, was marked as shaded at all (P2). A third participant went further, stating that “it’s not true that there is this much shade” near the start of the route, and that the map should show more shade later in the walk, near a set of bushes, and less at a point where it currently indicated shade on the wrong side of the street entirely (P3). Taken together, these accounts suggest that even the platform’s most literal and ostensibly objective layer, shade coverage, does not capture shade at the resolution participants actually experienced it: patchy, shifting within a few meters, and highly dependent on the exact line walked.

Figure 13

Atlas Leefomgeving, Shade on bike and walking paths layer for the Delft route



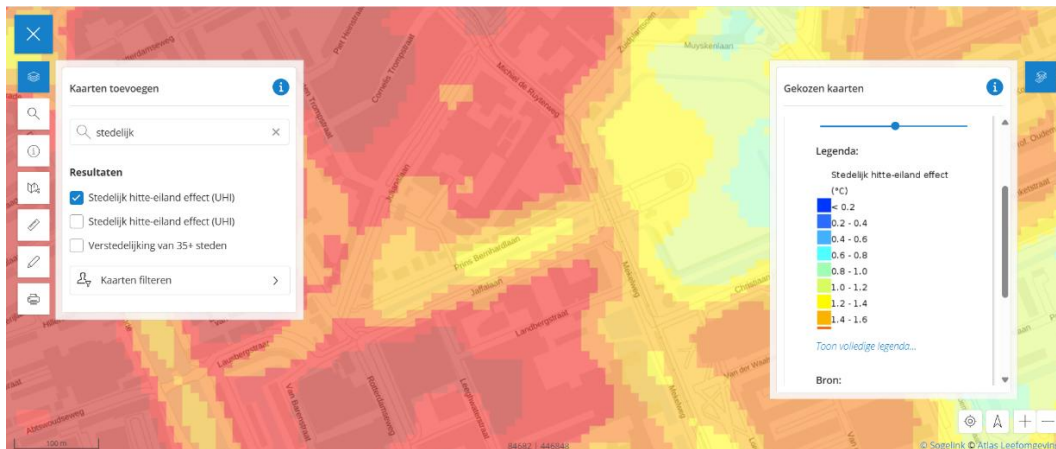
Note. Screenshot from Atlas Leefomgeving (n.d.), <https://www.atlasleefomgeving.nl>. Retrieved July 2026.

The **Urban heat island effect** layer (Figure 14) was described by one participant as the most intuitive of the three, but also as “a bit misleading” for that same reason: because it visually implies that a redder area is meaningfully hotter than an adjacent lighter one, when in the participant’s experience the difference in the field was negligible, and the map risked making them “much more worried than is warranted” about a stretch that, in practice, felt no different from its surroundings (P4). Separately, another participant questioned the layer’s basic logic, arguing that the platform’s classification of an “area” as hotter or cooler mattered far less to their comfort than the immediate presence or absence of shade at a specific point, and speculated that a location the map might read as cooler could still feel hotter in practice due to heat reflected off nearby walls (P6). Both comments point to the same underlying issue: the UHI layer aggregates

temperature over an area in a way that can flatten or misrepresent the sharp, localized swings in comfort that participants actually felt while walking.

Figure 14

Atlas Leefomgeving, Urban heat island effect layer for the Delft route

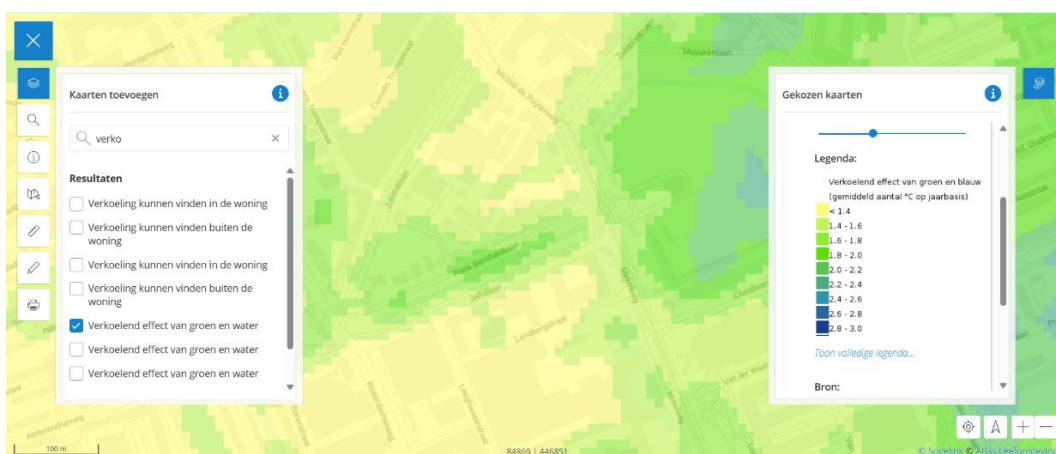


Note. Screenshot from Atlas Leefomgeving (n.d.), <https://www.atlasleefomgeving.nl>. Retrieved July 2026.

The **Cooling effect of greenery and water** layer (Figure 15) drew more measured responses. One participant found it broadly acceptable but suggested more green should be present in the map in the first section of the route (P3), while another person reported a greater amount of vegetation on the right side of a particular stretch, based on their own experience (P5). Another comment came from a participant who described one large tree near the end of the segment as a genuinely positive moment during the walk, offering noticeable shade and relief from the heat, yet this tree was not reflected at all in the map's cooling effect layer (P4). This suggests a disconnect between how the platform quantifies vegetation's cooling contribution and what is actually felt and valued at street level: a single tree can matter enormously to a pedestrian's lived experience while remaining invisible, or negligible, to a model built on big data. Notably, this same tree was removed a few weeks after the walk was conducted, a detail the researcher only noticed while revisiting the site later; this underscores how even a single significant vegetation feature can appear or disappear on a timescale the platform's data, static and infrequently updated, has no way of tracking.

Figure 15

Atlas Leefomgeving, Cooling effect of greenery and water layer for the Delft route



Note. Screenshot from Atlas Leefomgeving (n.d.), <https://www.atlasleefomgeving.nl>. Retrieved July 2026.

A recurring and more structural critique concerned the fact that the platform's layers represent a single fixed moment rather than current or continuously updated conditions, and, relatedly, that they cannot register short-lived, situational details that are not fixed properties of a location. One participant explicitly stated that having some kind of "live" data showing shadow hour by hour would be "much more reliable in terms of detail than a screenshot of a single moment" (P4) and another participant also commented on the same topic, claiming that he was not certain of the reliability of the data given the amount of time that had passed since the data on the platform was collected (P6). All these types of comments from participants indicate that the platform's data, however accurate at the moment it was captured, is experienced by users as dated and insufficiently responsive to how conditions actually vary hour to hour and day to day. This same structural limitation extends to temporary and situational features that are not just outdated but entirely absent from the platform by default: a large truck parked along the route, which one participant described as making that stretch noticeably hotter to pass, had no counterpart in the map's data, with the participant noting that the parking lot area was not marked as any warmer despite the truck's presence (P2). Wet pavement from someone watering nearby vegetation, and the increased humidity this produced, was similarly a purely situational detail with no possible representation in the reviewed layers (P5). One participant proposed, unprompted, that a useful tool would flag exactly this kind of temporary condition using an icon or photo, explicitly citing both the wet pavement and the parked truck as examples (Delft, P5). Wind and microclimatic airflow, described elsewhere in the walks as a wind-tunnel effect between buildings that made certain shaded spots feel cooler than expected, was likewise never mentioned by any participant as something reflected in the platform's data (Delft, P3).

Opportunities for Data Thickening

At the end of every interview, participants were asked to discuss with the researcher ways the platform's data could be enriched with more situated, human-generated information, offering an informal set of design directions independently of any prompt from the researcher.

A recurring idea was to make shade and heat data live and adjustable rather than fixed to a single modelled moment. Participants wanted to pick a specific hour or day, or see shadow hour by hour, so that the map would reflect the actual time of walking, since a static snapshot felt unreliable given how much conditions shift between morning and afternoon (P1, P4).

Closely related was a strong preference for crowdsourced feedback from other users. Participants imagined shady or sunny segments carrying photos and short notes left by previous walkers, to be tapped when deciding which way to go (P2, P4), or a Waze-style interaction in which users drop a pin and tap a symbol to flag heat or shade in real time, with the density of reports indicating where interventions such as tree planting might be needed (P6). One participant also proposed that users be able to mark temporary conditions, such as wet pavement or a parked vehicle, through a comment or picture, since these occur unpredictably and are not captured by the map (P5). Another suggested a timeline to compare current conditions with previous years, as trees grow and buildings are built or demolished, similar to Google Street View's historical imagery (P3).

Participants also proposed changes to route planning. They suggested "fastest vs. coolest" route options modelled on Google Maps' "fastest vs. eco" toggle, so that travel time could be weighed against thermal comfort (P2, P4). One participant also raised personalizing recommendations based on physical characteristics or logged preferences, while flagging the ethics of collecting personal physical data and uncertainty about how far to trust an algorithm making thermally informed decisions on one's behalf (P4).

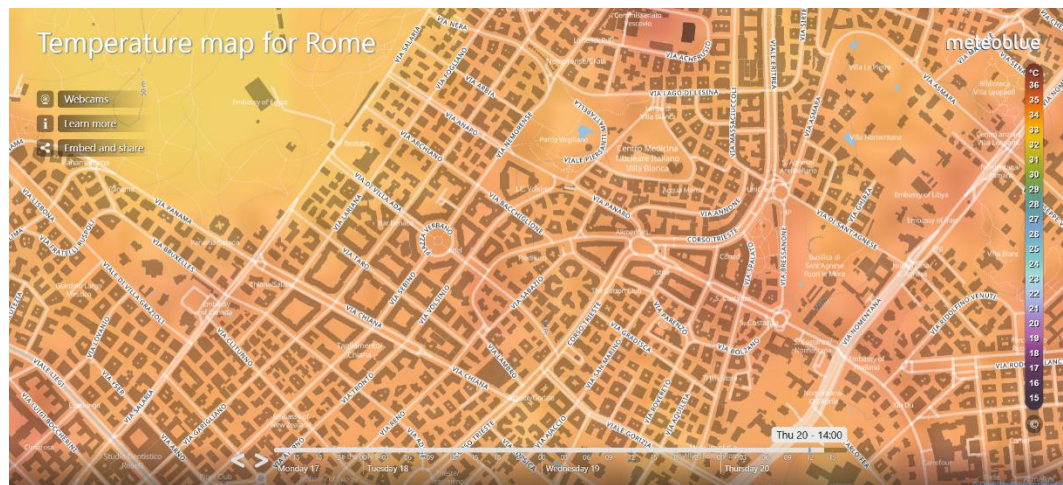
Platform Walkthrough: Rome

Because the Rome walkthroughs were conducted as a lighter, open-question comparison rather than the full three-layer walkthrough used in Delft, participants' feedback was less granular, but it converged on largely the same conclusion: the platforms captured the broad, citywide pattern of extreme heat but not the sharp, localized swings in comfort that participants had just experienced. Several participants noted, independently and in similar terms, that the Meteoblue

temperature map (Figure 16) appeared almost uniformly orange across the entire route, and that this uniformity made it difficult to relate the map back to any specific moment of their walk (P7, P8, P12).

Figure 16

Meteoblue City Climate, Urban Temperature layer for the Rome route



Note. Screenshot from Meteoblue City Climate (n.d.),

<https://www.meteoblue.com/en/weather/widget/setupheatmap>. Retrieved August 2026.

Where the map did register a meaningful difference, participants generally found it plausible but understated. Piazza Verbano, an open square without shade, was shown as slightly darker than its surroundings, and one participant confirmed this matched their experience of it as the most uncomfortable point of the walk (P9). Another participant who crossed the same square, however, felt the map should have marked it more severely, arguing that the newly planted trees there were still too young to provide meaningful shade despite appearing on the map (P11).

The comparison raised most consistently across the Rome interviews concerned Via Chiana and Corso Trieste, which were shown as the same shade of orange on the temperature map despite participants describing them as clearly different in comfort: Corso Trieste was repeatedly described as cooler, wider, and better ventilated, while Via Chiana, particularly its lower, treeless stretch, felt distinctly hotter (P7, P8, P10, P11, P12). As in Delft, this points to the map's area-based aggregation flattening street-level contrasts that participants experienced as sharp and immediate.

According to the participants, ShadeMap seemed somewhat more relatable, but it contained some inaccuracies or outdated information: one participant noted that a stretch of recently pruned trees still appeared shaded on the map, even though the thinned canopy no longer provided meaningful shade (P10), while another made a similar observation, pointing out that dried and yellowed vegetation near the end of the route (Piazza Istria) still registered as a shade feature on the map despite no longer functioning as one (P8).

Beyond these two layers, participants repeatedly and independently pointed to the same category of missing information already surfaced in Delft: transient, small-scale sources of heat or cooling that they described as inherently too specific for a map of this kind to capture. These included the restaurant exhaust fans and cooling breeze from home air conditioning units (P0, P9, P10), the passive cooling of the covered indoor market and of building entrance halls (P8, P9, P12), the momentary relief of stepping into the Church of San Saturnino (P11), and the wet pavement from watered balconies (P7). Several participants used near-identical language to describe why these moments could not appear on the platforms, calling them "too small and specific" to be picked up by a map built at this scale (P10, P12).

Delft-Rome comparison

Several patterns recur across both cities. Starting thermal state follows the same logic in both locations, route-dependent in Delft, where cyclists began already warm while others started neutral (Delft, P1, P4, P6), but more extreme in Rome, where car/AC and scooter starts produced a pronounced thermal shock and peak heat was described as a constant

baseline (Rome, P0, P7-P9, P12), plausibly reflecting the wider gap between ambient and indoor/vehicle temperatures (34-37°C vs 26-30°C). Clothing and equipment followed a similar asymmetry: noted only briefly in Delft (backpack, heat tolerance, P5), but elaborated in Rome through fabric type, a helmet worn in full sun, and water as an active coping strategy (Rome, P9, P10, P12).

Material and surface effects were the most consistent finding across both cities, radiant heat from concrete, asphalt, and glass was confirmed independently (Delft, P0, P3; Rome, P9). Anthropogenic heat sources, by contrast, were far more developed in Rome, restaurant exhaust and venting AC units (Rome, P0, P10) versus a single idling truck in Delft (Delft, P2), probably due to the higher concentration of commercial activities on the ground floor in Rome compared to Delft.

Microclimate/airflow and vegetation nuance shared the same underlying mechanisms across cities but surfaced through different vocabulary: wind-tunneling and enclosed squares in Delft versus street-width comparisons and entrance-hall drafts in Rome (Delft, P0, P3, P4; Rome, P7, P10-P12); and a shared tree/corridor distinction in both, extended in Rome to a temporal, managed dimension (recent pruning, dried flowerbeds; Rome, P8-P10).

Refuges and interior cooling were a prominent theme in Rome (entrance halls, basements, markets, deliberate AC detours; Rome, P0, P8-P12) but nearly absent in Delft, likely reflecting building typology differences, though the participants' familiarity with the Rome site may also have shaped this. Contingent/temporary factors converged strongly (red lights, wet pavement) in both cities, with Rome adding a more critical, trade-off-aware framing (added humidity, closed shops; Rome, P0, P7, P9, P10).

The clearest divergence was behavioral routing: habitual and unreflective in Delft versus actively, reactively negotiated in Rome, more likely a function of differing heat severity during data collection than a cultural difference. Platform walkthroughs differed by design (full three-layer protocol in Delft vs. lighter open-question format in Rome), yet converged on the same core critique: area-based aggregation flattens street-level contrast, arguably the study's strongest evidence for this problem's generality. Finally, sample differences (recruitment pool, researcher familiarity, short routes) qualify the comparison overall and are discussed further in Section 6.3.

4.3 Design Requirements

The findings from the platform review and user research presented above translate into four interconnected clusters of design requirements: how data should be integrated, how it should be made interpretable, what level of detail it should operate at, and what role generative AI should play in this project.

Taken together, the literature review, platform review, and user research converge on a consistent picture: existing tools for urban heat data are technically capable but interpretively thin, while the ethnographic walks surfaced precisely the thick, contextual data that this thinness leaves out. This section translates that combined evidence into the design requirements that inform the concept and prototype development described in Chapter 5.

1. Data Integration: Thickening Big Data with Contextual Data

The core requirement of the prototype is to combine big urban heat data with contextual data, rather than presenting either in isolation, following the thickening logic established in the literature (Mortati & Cautela, 2025; Adler-Nissen et al., 2021). This translates into the following concrete requirements:

- The tool must integrate quantitative urban heat data with a second, thick data layer capturing lived experience, rather than presenting quantitative layers on their own, as none of the four analytical platforms reviewed (Atlas Leefomgeving, ShadeMap, Meteoblue, Klimaateffectatlas) offer this (Platform Review Findings, 4.1).
- The tool must be able to register temporary, human-scale heat sources tied to a specific moment rather than a fixed property of a location, through crowdsourced, photo- or note-based contributions from users. None of these transient sources appear in any reviewed platform's data (Delft, P2, P5; Rome, P0, P9, P10), and the

crowdsourced format was proposed independently by multiple participants using a “Waze-style” analogy (Delft, P2, P4, P6).

2. Interpretive Support and Visual Communication

Beyond integrating two data types, the tool must support the interpretive step that current platforms leave entirely to the user, by presenting the combined data in a form that conveys meaning rather than only values (Sharma et al., 2014; Bhatia, 2014). The judgment itself remains with the user, in line with the intent to frame interpretation rather than automate it (Section 1.3).

- The tool must present big and thick data together in a visualization that shows what the data implies for a specific site, through visualization and contextual data rather than raw values alone, instead of adding another analytical layer that still requires users to draw their own conclusions. This addresses the gap identified across the analytical platforms reviewed (Section 4.1; Section 1.2).
- The visualization must be grounded in the user’s own site and observations, and not in a fixed, pre-authored scenario. This addresses the limitation of Ongekendheet.nl, the only platform reviewed that makes climate data legible through a story, but at the cost of adaptability (Section 4.1).
- The tool should explain thermal conditions through visible, human-scale features, communicated through pictures and a pedestrian-level view rather than only abstract modelled values such as PET or UHI intensity. This follows Transform Transport’s pedestrian-eye approach and the participants’ own vocabulary during the walks (Sections 4.1 and 4.2).

3. Detail and Usability

A recurring finding across both the platform review and the user research is that existing tools aggregate heat data at a spatial resolution too coarse to capture how thermal comfort is actually experienced at street level.

- The tool must resolve the area-based aggregation problem that caused participants to perceive materially different streets as visually identical on existing maps, and caused the UHI layer to be described as “misleading” for implying meaningful differences where none were felt (Delft, P6; Rome, P7, P8, P10, P11, P12), by operating at street level rather than zone level.
- The tool must remain usable by non-expert users without GIS or data-science expertise, extending the accessibility already achieved by Atlas Leefomgeving into the interpretive layer that it currently lacks (Problem Statement, 1.2; Platform Review Findings, 4.1).

4. Role of Generative AI

Generative AI is used in this project to build the prototype, not to interpret the data or make it meaningful for the end user. This separates two uses of AI: as part of the prototype’s development process, and as a feature the user interacts with inside the prototype.

- The tool must not rely on AI to interpret the combined data or decide what it means. It should present the big and thick data together and leave the judgment to the user, in line with the literature’s concern that automated, “black box” analysis undermines trust and cannot fully replace human judgment (Rathod, 2023; Sun & Scanlon, 2019; Section 2.2). The user research points the same way: one of the Delft participants questioned how far to trust an algorithm making thermally informed decisions on their behalf (Section 4.2).
- Whether the prototype should also include a user-facing AI feature is not assumed at this stage. It was therefore tested during the prototype evaluation (Section 5.2).

5. PROTOTYPING

5.1 Concept and Prototype Development

From literature to sketches

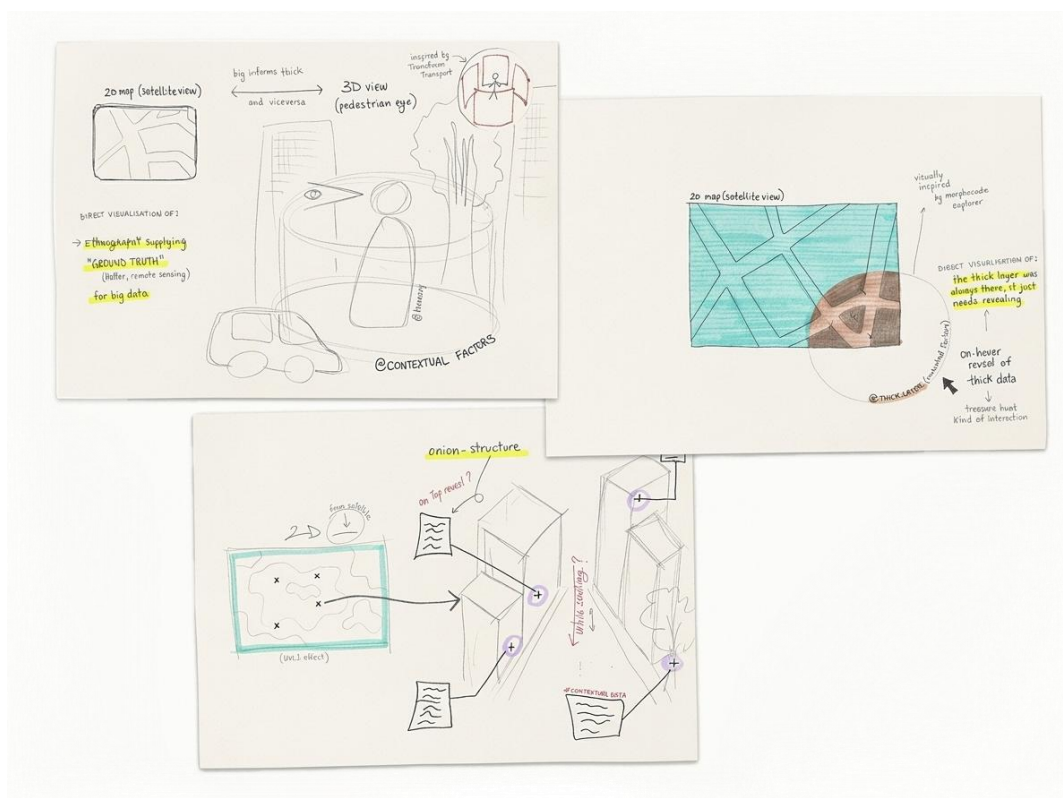
Concept development and prototyping did not happen in sequence but largely in parallel, together with user testing: refining the concept meant testing what vibe coding tools could actually build, testing those tools shaped which parts of the concept were worth pursuing further, and user testing of each iteration then fed back into how the prototype was refined.

The starting point for concept development and prototyping was the thickening methods reviewed in Section 2.3. **Ground-truthing**, in which ethnography supplies a direct, on-the-ground check of what big data is really capturing (Bjerre-Nielsen & Glavind, 2022), the **“twin-move”** described by Adler-Nissen et al. (2021), of making big data thick by returning to where it was produced and making thick data big by using quantitative checks to flag where its meaning is unclear, and Mortati and Cautela’s (2025) **“onion-structured”** model, in which big and thick data are layered rather than merged, each adding a further degree of contextual depth without replacing the one beneath it, were **translated visually** through hand sketches (Figure 17). This was a way of exploring how a map-based tool could hold both the quantitative layer from platforms like the Atlas Leefomgeving and the contextual layer collected during the thermal comfort walks, without treating either as subordinate to the other, or losing the layers in between.

Existing platforms also shaped specific interactions of the digital prototype: the pedestrian eye-view was inspired by Transform Transport, an approach carried over from a different domain than urban heat data (Section 3.1), and the hover interaction was inspired by Morphocode Explorer platform.

Figure 17

Paper sketches of the first design concept iteration for the thickening prototype



Note. Hand-drawn by the researcher on paper.

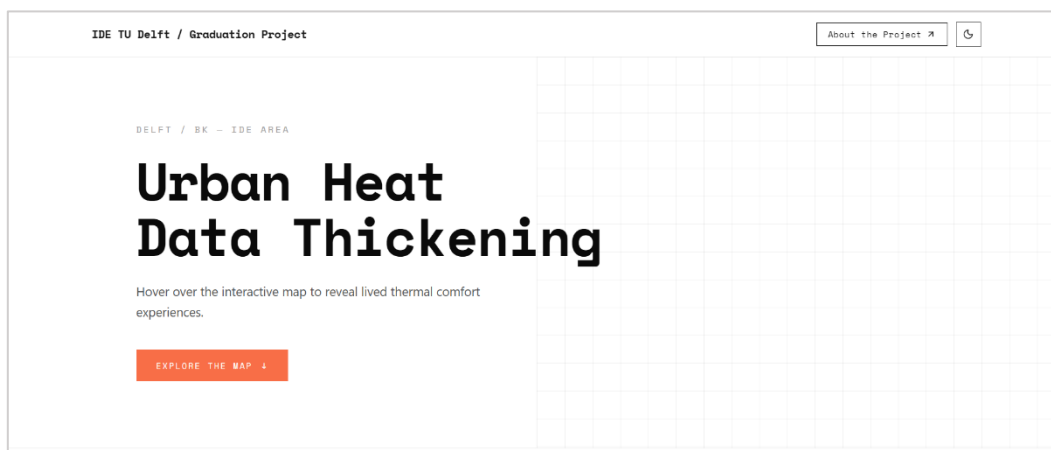
Prototype V1

To move from sketches to something testable, Claude was used to draft a PRD (Product Requirements Document) for **Google AI Studio**, based on the thesis report written up to that point. This PRD was revised row by row by the researcher before being submitted to Google AI Studio. The initial build worked to some extent: it combined the big and thick data layers as prompted, though it still lacked some of the more complex features envisioned for the final tool, such as a 3D view and the big data layer for the map, and needed further refinement on the visual style and user interactions.

Building on this, a **hover effect** was attempted that would reveal contextual factors directly on the map as the user moved their cursor over it, inspired by the Morphocode Explorer interface. This did not work in Google AI Studio. To explore whether another tool would handle the interaction better, Figma Make was tested in parallel: it proved easy to edit directly, but less capable of handling more complex functionality that required an API key, which limited its usefulness for a data-driven prototype like this one. Returning to Google AI Studio with a more detailed prompt, the hover effect was rebuilt and, after some refinement, worked as intended.

The resulting prototype opens on a homepage that introduces the project and invites the visitor to scroll down into the interactive map; in the top right corner, it also provides a light/dark mode toggle and a link to the TU Delft repository where the final graduation report will be published (Figure 18).

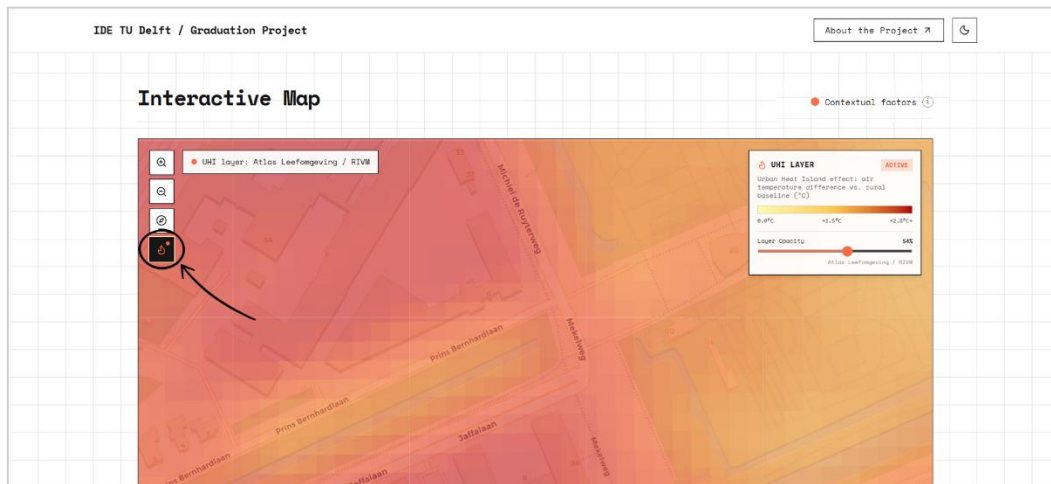
Figure 18
First version of the platform homepage



Note. Screenshot from the digital prototype, <https://thickening-prototype-3.ai.studio/>.

Below this, the prototype is structured as a single-page, map-based tool organized as a set of layered representations, moving from the most aggregated to the most situated and following the **“onion-structured”** model of thickening described by Mortati and Cautela (2025), in which each representation adds a further degree of **contextual depth** without replacing the one beneath it. At the base sits a 2D satellite map centered on Delft route area (Faculty of Architecture to IDE), onto which the first of these layers, an Urban Heat Island (UHI) layer sourced from Atlas Leefomgeving, can be turned on to overlay the basemap (Figure 19).

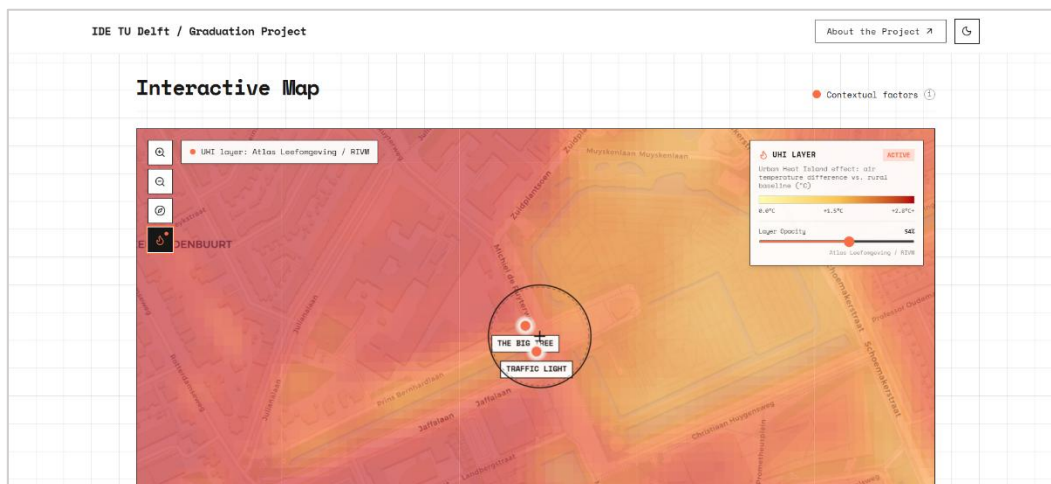
Figure 19
Toggleable Urban Heat Island (UHI) layer on the Interactive Map



Note. Annotated screenshot from the digital prototype, <https://thickening-prototype-3.ai.studio/>.

The contextual layer is revealed through a hover interaction: moving the cursor across the map surfaces a set of dots corresponding to the **contextual factors** collected during the thermal comfort walks, such as the “Big Tree” and the “Traffic Light,” located on their specific locations (Figure 20).

Figure 20
Hover effect revealing the contextual factors on the Interactive Map

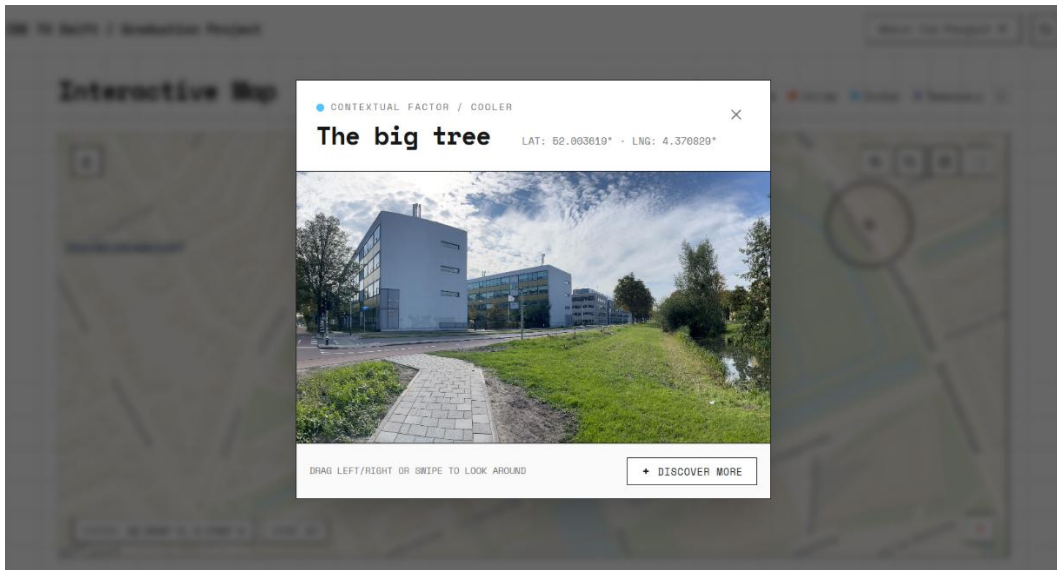


Note. Screenshot from the digital prototype, <https://thickening-prototype-3.ai.studio/>.

Clicking on a dot moves the visitor from the map into a street-level panorama of that location, where further notes, quotes, and images from the walks can be expanded alongside the image, surfacing contextual detail about the thermal comfort of that spot (Figures 21 and 22). This operationalizes the “**ground truth**” role that ethnographic data is argued to play alongside big data (Bjerre-Nielsen & Glavind, 2022); Section 6.1 discusses this link, and the prototype’s relation to the broader thickening literature, in more detail.

Figure 21

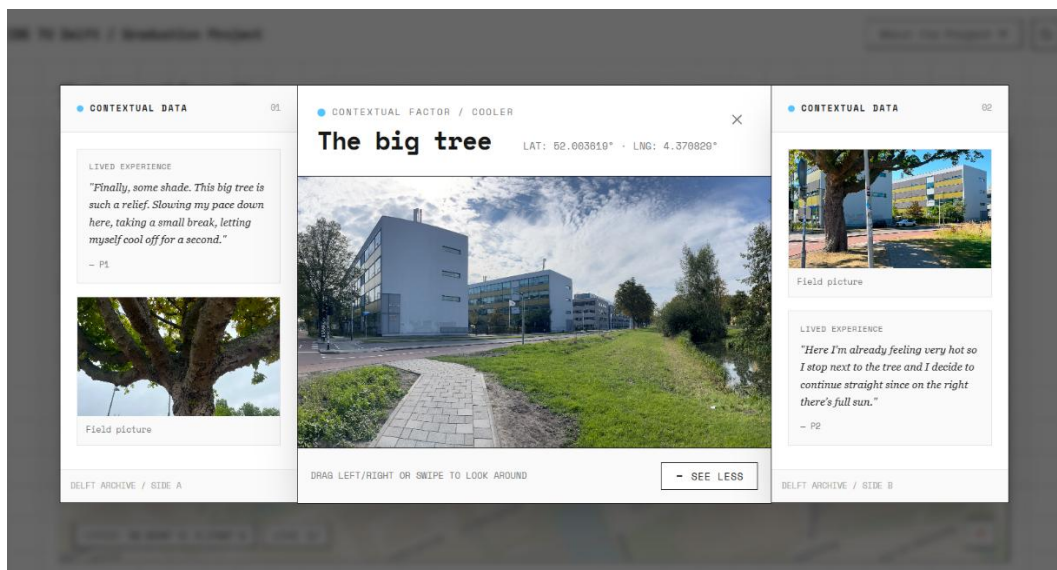
Pop-up window with pedestrian view of a spot on the map



Note. Screenshot from the digital prototype, <https://thickening-prototype-3.ai.studio/>.

Figure 22

Pop-up window with contextual details about a spot on the map



Note. Screenshot from the digital prototype, <https://thickening-prototype-3.ai.studio/>.

5.2 Prototype Evaluation

The prototype was evaluated in three rounds with six participants in total. In the first round (V1), it was tested remotely in a think-aloud session with one participant from the Rome thermal comfort walks, and presented in a walkthrough to the two thesis supervisors. The second round (V2) was a structured think-aloud session with one participant from the Delft walks. The third round (V3) involved two new participants, non-expert master's students who had not taken part in the walks and were unfamiliar with the project beyond a brief introduction.

Prototype V1: First Evaluation

The prototype was first tested remotely with one of the participants from the Rome thermal comfort walks, in a **think-aloud session**. This test surfaced two findings that would later be echoed by the supervisors: the participant (a non-expert user) needed no prompting from the designer to discover the hover interaction, moving the cursor across the map and finding the contextual points on their own, but struggled with the platform's vocabulary, confirming that terms such as thickening were not self-explanatory on first encounter.

The prototype was then tested informally during a meeting with the thesis supervisors, where it was presented as a **walkthrough** rather than a moderated user test. At this stage, each contextual factor already opened its own street-view scene, photos, and notes, but all points shared the same visual style: an orange dot, revealed through the hover-lens. The feedback gathered at this meeting falls into two areas: how the contextual layer communicates divergence from the big data layer, and how accessible the prototype is to a non-expert audience.

The supervisors noted that showing every contextual factor in the same color flattens a distinction the underlying data already makes: some points add more nuances to what the UHI layer shows, while others actively contradict it. The big tree from Delft activities, for instance, sits in an area the UHI layer marks as consistently red, yet participants reported feeling relief from the heat there, a divergence the current dot color does nothing to surface. Their suggestion was to categorize contextual factors and assign each category a distinct color, accompanied by a legend next to the map, so that a point's color communicates how it relates to the big data layer. This treats **color** as part of the **thickening** itself, not just as a decoration: as argued in Section 2.3, visualization is not a neutral layer applied once thickening is complete, but part of the thickening process itself, and encoding divergence directly into color would make that process, rather than just its content, visible on the map.

The second point concerned the prototype's accessibility to **non-expert users**, the intended audience defined in Section 1.2, echoing what the remote think-aloud test had already surfaced. The supervisors observed that the platform currently assumes some familiarity with the project's own vocabulary, including terms such as thickening, without explaining them on the interface itself. Their recommendation was to adjust the tone of the platform to be more understandable on first encounter, for instance by expanding the homepage to introduce the project and its key terms in plain language before the visitor reaches the map, rather than relying on the visitor to already understand what thickening, or a contextual factor, means.

Prototype V2: Second Evaluation

In response to the first point raised during the supervisors' meeting, each contextual factor was assigned to one of five categories, rather than displayed as uniform orange dots. The categories were developed by the researcher, building on the grouping of contextual factors described in Section 3.2. From the Delft walks, only the factors related to the UHI layer were selected, leaving out those that referred to the other two layers shown in the platform walkthrough (shade and cooling effect of greenery and water), which gave the eleven points in Table 3. Each point was compared with the layer's reading at its location and with what participants said about it in the platform walkthrough.

Four categories are defined by a point's relationship to the UHI big data layer. A factor adds nuance when the layer is too coarse to capture that level of detail. It is marked hotter or cooler when it contradicts the layer's reading, and temporary when it is not a fixed property of the location but something that happened once and may happen again. Since the layer shows area-level heat island intensity rather than street-level comfort, these categories work as signals about where to look more closely, not as measurements.

The fifth category, opportunity, works differently: instead of relating a point to the layer, it marks a spot where thermal comfort could be improved with an intervention such as greenery, shade, or shelter. It is based on the Rome findings, such as the exposed Piazza Verbano, where young trees still give little shade, and the treeless stretch of Via Chiana, and on a Delft participant's idea of showing where interventions like tree planting are needed (P6). It would be particularly valuable for residents, who could report what it is like to live on a specific street, and for urban planners and local authorities, who could act directly on that feedback. Because no point on the Delft route corresponds to it, the category is available in the legend and in the "Add contextual factor" panel, but no point in Table 3 uses it (Section 7.1).

Table 3.

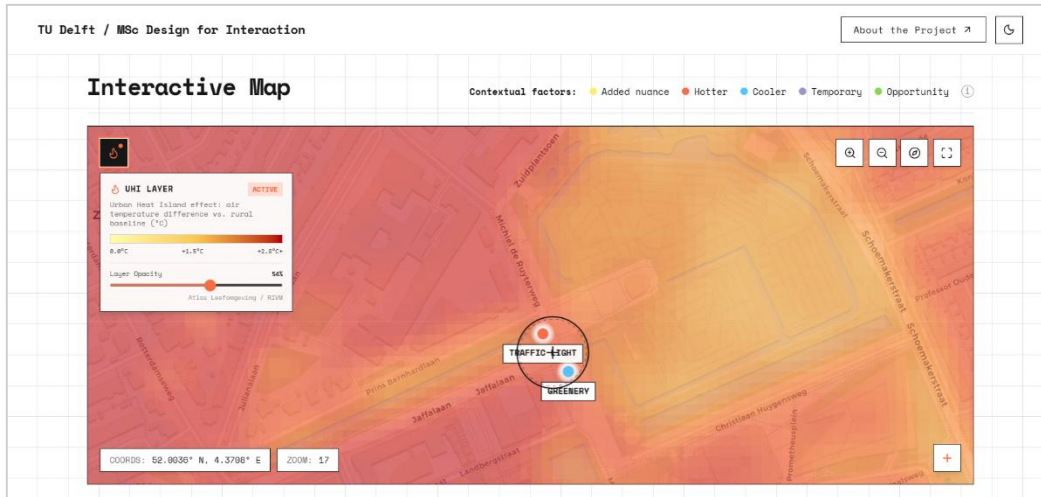
Categorization of contextual factors on the Delft route by their relationship to the UHI big data layer.

Contextual factor	Category	Color tag	Mentioned by
Sun/shade split	Added nuance	#FFF375	P0; P3; P5
Patchy vegetation	Added nuance	#FFF375	P2; P3; P6
Traffic light	Hotter	#FF7256	P0; P5
Parking lot	Hotter	#FF7256	P0; P3
IDE square	Hotter	#FF7256	P0; P2
The big tree	Cooler	#46C1FF	P1; P2
Bike parking	Cooler	#46C1FF	P2
Shaded stretch	Cooler	#46C1FF	P4
Greenery	Cooler	#46C1FF	P2, P5
Parked truck	Temporary	#A292CA	P2
Wet floor	Temporary	#A292CA	P5

Note. A fifth category, Opportunity (#7ED957), is included in the prototype but is not yet assigned to any Delft point (see text).

Figure 23

Categorization of contextual factors, translated visually in the digital prototype



Note. Screenshot from the digital prototype, <https://thickening-prototype-3.ai.studio/>.

This iterated version of the prototype, now incorporating the color-coding and legend described above, was tested with another participant, from the Delft thermal comfort walk, in a **structured think-aloud session** (see Appendix D, User Testing Protocol). The session began with free exploration of the homepage and map, without guidance, to test whether the user could make sense of the platform independently; the user was then guided to three contextual points partially drawn from their own walk: the shaded stretch near the IDE building, the sun/shade split, and the big tree; for each, they were asked what the point's color suggested before and after clicking it; a legend check followed, asking the participant to explain it in their own words; the session closed by asking what the prototype had added to their understanding of the data, and what remained unclear.

The homepage still used terms such as “thickening” without explanation, so this test reconfirmed the accessibility issue raised in the supervisors’ feedback and in the earlier remote think-aloud session: the participant needed the terminology explained. Three further usability issues emerged. The map was cut off at the top and bottom, limiting how much of it could be seen at once. The legend signaled that the dots carried different meanings but did not make clear enough what each color meant, so it needed additional explanation. The UHI layer toggle was not noticed during free exploration and had to be pointed out by the researcher, meaning the three-layer structure of the prototype was not self-evident on first encounter.

The **big tree spot** first caused confusion: the participant could not reconcile the point’s label with the panoramic street view shown, which contained no tree. Only after opening the “Discover More” section, with the notes and photos collected during the walk, did they realize the tree had since been removed and had once provided noticeable relief from the heat along that stretch. This suggests that the mismatch, while unplanned, functioned productively: it made the participant actively reconcile two conflicting accounts of the same location rather than passively read one, without any instruction from the researcher.

Despite these usability gaps, once the categorization legend and UHI layer toggle had been explained, the participant was able to use the color-coded points meaningfully: hovering on the dots, they recognized where their own experience matched or diverged from what the big data layer displayed, producing exactly the kind of **error-guided, twin-move** recognition described in Sections 2.3 and 6.1. The participant confirmed that the thickening had helped them understand more about the context than the underlying heat map alone would have. This suggests that the categorization and color-coding successfully addressed the first point raised in the supervisors’ feedback, while the accessibility concerns raised across both rounds of testing remain to be addressed in the final testing (next section).

Prototype V3: Final Evaluation

In response to the accessibility concerns raised across both rounds of testing, four changes were made to the prototype.

The **homepage** was expanded into a short *scrollytelling* (a web design storytelling technique where content evolves, animates, or changes dynamically as a user scrolls down a page) sequence that introduces the project's key terms, including “thickening” and “big data,” in plain language before the visitor reaches the map, rather than assuming prior familiarity with the project's vocabulary (Figure 24). The **interactive map** was resized to always fit the screen, rather than being partially cropped as in the previous test, and a fullscreen toggle was added for a more immersive view (Figure 25). The **categorization legend** was made self-explanatory by adding a short explanation revealed on hovering each category, clarifying in place what each color means relative to the UHI layer, rather than requiring the researcher's explanation (Figure 26). Finally, the **UHI layer toggle** was made more noticeable through a short guided walkthrough that appears on first visit, pointing the visitor to the toggle and how to use the interactive map, making clear to the user how they should interact with it (Figure 27).

Figure 24

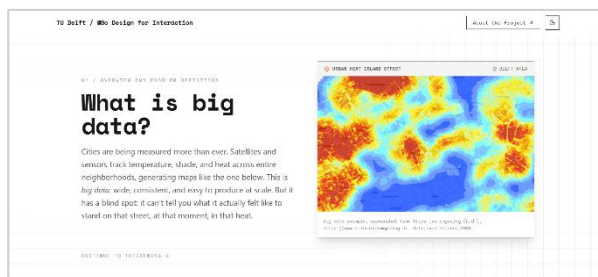


Figure 25

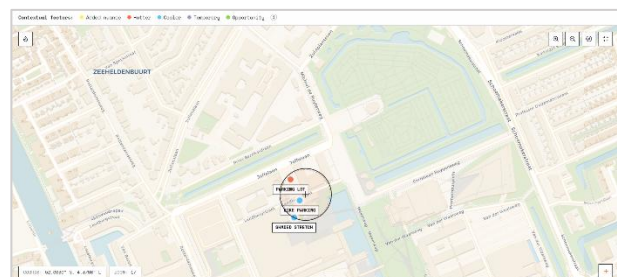


Figure 26

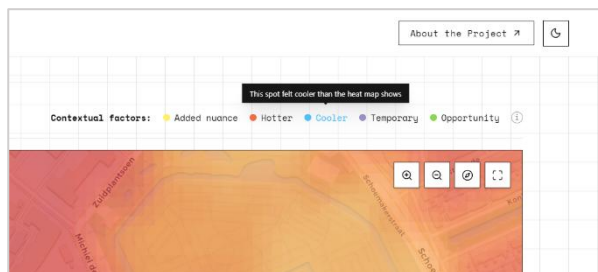
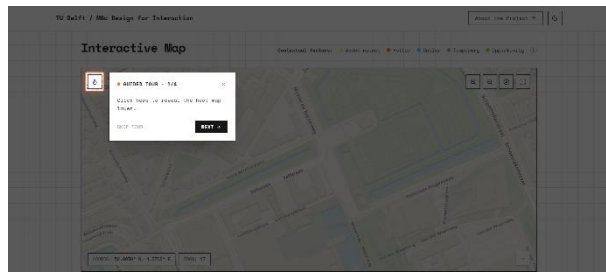


Figure 27



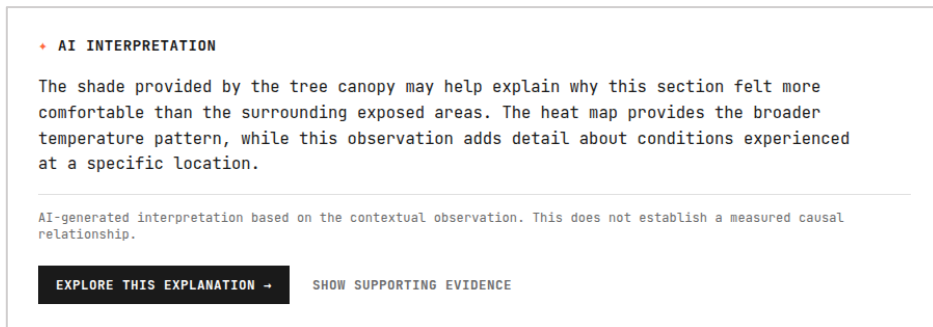
This iterated version of the prototype was tested with two participants who had not taken part in the thermal comfort walks and were unfamiliar with the project beyond a brief introduction, to check whether the accessibility changes held for genuinely new, non-expert users. Both correctly described the project's purpose and the relationship between the big data and contextual layers after exploring the homepage alone, discovered the contextual points unprompted, and, unlike the participant in Prototype V2 Testing, understood how to use the UHI layer toggle once the guided walkthrough pointed them to it. The big tree again produced a brief moment of confusion, resolved once both participants opened the additional notes and photos on their own, reproducing the same error-guided recognition reported in the previous test. In the legend check, both explained the four categories correctly in their own words (the fifth category, opportunity, was not tested, since no dot on the interactive map is assigned to it), with one noticing the legend through the guided walkthrough and the other unprompted, resolving the discoverability issues raised across the earlier rounds of testing.

This final round of testing also assessed the potential added value of an AI feature within the contextual factor popups: a parallel version of the prototype was shown to both participants, in which opening a point revealed an additional AI interpretation panel generating a short natural-language explanation of that point's relationship to the UHI layer (Figure 28). The two participants reacted differently. One questioned whether the connections it drew were genuinely

supported by the data rather than invented, echoing Rathod's (2023) finding that AI-driven automation cannot fully replace human judgment in interpreting subjective factors, while the other found the explanations useful but felt it made the experience more passive, as they were reading an interpretation rather than making the connections themselves. Both reactions support the project's earlier decision to keep interpretation with the user rather than the AI (Section 2.2). Both participants confirmed that the prototype helped them understand something about the locations that the heat map alone would not have shown, with their only further requests concerning scope, such as expanding the map to other locations or opening it to further contributions over time, rather than any difficulty using the prototype itself.

Figure 28

AI feature, providing interpretation of the data present in the interactive map



Note. Screenshot from the digital prototype, <https://thickening-prototype-3.ai.studio/>.

5.3 Final Prototype

The final version of the prototype consists of a scrollytelling homepage (Figure 29) that introduces the project and its key terms in plain language, addressing the accessibility concerns raised across testing (Section 5.2). It is followed by an interactive map of the Delft route, which overlays the toggleable UHI big data layer, adjustable in opacity, on the underlying street map. Color-coded contextual factor points, categorized by their relationship to the layer (Table 3), surface this comparison without the need to open each point. They are revealed through a hover-lens and can be inspected in a full-screen view. Opening a point reveals the street-view panorama, lived-experience quotes, and field pictures collected during the thermal comfort walks, the thick data that the big data layer alone cannot capture. A guided walkthrough introduces first-time visitors to these interactions, and a step-by-step visit is shown in the User Journey below (Figures 30 to 44). The working prototype can be accessed at <https://thickening-prototype-3.ai.studio/>.

Figure 29

Final version of the platform's home page, displayed in light mode.



Note. Screenshot from the digital prototype, <https://thickening-prototype-3.ai.studio/>.

User Journey

Figures 30 to 44 walk through a full visit to the final prototype, from the homepage to adding a new contextual factor, illustrating the interactions described above.

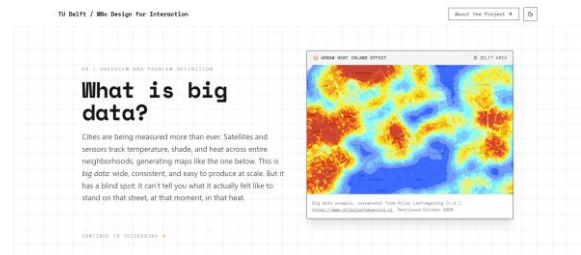
STEP 1 · Figure 30

Homepage, inviting the visitor to scroll into the project.



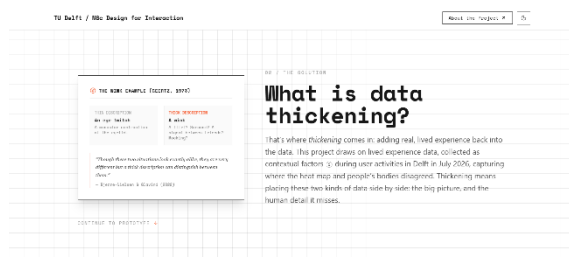
STEP 2 · Figure 31

First homepage section, introducing the concept of big data and its main gap.



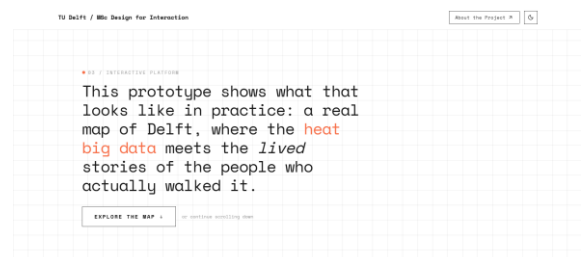
STEP 3 · Figure 32

Second homepage section, introducing the concept of data thickening.



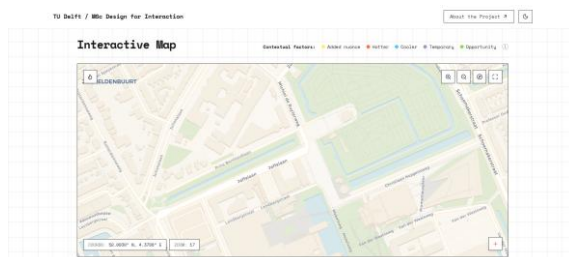
STEP 4 · Figure 33

Third homepage section, leading the visitor into the interactive map.



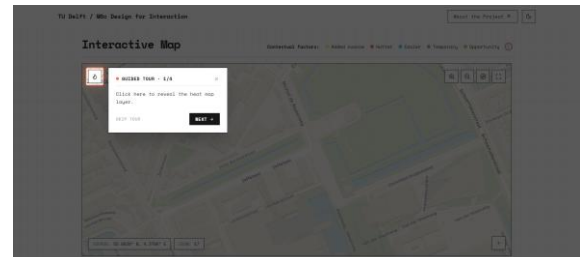
STEP 5 · Figure 34

Interactive map of the Delft route, with the contextual factor legend and UHI layer toggle.



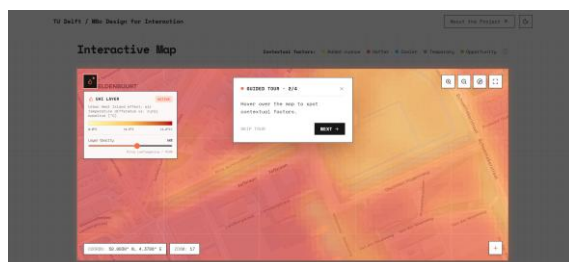
STEP 6 · Figure 35

First step of the guided walkthrough, pointing the visitor to the UHI layer toggle.



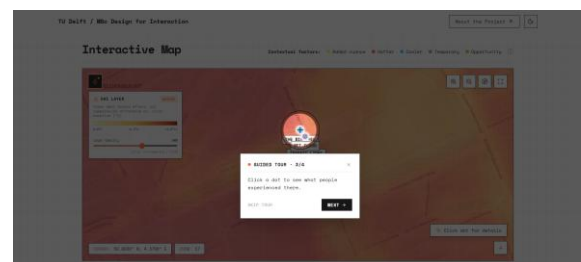
STEP 7 · Figure 36

Second step of the guided walkthrough, prompting the visitor to hover over the map.



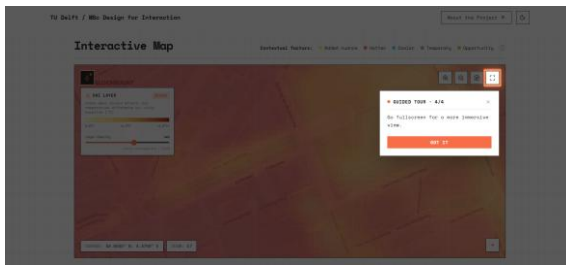
STEP 8 · Figure 37

Third step of the guided walkthrough, prompting the visitor to click a contextual factor point.



STEP 9 • Figure 38

Fourth step of the guided walkthrough, prompting the visitor to switch to fullscreen view.

**STEP 10 • Figure 39**

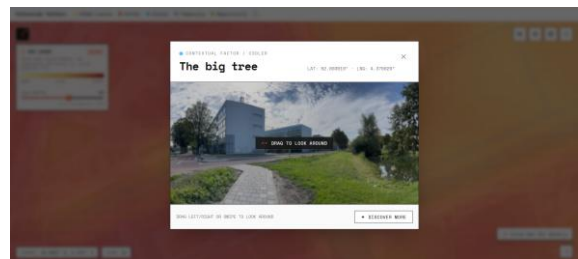
Fullscreen view of the interactive map, with the UHI layer active.

**STEP 11 • Figure 40**

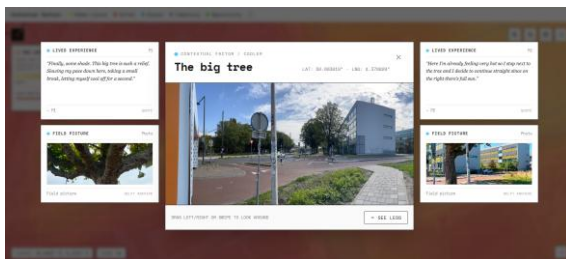
Hover-lens revealing a cluster of contextual factor points.

**STEP 12 • Figure 41**

A contextual factor point opened, showing its street-view panorama.

**STEP 13 • Figure 42**

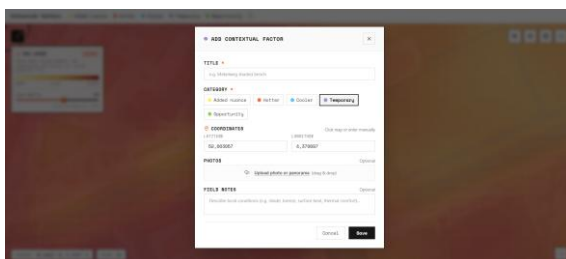
Expanded popup, showing lived-experience quotes and field pictures alongside the panorama.

**STEP 14 • Figure 43**

“+ Add Contextual Factor” button.

**STEP 15 • Figure 44**

“+ Add Contextual Factor” panel, where users can submit a new point with a title, category, coordinates, photo, and field notes.



Note. Screenshots from the digital prototype, <https://thickening-prototype-3.ai.studio/>.

6. DISCUSSION

6.1 Contribution to Research

The literature reviewed in Section 2.3 offers a body of concrete strategies for thickening big data, developed almost entirely outside climate or urban research, in fields such as digital sociology, anthropology and international relations. This project's contribution is not a new thickening strategy, but the translation of several existing ones, through visualization, into the interactions and layout of a single visualization-based prototype applied to urban heat. Table 4 maps this correspondence explicitly: the prototype's onion-structured layering operationalizes Mortati and Cautela's (2025) layered model of thickened data, and their framing of the designer as a bridge between thin and thick data, now extended to the end user. Its hover-lens applies Bjerre-Nielsen and Glavind's (2022) ground-truthing and Adler-Nissen et al.'s (2021) twin-move to flag where lived experience diverges from the big data layer, following the same error-guided attention logic Munk et al. (2022) describe for model misclassifications. The contextual factors it surfaces follow Albris et al.'s (2021) approach to structured fieldnotes, and function as thick description in Geertz's sense (1973, as cited in Bjerre-Nielsen & Glavind, 2022). Taken together, none of these individual moves is new to the literature; what is new is applying them together to a domain, urban heat, where, as far as the reviewed literature shows, this framework has not yet been systematically used, and doing so through an interactive visualization rather than a static report or dataset.

Table 4.

Correspondence between the prototype's design features and the thickening methods they draw on from the literature (Section 2.3).

Source	Existing Method	Prototype Feature	Novel Contribution
Mortati & Cautela (2025)	Designer as a bridge	The prototype itself, aimed at a non-data-expert audience.	Bridging moves from designer to end user.
Mortati & Cautela (2025)	Onion-structured layering	Base map / UHI layer / categories / hover layer / street view / notes	Treats the layered structure as a literal interaction design, not a metaphor.
Bornakke & Due (2018)	Big-Thick Blending	Two datasets visualized through one interaction, kept distinct rather than merged into a single value.	Operationalized at the level of visual and interaction design.
Adler-Nissen et al. (2021); Bjerre-Nielsen & Glavind (2022)	Ground-truthing and the twin-move	Hover-lens revealing contextual factors from the walks and flagging where they mismatch the big data layer.	Applied to urban heat big data, where it appears not to have been used before.
Munk et al. (2022)	Error-guided attention	Color-coded dots indicate where the data require closer attention.	Same method applied to a new domain, urban heat.
Albris et al. (2021)	Structured fieldnotes combined with follow-up interviews	Contextual factors (images and annotations) collected during the ethnographic walks.	Same method applied to a new domain, urban heat.
Bjerre-Nielsen & Glavind (2022)	Thick description	Street-view scenes paired with notes and photographs from the ethnographic research.	Explains why a location feels the way it does, rather than only reporting the data point (Geertz, 1973).

Returning to the platform review (Section 4.1), Table 5 shows that none of the platforms reviewed combined big data, thick data and a visualization that makes them meaningful to non-expert users, whereas the thickening prototype developed for this graduation project combines all three.

Table 5.

Platforms reviewed in Chapter 3 compared against the three elements of this project, with the prototype added in the last row.

Platform	Big data	Thick data	Visualization / meaning
Atlas Leefomgeving	✓	X	X
ShadeMap	✓	X	X
Meteoblue	✓	X	X
Klimaateffectatlas	✓	X	X
Hotterdam	✓	✓	X
Transform Transport	✓	✓	X
Ongekendheet.nl	✓	X	✓
Hugging Face	X	X	X
RAWGraphs	X	X	X
Claude	X	X	X
Thickening prototype (this project)	✓	✓	✓

Note. A tick means the platform provides the element, a cross means it does not. Morphocode Explorer is not included because it was reviewed only for its interaction design (Section 4.1). The ratings are based on the author's assessment of each platform.

6.2 Discussion of Findings

This section answers the research question, *how can urban heat big data be thickened with contextual knowledge and made meaningful through visualization for non-expert users?*, by working through its four sub-questions in turn.

SQ1: What contextual factors shape thermal comfort, and how are these currently addressed by existing platforms?

The thermal comfort walks conducted in Delft and Rome (Section 4.2) surfaced nine recurring themes, derived through an inductive grouping of the walk data (Section 3.2): personal and physiological starting state, personal equipment and clothing, material and surface effects, anthropogenic heat sources, microclimate and airflow, vegetation nuances, refuges and interior cooling infrastructure, temporary and contingent factors, and behavioral and routing factors. Several of these, the “double exposure” of direct and radiated heat, wind-tunneling between buildings, and the gap between a single isolated tree and a continuous shaded corridor, recurred independently in both cities despite their different climates and building typologies, suggesting they are not incidental but constitutive of how thermal comfort is experienced at street level. None of the platforms reviewed in Section 4.1 capture this layer. The four analytical platforms (Atlas Leefomgeving, ShadeMap, Meteoblue, Klimaateffectatlas) were found to be strong on data access but weak on interpretation and context, while the platforms that depart from this pattern each resolve only part of the gap: Hotterdam pairs big data with resident-level data but is delivered as a static report, Transform Transport adds a pedestrian-eye view but has no interpretive layer for non-experts, and Ongekendheet.nl closes the data-to-narrative gap only by removing the user’s own data entirely, offering a fixed, pre-authored scenario rather than one grounded in their own site. This confirms the thin/thick gap that motivated the project (Section 1.2) and establishes the specific contextual content that the first design requirement cluster in Section 4.3 was built to integrate.

SQ2: How can such contextual data be meaningfully integrated with quantitative urban heat data?

This project translates established thickening methods into the structure of a single interface (Section 5.1, elaborated further in Section 6.1). The prototype’s layered structure of base map, UHI layer, and hover-revealed contextual layer operationalizes Mortati and Cautela’s (2025) “onion-structured” model of thickened data. Its hover-lens applies Bjerre-Nielsen and Glavind’s (2022) ground-truthing and Adler-Nissen et al.’s (2021) twin-move to check what the big data layer does, and does not, capture at a given point. The contextual factors it surfaces, in the form of images and annotations collected during the walks, follow Albris et al.’s (2021) approach to structured fieldnotes and function as thick description in Geertz’s (1973) sense. Following Bornakke and Due’s (2018) Big-Thick Blending, the two datasets are kept distinct rather than merged into a single value, and are surfaced through one interaction rather than one composite reading. Thickening, in this project, is therefore not a new method but a new application: as far as the reviewed literature shows, the first translation of this specific combination of moves into the domain of urban heat, through an interactive visualization rather than a static report or dataset.

SQ3: How can visualization and generative AI support this integration for non-expert users?

Following the literature reviewed in Section 2.3, this project treats visualization not as a neutral step applied once thickening is complete, but as part of the thickening process itself. This is made concrete through the prototype’s five-category color-coding (Added nuance, Hotter, Cooler, Temporary and Opportunity; Section 5.2, Table 3), which applies Munk et al.’s (2022) error-guided attention logic: rather than smoothing over a mismatch between the big data layer and lived experience, the prototype marks it as a signal worth a closer look, surfaced through color before the user even opens a point.

Generative AI’s own contribution to this process was tested directly, as a parallel version of the prototype added an AI interpretation panel to each contextual factor point, generating a natural-language explanation of its relationship to the UHI layer. The two participants who saw this version were cautious about it: one questioned whether the connections drawn were genuinely supported by the underlying observations, and the other felt the explanations made the experience more passive (Section 5.2), echoing Rathod’s (2023) finding that AI-driven automation cannot fully replace human judgment when interpreting subjective factors. For these participants, then, generative AI’s contribution to making the data meaningful lies in building the interface itself (Section 5.1), rather than in interpreting the data on the user’s behalf.

SQ4: How do non-expert users interact with and evaluate the prototype?

Across the three rounds of testing described in Section 5.2, non-expert users engaged with the prototype's core interactions, discovering the hover-lens and contextual points largely unprompted. Four usability issues, however, had to be addressed before users could interact with the platform independently: unfamiliar vocabulary, a partially cropped map, a legend that did not explain itself, and the low visibility of the UHI layer toggle. Once these were resolved, participants with no prior exposure to the project, including the walks themselves, were able to interpret the color-coded categorization correctly in their own words, indicating that the thickened data could be read without researcher mediation.

A specific moment from the V2 and V3 sessions (Section 5.2) adds to this. When participants opened the “big tree” point, expecting to see the tree described in its own thick data, they were instead shown a panoramic view with no tree present, and only understood why after expanding the point's notes and photos to find that the tree had since been removed. This confusion, and the sense-making that followed it, shows the same twin-move and error-guided attention the prototype was designed to support (Section 6.1), just prompted by an unplanned mismatch between the data and the current state of the site rather than between the big and thick data layers themselves. It also points to a limitation of thickening itself: a contextual factor, once collected, does not stay accurate indefinitely. Thickening big data with contextual knowledge is, in this sense, not a one-time correction to a static gap but an ongoing process, since thick data can go out of date as readily as the conditions it describes change. A historical timeline, distinguishing when a contextual factor was collected from when it was observed to no longer hold, is proposed as future work for this reason (Section 7.1).

Beyond how participants used the prototype, the tests also suggest what makes combined big and thick data readable for non-experts. First, the two layers worked when they were kept distinct but placed on the same map, with the UHI layer toggleable and the contextual points categorized by how they diverge from it: participants could see where their own experience matched or contradicted the heat map, and, once the legend explained itself, described the four categories correctly in their own words. Second, thick data was most effective when revealed progressively (hover-lens, then street view, then notes and photos), which participants largely discovered unprompted and which let them check a point against its evidence. Third, this structure was not self-evident to non-expert users and needed support in the interface itself: key terms in plain language, explanations of the legend in place, and a guided walkthrough of the layers. Finally, participants' distrust of the AI interpretation suggests that the interpretive step is better supported by showing evidence users can inspect than by generating a conclusion for them. With only four participants besides the supervisors' feedback, these are indications rather than validated design principles (Section 6.3).

Overall Answer

Taken together, these findings suggest that urban heat big data can be thickened with contextual knowledge by translating established thickening moves (onion-structured layering, ground-truthing through the twin-move, error-guided attention, and structured fieldnotes as thick description) into the interactions of a single, layered visualization, rather than by inventing a new thickening method. The prototype demonstrates the feasibility of this approach: it is a working, publicly accessible application built on an open data layer and on data collected in the walks. The iterative testing (Section 5.2) indicates that non-expert users could interpret the thickened data independently once the usability issues raised across testing were resolved, and that, for them, the visualization needs to show where thick data diverges from big data and let users inspect the evidence themselves. This supports the desirability of the result, although it rests on a small sample. The generative AI feature, by contrast, did not clearly add value for the participants who saw it, as they preferred to engage with the underlying data themselves. The longer-term viability of the prototype remains open, as it depends on keeping the thick data up to date and on contributors beyond the researcher (Sections 6.3 and 7.1).

6.3 Limitations

The findings of this study should be interpreted in light of the following limitations.

Ethnographic Research

Sample size and route

The user research involved six participants in each city, which limits how far the findings can be generalized. A much larger sample, ideally of a hundred or more participants, would have made the patterns more representative, but this was not feasible within the scope of a graduation project. The results of the walks were also very consistent, both within and between the two cities. This consistency is encouraging, but it may partly result from the routes themselves: both were short, at less than 1 km, and may have led participants to a similar experience. Longer or more varied routes might have produced more divergent observations.

As all participants in both cities were Italian, the findings may also not represent how people from other cultural backgrounds experience and cope with heat, and differences between the two cities are more likely to reflect place and heat conditions than cultural background.

Heat and perception

Heat may also have affected what participants noticed. Accumulated heat stress can make it harder to notice changes in one's surroundings, an effect that Gallacher and Boehnke (2025) also observed in their own walks, where they shortened their route for this reason. This may be especially relevant in Rome, where recorded temperatures reached 34–37°C and one participant described summer heat as a constant baseline (Rome, P12). Some subtle differences in comfort along the route may therefore have gone unreported.

Proximity to the researcher

The Rome participants were recruited from the researcher's personal network, and they knew the project and the researcher well. They were also from outside the design and research field, and the platform comparison in Rome was kept lighter than in Delft. They may therefore have been less critical of the platform data and more inclined to rely on the researcher's suggestions, possibly even more than the Delft participants, who were themselves recruited from the researcher's own campus environment and may share a design perspective with her. Both groups may thus have been influenced by their closeness to the researcher, which could reduce the independence of their observations.

Platforms and timing

The two cities were compared against different platforms, since the Atlas Leefomgeving covers only the Netherlands: Meteoblue and ShadeMap were used in Rome instead. The comparison between the two cities is therefore not directly comparable. In addition, the walks took place on four and three days in each city (10, 14–16 July in Delft and 4–6 August in Rome), so the observations may partly reflect the specific conditions of those seven summer days.

Data analysis

The themes were identified and grouped by a single researcher, who also took part in the walks as a participant, and the same researcher assigned the categories used in the prototype (Section 5.2), so another analyst might have grouped or categorized the data differently. No inter-coder check was carried out.

Final Prototype

Sample size

The digital prototype was tested with only six users across all rounds of evaluation, including the two thesis supervisors, which limits how confidently the findings on usability and comprehension can be generalized. A larger sample would have made it possible to distinguish individual reactions, such as the specific usability issues raised by one participant, from patterns likely to hold across a broader user base. This was not feasible within the scope of a graduation project, given the time required to iterate the prototype between rounds of testing. The consistency observed across the last three participants, particularly the ability to interpret the color-coded categorization correctly once the accessibility issues were resolved, is encouraging, but should be treated as an initial indication rather than a validated result. The generative AI feature was tested in only one round with two participants, so its findings are indicative and are taken up in Section 7.1.

Crowdsourcing at scale

The prototype allows users to add their own contextual factors, but it was not tested with contributors beyond the researcher. All thick data in the final prototype comes from the thermal comfort walks, covering the route from the Faculty of Architecture building to the Faculty of Industrial Design Engineering in Delft. For the same reason, the opportunity category, which is based on the Rome findings, has no contextual factors assigned to it in the current prototype and was not tested with participants, so how useful it is and how users would apply it remain open (Section 7.1). A crowdsourced layer depends on a large and varied group of contributors to cover more locations, capture temporary conditions as they happen and keep older entries up to date. At this scale, the prototype shows how thick data can be contributed, but not whether people would contribute it or how reliable the result would be.

Language

All participants were Italian speakers, and the transcripts of the sessions in both cities were in Italian. They were translated into English with DeepL and edited for better comprehension. Translation and editing may have altered some of the nuance of participants' accounts, which matters in a study that relies on their own words. The prototype has a related limitation: it was designed to work with data in English only. This limits its use for people who describe their experiences in other languages, and it echoes a concern from the literature review: Rathod (2023) found that AI models struggle with feedback written in languages other than English and with nuanced cultural context (Section 2.2). Since contextual knowledge is often expressed in local languages, extending the prototype to other languages is a priority for future work (Section 7.1).

7. CONCLUSION

7.1 Future Work

Several directions follow directly from the limitations and observations discussed above. The clearest is to test the **prototype's contribution feature** (Figures 43 and 44) with a real community of users. The prototype already lets users add their own photos, notes and observations of temporary conditions, but it currently holds only the data collected for this research. Deploying it beyond the research setting, with a large and varied group of contributors, would show whether crowdsourced thick data can keep the prototype continuously updated, closer to how thick data is collected in practice, and it would also raise questions about how to moderate and validate contributions. Extending it to other cities, such as Rome, would also allow the opportunity category to be populated. This category would be most valuable for residents, who could propose improvements to their own neighborhoods for city planners to act on.

Other extensions concern the richness of the visualization itself. A **time-adjustable** heat and shade layer would let users explore how conditions change across the day and the year rather than viewing a single static snapshot, and a fully **walkable 3D view** could make the experience of a street more immediately legible than a panoramic view of it. Participants in both cities also suggested features the current prototype does not yet support, such as **route planning** that lets users choose between the fastest and the coolest path, and a **historical timeline** showing how conditions at a location have changed over time.

The **generative AI** feature is a further direction worth exploring. It was tested only in the final evaluation round, with two participants, and their reactions differed: one questioned whether the connections it made were supported by the observations, while the other found the explanations useful but felt that reading them left less room to explore the evidence personally. These first reactions point to open questions that this project could not examine within its scope and time: how such explanations could show the evidence they rely on, whether they could support rather than replace the user's own interpretation, and how they affect trust and engagement over longer use.

The prototype would also benefit from being tested more broadly. It was developed and evaluated using a small set of participants and only Delft data; extending it to other routes, cities, climates, and times of year, with the ambition of making it usable worldwide, would test how well the current design choices generalize beyond the conditions it was built on. Testing with other user groups, such as researchers and planners who engage with urban heat data more regularly, or professionals from other fields, would similarly show how the prototype's current focus on non-expert users needs to adapt for audiences whose needs differ. Finally, the prototype could be extended to other languages, so that contextual knowledge can be shared in people's own language.

7.2 Personal Reflection

I came to this project with an interest in data visualization, developed through earlier projects in which the challenge had been to make data meaningful, but with almost no prior knowledge of urban heat or climate research. The first phase was therefore a steep learning curve: familiarizing myself with the urban heat literature, the vocabulary of big and thick data, and the thermal comfort factors relevant to Delft and Rome before I could start designing in a meaningful way. Regular feedback from my supervisors helped me build the contextual grounding I lacked at the outset.

Several challenges shaped the project. The first was recruitment: the initial target group of academic researchers turned out to be too small and hard to reach within the timeframe, and I had to redefine the user group (Section 3.2), which meant rethinking who the prototype was for rather than only whom I could test it with. The second was working across two cities and in a language other than the one the report is written in, which required careful handling of translation and of the differences between the two data sets (Section 6.3). The third was the pace of prototype iteration: each round of testing raised issues that were quick to identify but took time to resolve, and I had to prioritize which ones mattered most within the scope of a graduation project.

These challenges contributed to my growth as a designer and researcher in three ways. First, I learned to treat qualitative data as rigorous evidence rather than anecdote: grouping the walk data into themes and then relating them to a quantitative layer required me to be explicit about my own choices and their limits, as a single researcher analyzing the data (Section 6.3). Second, I saw how much a visualization can do in conveying meaning and not only in displaying data. Across the testing rounds, a simple change in color-coding or interaction determined whether a non-expert user understood the relationship between big and thick data, which made the abstract ideas in the literature concrete. Third, using generative AI to build the prototype while deliberately keeping interpretation with people, as argued in Section 4.3, made me more aware of where automation helps a design process and where it should not replace judgment.

The project also changed how I work. The early phase relied more on guidance, while the later phase, particularly the iterative prototyping and user testing in Chapter 5, allowed me to take greater ownership of the direction of the work. This progression from supported exploration to independent execution strengthened my confidence in making and justifying design decisions on the basis of evidence from users. I take this, together with a clearer view of how user research, prototyping and data can be combined, into my future work at that intersection.

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APPENDIX

A. AI Declaration

Generative AI tools were used to support the coding of the final prototype, including both the base interface and the generative AI-supported version tested in the user evaluation (Section 5.2). Specifically, I used Claude and Google AI Studio to support the coding and development of the prototype, and Figma Make to test an early version of the prototype's interface. DeepL was used as a translation tool after the user research. Claude was also used to refine the writing style of this report, including proofreading for spelling, grammar, and typographical errors.

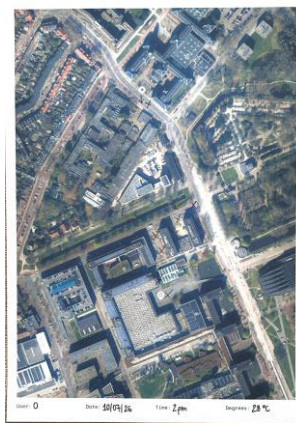
I critically reviewed and adapted all AI-generated outputs, recognizing their limitations and the challenges involved in evaluating their reliability. I remain responsible for the research and design decisions, interpretation of findings, accuracy of references, and final content of this master thesis.

B. Delft User Activities

B.1 Informed Consent (P0-P6)

Delft University of Technology HUMAN RESEARCH ETHICS – INFORMED CONSENT PARTICIPANT INFORMATION You are being invited to participate in a research study titled “Thermal Comfort Walk”. This study is being conducted by Virginia Pastore from the TU Delft. The purpose of this user research study is to understand how thick data in urban climate research can be integrated with big (3D) data. The study will take you approximately 20-30 minutes to complete. The data collected will be used for academic purposes, including a master's graduation project, potential publication, design application in the development of a research support tool/platform, and educational use within TU Delft. We will be asking you to take notes about your thermal comfort during a walk in TU Delft campus, from the Architecture building (BK) to the Design building (DC) and consequently to answer some questions about the data you just collected. This user's activity is anonymous and does not involve the collection of personally identifiable information. Any data collected during the interview (such as audio recordings) will be stored securely and will be accessible only to the researcher; only an audio transcript will be included in the appendix of the final thesis report. All data will be anonymized and handled in accordance with data protection regulations. This study does not involve open data sharing of individual responses; only aggregated and anonymized results may be used in publications or presentations. Your participation in this study is entirely voluntary and you can withdraw at any time or decide to not answer to some questions. For questions or more information, please contact: Virginia Pastore (Master's Student, TU Delft) Abhinav Singh (Responsible Researcher / Supervisor)	EXPlicit CONSENT POINTS PLEASE TICK THE APPROPRIATE BOXES <table border="1"> <thead> <tr> <th></th> <th>Yes</th> <th>No</th> </tr> </thead> <tbody> <tr> <td colspan="3">A: GENERAL AGREEMENT – RESEARCH GOALS, PARTICIPANT TASKS AND VOLUNTARY PARTICIPATION</td> </tr> <tr> <td>1. I have read and understood the study information dated 25/03/2024, or it has been read to me. I have been able to ask questions about the study and my questions have been answered to my satisfaction.</td> <td>☐</td> <td>☐</td> </tr> <tr> <td>2. I consent voluntarily to be a participant in this study and understand that I can refuse to answer questions and I can withdraw from the study at any time, without having to give a reason.</td> <td>☐</td> <td>☐</td> </tr> <tr> <td>3. 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B.2 Printed Maps (P0-P6)



P0



P1



P2



P3



P4



P5



P6

B.3 Transcripts

Translated from Italian by the researcher and edited for clarity.

Participant 0

Date: 10/07/26 | Time: 2pm | Degrees: 28°C

Part 1 – Description of the Walk (written notes)

- During summer days I always walk on the right side of the street (more shadow and green). The rest of the year (when it's sunny) I walk on the left to catch as many rays of sun as possible.
- Segment 2 is similar to segment 1 but it's a bit warmer since at 2pm there's less shadow from the trees on the right. Hottest spot for me: waiting for the green light.
- Then: I always pass by the right side of the building here, out of habit, but I feel there's also more shadow (even if on the left it seems more green during spring/summer), it's also very windy here since there are not close buildings on the right side of the street.
- Very hot and uncomfortable spot: parking lot. I tried to pass by as close as possible to the shadow on the left. Concrete on the ground and cars that increase the sun's light and heat, also a lot of windows reflecting the sun.
- Usually here is always in the shadow, but not at this time of the day apparently so I walked as close to the building as possible.
- IDE square: same as the pavement of the parking lot and at this moment there's no wind maybe because of the buildings geometry and position and time of the year and day.

Participant 1

Date: 14/07/26 | Time: 2pm | Degrees: 30°C

Part 1 – Description of the Walk (written notes)

- Arriving already hot, still warm from the bike ride. No shadow here at all, not a single bit. I already know I'm going to sweat before I even reach IDE. Walking fast now, I just want to get through this part quickly.
- Finally, some shade. This big tree is such a relief. Slowing my pace down here, taking a small break, letting myself cool off for a second.
- Continuing straight, this side is green and shaded, feels a lot better. Checking the right side... too sunny over there, no trees at all, glad I didn't go that way.
- Turning right now toward the bike parking, and this is rough. Sun everywhere, barely any vegetation, might honestly be the worst part of the whole walk.
- Still here, still hot, actually hotter than I expected. Didn't think this spot would feel this bad.

Part 2 – Platform walkthrough (audio transcripts)

U: Okay, so, looking at this first map here, the one with the shadow paths... it's marked that there's a lot of shadow on this side, on the right, and then a little bit less on the left. But, I mean, honestly, when I actually walked through here, there was no shadow at all. Like, none. The only bit of shade I actually got, the only one I could really point to, was from that one big tree, right here. That's it, that's the only shadow I remember from this whole stretch.

R: And what about right after that, when you crossed the street?

U: So, right after that, I decided to just keep going straight, because on the right it seemed way more sunny to me, so I avoided it, I just didn't want to deal with that side. And if I look at the map now, it shows shadow on both sides, like roughly equal amounts on the left and the right. But that's not really how it felt at all, the difference between the two sides was a lot more pronounced than what's shown here. It wasn't subtle like this, it was pretty obvious which side you wanted to be on.

R: Okay, and is there anywhere else where you noticed a gap between the map and what you actually experienced?

U: Yeah, also, from about here to here, again, there was just no shadow. Or, I mean, maybe a tiny, tiny bit, but it was so small it wasn't even noticeable, you wouldn't really register it as shade while you're walking through it, it might as well not be there.

R: And what about the second map, the one with the heat coefficient?

U: Looking at that one now... honestly, if it were up to me, I would've just marked this whole stretch the same color, the red one. Because it was all hot, like, uniformly hot, in the same way the whole way through, I couldn't really tell you where it got worse or better. There wasn't really a variation I could feel walking through it.

R: And the last part of the route, does that match up better?

U: Yeah, the last part, that one actually matches, that's pretty similar to what I felt walking through. So it's really just this middle stretch where the map and my experience don't really line up.

R: Is there anything you feel like the platform is missing, or something you'd want to see added?

U: Yeah, actually, thinking about it now... I think it would really help if there was, like, a live layer, something you could adjust yourself, like pick the hour, or the day, and see how the shadow changes. Because right now it just feels too static and unreliable, like this one moment in time, but the sun moves so much throughout the day that what's shaded at 10am is completely different from what's shaded at 2pm, like I experienced. So having something customizable, where you can just slide it to whatever time you're actually walking, that would make it feel a lot more accurate to what you'd really encounter.

Participant 2

Date: 14/07/26 | Time: 5pm | Degrees: 29°C

Part 1 – Description of the Walk (written notes)

- This first half of the route is mostly sunny, there are some shadow spots from the trees and bushes alternate to the sun
- Here there was a big truck parked (very hot to pass by it)
Here I'm already feeling very hot so I stop next to the tree and I decide to continue straight since on the right there's full sun (almost no shadow from vegetation nor the building)
- Here there is a very pleasant corridor of vegetation and shadow
- Followed by the worst part maybe, from here until the square is very sunny and there's no way to cover from the heat
- So I decide to pass under the bike parking lot for the last segment of the walk

Part 2 – Platform walkthrough (audio transcripts)

U: So, walking from Architecture over to IDE, the alternation between sun and shade is actually a lot more detailed than what's shown here. It's not just, like, sun or shadow, it kind of shifts in and out the whole way, back and forth, constantly. Right around here, though, there was no shade at all. Like, none. Fully exposed. And on the map, this is actually marked as shadow, so that's already a bit off.

R: Okay, and were there other spots like that, where the map didn't quite match?

U: Yeah, this part right here, honestly, this was the worst part of the whole walk. This is where it really got to me, like, this is the point where I started feeling it the most. And I see on the map, this might be the parking lot? It's actually marked as shadow, if I'm not wrong, which doesn't match at all with how it felt.

R: Was there anything else around that area that stood out to you?

U: I don't know if it's important, but in this part right here, there was a big truck parked, and I felt more heat on the right side of my body while passing by it, just from being close to it, but it was very subtle. And then I see the parking lot here isn't marked as fresher either, so that whole section just felt off compared to what's shown.

R: Yes that's super valid! And what about the greenery layer, the last one?

U: Well... the last map, I would say it's okay, it's decent compared to my experience. Just here, though, I felt it was definitely more cool and green than what's shown, so I would have expected more green in that spot.

R: Is there anything you'd want to see in a platform like this, feature-wise?

U: Yeah, actually, I would like to see something like Google Maps' fastest versus eco route toggle, but instead, fastest versus coolest. And then, on the coolest route, each shady or sunny segment would have a small photo dropped by a previous walker, something real and tangible, from someone who actually walked it.

Participant 3

Date: 15/07/26 | Time: 1pm | Degrees: 29°C

Part 1 – Description of the Walk (written notes)

- I started my walk without feeling particularly hot or cold. I noticed that the path was completely exposed to the sun, with no shade anywhere, so I instinctively moved to the left, staying close to the building to catch every little strip of shade
- I crossed the street and immediately noticed a difference on the right side: patchy shadows coming from the bushes there, and the air that passed through them, seemed a little cooler, maybe for some wind slipping through the leaves. My thermal comfort improved for a moment.
- After crossing the street again, I decide to turn right (toward the parking lot) because it seems closer, and also, I don't feel like running into people today (this area is usually quieter)
- Now there's a lot of shade, cast by the building on the left: the shadow is much more pronounced than the one from the bushes earlier, with a solid patch of shade. There's also a bit of a breeze here, maybe because of a wind tunnel effect between the buildings, which makes the shade feel even cooler than it probably is.
- Just crossed the parking lot and I'm feeling very hot again, no trees, no shade from buildings, just bare asphalt reflecting the heat upward, continues like this until IDE

Part 2 – Platform walkthrough (audio transcripts)

U: So, I feel like it's not really true that there's this much shade here. Looking at the map, it shows a lot, but actually it was just a strip, close to the building, on the left, that's the architecture building. There was way more sun since it was like 1:20pm That's the only real shade I remember from that spot.

R: Okay, and what about further along the route?

U: Then, there was a lot more shadow later on, here, and I think that was because of the bushes, if I remember correctly, that's what was giving the shade there. More or less, like it was not consistent. And then, in this part right here, I would honestly switch the shadow completely, like, flip it. Because it was actually sunnier on the left side, not the right, so the map has it backwards from what I actually experienced walking through.

R: And how did the temperature feel overall in that first section?

U: Okay, and then, yes, the first part was really hot, that part checks out, that matches what the map is showing. Maybe it felt slightly cooler because of the wind at some point, I think there was some wind there, just a little bit. But here, I would highlight more of a difference between the left and the right side. On the map it looks pretty much equal, like both sides are the same, but it really wasn't, there was a very clear gap between the two, you could definitely feel which side was better to walk on.

R: And what's your take on the greenery layer?

U: And then, the greenery layer, yeah, that one seems pretty good to me actually, it lines up fairly well with what I remember. I'd just add a bit more cooling effect in the first part, that's really the only thing that felt different to me there, everything else about it seems accurate.

R: Is there anything else you think could be useful to add to a platform like this?

U: Hmm, I'm not really an expert on any of this, the whole urban heat thing, so I don't know the right terms or anything, but... I think it would be important to see how things change across the years, you know? Like, not just one summer, but comparing, I don't know, this year to like five years ago, or ten. Because trees grow, buildings change, stuff gets

built or torn down, so what was shady a few years ago might not be anymore, or the other way around. So having something like a timeline, where you can kind of scroll back and see how it used to be versus now, like I always do this with Google Street view for example to see how a neighborhood was in 2015. I think that might be really useful, even if I couldn't tell you exactly why in, like, technical terms.

Participant 4

Date: 15/07/26 | Time: 4pm | Degrees: 29°C

Part 1 – Description of the Walk (audio transcripts)

- Just before reaching the campus entrance, it's unbearably hot walking through the unshaded sections. It's really refreshing to walk under a tree, I mean, right underneath the shade. [...] And walking is a bit tedious, too; I feel tired. I can tell when my walking is a bit calculated to avoid the heat, you know.
- I definitely head for the shade, because it's just too hot, and even though, to be honest, as I get closer to the turn I have to make, I feel almost a little scared, let's say, because I see there's so much sun. But I'm not discouraged anymore because, in the end, I know I have to get there, so I have to walk through this sunny stretch, and I try to do it as fast as possible.
- So I started the walk already feeling a little hot and I immediately crossed over to get into the shade and walk there, because it's a little better than being in the sun. Now I keep walking.
- I keep going straight and don't turn right away into the little square, knowing I have to get to IDE, and I'm very used to going to IDE via this route, so even though I usually come from the opposite side, it still feels much more natural to me here.
- Then, as I approach the intersection where I have to turn, I'm actually glad to discover that this last stretch is in the shade, so I feel like I made the right choice.
- Definitely the right choice, because now these last 5 meters are in a very cool, heavenly spot, and it's easier to walk, I just love it.

U: So, I set off and immediately crossed the street because I realized that on the other side (to the right) there was a stretch that was much more shaded than where I was, so of course I moved over there, also because on this side there were issues with crossing and so on, while over there it was a bit more direct. As I continued, it was breezy here at the end, so it was peaceful. The only thing was: when I got around here, I felt like my walk was a bit lackluster, so to speak, because walking straight for all that time with the alternating hot sun and shade was very physically tiring.

Here, when I reached the intersection with the traffic light, I crossed straight ahead, because on this side everything was in the shade all the way to the next intersection I had to reach. So I was really tempted to go that way, also because the sidewalk curves around the bend; it felt instinctive to go straight (instead of turning right).

Then, since I had to get to the little square, I turned here, just before turning, I was already feeling discouraged (I mentioned this in the audio while I was walking), because I could already see it was full of sun and I wanted to cross it as quickly as possible, even though I knew that afterward I'd end up in this section, heading toward the bicycles, because the sun was positioned like that. So it's all sunny here, except for this last little stretch right here.

In fact, I turned toward the bikes here, because I always come this way: even when I park at TPM, it's second nature for me to go to the university via this street. Walking it from the opposite direction, I instinctively recognized that little spot there, and I was really happy; I started walking briskly again because everything there was in the shade. In fact, I even slowed down a bit there to catch my breath and see if I was working up a sweat.

After the sun, it's also much windier here, so in the end, before reaching your destination, it gives you a bit of energy back. But I have to be honest: you still have to walk a bit under the sun.

R: So would you say this part here is the most tiring?

U: Yes, yes, absolutely. But they're two different kinds of challenges: the first part was more about the length and monotony of the stretch, but you still have trees, so that part is less tiring. After that, though, it's mostly concrete. So, paradoxically, I struggled more with this last part because it was really much hotter, with the sun beating down directly. If I had to walk a longer stretch like this, I'd still reach the same level of fatigue, but I just don't feel it as much.

R: And you're feeling a little hot, I imagine, because of the sun, too?

U: Exactly, yeah, much hotter by the end, especially after the last song, I've cooled off a bit, but... it's not like I'm still feeling it right now, because I'm sitting still, doing this interview. But right when I got here, I was feeling... yeah, I was already feeling a little sticky.

Part 2 – Platform walkthrough (audio transcripts)

U: Starting from this, for example, it says here, this is where I started, that there's actually more shade on the right side, and I did, in fact, cross over there. On this point, I agree with the map regarding the shade and its extent, partly because I think it's the most reliable data available today, since, after all, the shade doesn't change much over time, so this matches my experience.

As for this other one, well, it makes sense that the buildings are warmer. In my opinion, the closer you are to a building, the warmer it is. If I had to choose, I'd say this red one [UHI effect] is already the most intuitive of the three. But it's a bit misleading, because it seems like this stretch of road is cooler than the one I'm walking on now, when in fact it might all be equally "red," so this would make me much more worried than is warranted.

As for the greenery one, though, I have to be honest: I'd rate this first section a 4, yes these are coefficients, not temperatures. Okay, yes, there are more trees here, but in terms of perception, all the way up to the intersection with the traffic light, this part was pretty much the same, except for the end, where as you approach the traffic light there's one more tree, but it's just a very small part, so this, for example, felt different to me.

R: How would you include the data you just collected, based on your experience walking, with a platform like the Atlas for example?

U: I'm not sure... I guess something intuitive like Waze. If I had to find the best route, I'd start with a map like this, with shadows, the most intuitive one. One that shows the double shadow, on the right and left, hour by hour, so I can clearly see, depending on the time, where the sun is and where the shadow is, "live" data, which is much more reliable in terms of detail than a screenshot of a single moment.

Actually, I'd much prefer these, feedback left by people who've just been there, who post a photo and say, "Look, it's much hotter here,"

so that if I have a route and see the feedback markers, I can tap them and decide, "I'll go that way, but not that way". But at the very least, it would be nice to have, like on Google Maps, an option that shows the route with the most shade, at least two options: the fastest one and the shadiest one, because I'd always want to be able to evaluate the fastest route and see how much of it is in the sun.

R: So you mean visual feedback, like photos, for example?

U: Yes, because in the end, feedback like this, drawn from the real-life experience of people who've been through it... think of the most trivial example: if I need to go see a friend, I open Google Maps, I don't have all that time to weigh my options, so Google Maps tells me, "Look, this is the fastest route" okay, I check the travel time; "this one has the most shade" I click on it, glance at the route for a moment, exactly, I click on it, see the route, and remember it, and with the feedback, I also see the part that's like that. I'd much prefer that, because right now Google Maps always gives me the fastest route, but I never know what it'll actually be like: maybe the fastest one is also the hottest one.

And maybe it could also offer some kind of personalization, meaning the app could come to understand my preferences and habits a little better. Honestly, if I were in the designer's shoes, I wouldn't know what kind of personalization to include. The basic stuff, like height, weight, age, and so on, physical data, but there are two issues there: one is ethical, regarding the data, and the other is that I don't know how much I could trust what the app tells me, because it's still a machine making decisions for a person based on their personal data, and I don't know how well the person can "respond" to that.

And if I can also log my experience, so if, through personalization, the app recognizes a pattern where I always choose this side of the road, etc., it can at least calculate my routes accordingly. But anyway, I think that's up to you; you decide what to include in the app. After all, I haven't really had much to do with apps, so I don't even know how far an app can go with features like this.

Participant 5

Date: 16/07/26 | Time: 1pm | Degrees: 26°C

Part 1 – Description of the Walk (written notes)

- Okay so right now I'm really hot, and I'm already sweating a lot, mostly because of the backpack on my shoulders. It's been pressing on my back since I left home and that just makes everything warmer. But honestly it's normal, it's always like this for me during summer, I just sweat more than other people I think.
- There is a lot of green on the right side of the road, left is full asphalt and buildings
- I continue walking. The pavement here is wet, I don't know why. Maybe someone watered the grass nearby, or maybe it rained a bit earlier and I didn't notice. Oh here he is, there's a man in yellow watering the bushes. Because of that the air feels more humid, like it's sticking to my skin a bit. It's a different kind of uncomfortable than just being hot, it's more heavy, if that makes sense. I feel like I can breathe the water.
- Fortunately the light is green so I can get through quickly. Usually when I pass by here it is horrible that you need to wait in the sun without any kind of shade to take a break from the sun
- This was the only pleasant part (also to see), the rest from here to IDE was totally sunny and hot, no noticeable differences noted down

Part 2 – Platform walkthrough (audio transcripts)

U: Okay so, I started off very sweaty, that was maybe from the backpack, I thought about it right here at the beginning of the route. It had been pressing on my back the whole way coming here, so by the time I started walking I was already feeling it a lot.

R: And how does that compare to what the map shows here?

U: Well, this part isn't really about the map, that was more just my own situation, with the sweating. But then, moving on, here it was more humid, this is the spot I mentioned with the wet pavement, and the man watering the bushes. I don't know if I would call that cooler, actually, or if it was worse, because it was a different kind of uncomfortable, it wasn't heat exactly, it was more like heaviness, humidity sticking to me.

R: Okay, and then what about this next section?

U: Then here, at the crossing, this is where you usually have to wait to cross the street, and it's usually very hot standing there, waiting for the light. But the light was green when I got there, so I didn't actually have to stop, thankfully, so I can't really say how hot it would've been if I'd had to wait.

R: And looking at the greenery map specifically, does that match what you remember?

U: Thinking about the last map, yeah, I would definitely signal more green on my right side, there was more vegetation making the road cooler there than what's shown, at least that's what I felt passing by.

R: Is there anything else you'd want to see on a platform like this?

U: Yeah, actually, it would be cool to have a tool that signals things that are temporary, like the water I saw earlier, from the watering, or like, I don't know, the truck someone else mentioned to me. Something that isn't always there, but that changes how hot or cold a spot feels in that moment. Maybe it could signal it with an X like I did on the map, or a picture, and it just tells you, this spot is hotter or colder right now, because something temporary like that could always happen.

Participant 6

Date: 16/07/26 | Time: 2pm | Degrees: 27°C

Part 1 – Description of the Walk (audio transcripts)

- I'm starting the walk feeling pretty neutral, maybe because we talked a bit before I started walking. So, I took this first photo here simply because I want to show that I tend to stay as far in the shade as possible. And, since the shade here isn't constant, I'm standing right under it anyway.

- Then I took the photo here, for pretty much the same reason, mostly because of the bush, which is more annoying. But I also noticed that when people walked by, I still tended to move immediately to the right and let them pass on the sunny side.
- So, in general, when it's hot, I follow the "patches" of shade since I feel almost twice as much heat in the sunny spots, and when there's a gap between one patch of shade and another, I try to walk faster.
- And here, actually, I took another photo because I could have gone either to the right or to the left. But I don't know why, in my mind, this path to the right seemed longer, even though it was shadier; I would have taken that one, but I think it was simply because I never take it, I thought it was longer.
- **R:** Are there any particular reasons you took this route instead of the other one?
- I've always done this; I don't know why, I went this way even though there's actually more shade over there. And then I took another photo here for the same reason: I could have gone this way or that way, but here it's totally "savanna" [all sun, no shade], so I figured, whatever, I'll just go this way.
- I tried to keep the green on my left to catch some shade but didn't work too much
- So I decided to pass by the bike parking to get to IDE, since it's always cooler even if it's open, it's like being in a church I don't know why, maybe because of the wind tunnel inside it

Part 2 – Platform walkthrough (audio transcripts)

R: Do you notice any differences between these data and the experience you just had?

U: I want to understand a bit about how reliable this is, in the sense that this doesn't seem to take shade into account: maybe the map says it's cooler here, but if I'm in the sun, it actually feels hotter to me, because maybe there are walls reflecting heat and so on, even though I'm in the shade. So I'm not sure, I felt that it wasn't so much a matter of the area as it was simply whether or not there was shade, as far as the heat is concerned. Also because I think the temperature differences between areas are very slight anyway.

Then, for example, here: I said I went this way instead of that way, even though there was more shade here, but I see that the map shows the opposite, for example.

R: Yes, because it depends on the day and the time of day.

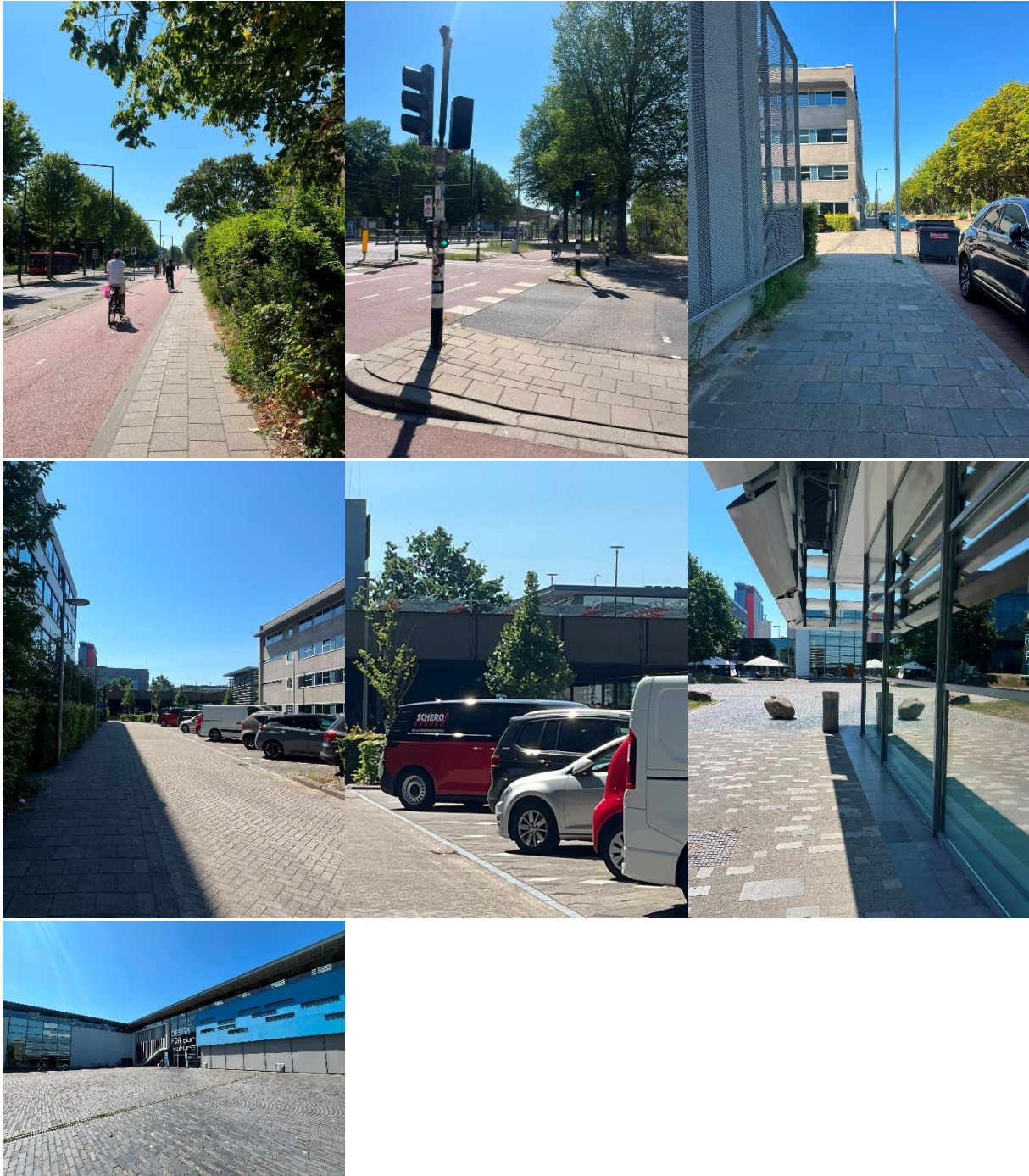
U: Exactly, exactly, it depends on the time of day.

R: How would you integrate the type of data you've collected so far while walking with the data from the Atlas, what kind of tool do you think would be most helpful for a feature like this?

U: At home when I drive my car I always use Waze instead of Google Maps, I think is the most straightforward example. Imagine that while you're going from one place to another, at some point you say, "Man, it's really hot here," then you open the app and drop a pin, without even having to type anything. You tap once, a series of symbols pops up, and you select the one for heat or shade. And maybe, the more reports are made at that spot, the more it means there's a need, in that location, to create some shade, like a tree-lined path or something. That's the only way I can think of now. But I don't know what makes people use these kinds of features spontaneously, but yes Waze works really well and it's used a lot by users.

B.4 Pictures

P0:

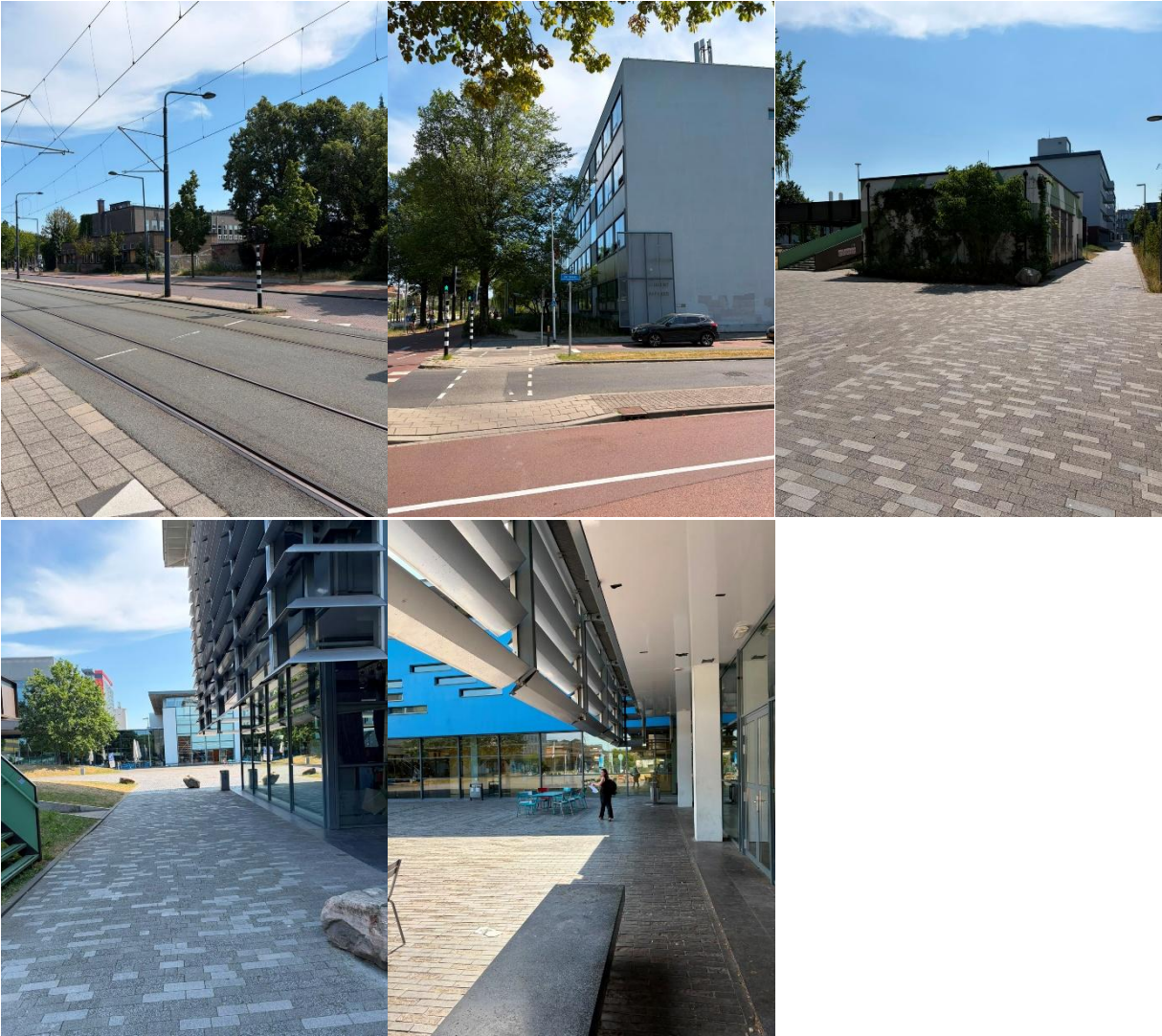


P1:

P2:



P3:

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P5:



P6:

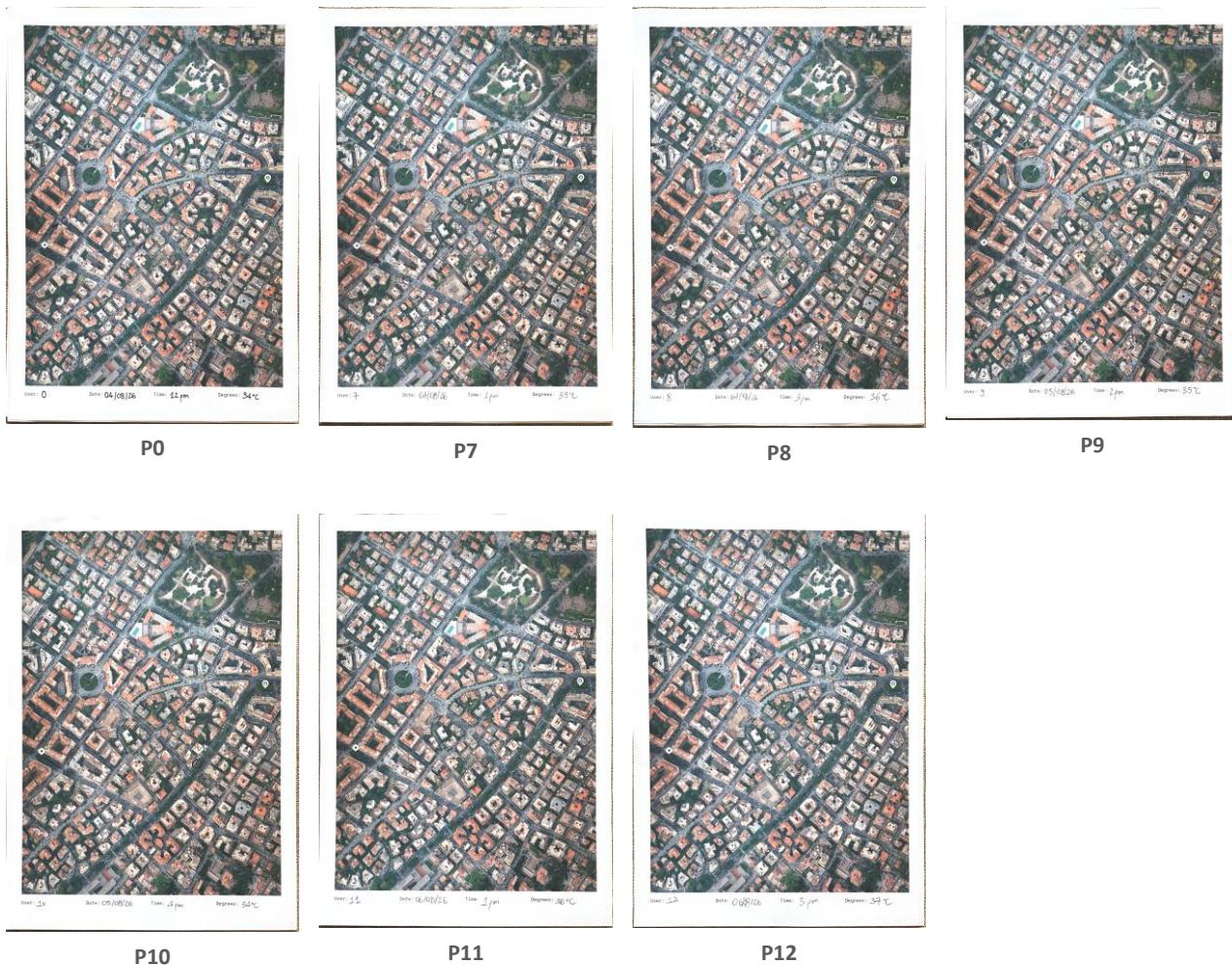


C. Rome User Activities

C.1 Informed Consent (P0, P7-P12)

Delft University of Technology HUMAN RESEARCH ETHICS - INFORMED CONSENT																																								
PARTICIPANT INFORMATION You are being invited to participate in a research study titled "Thermal Comfort Walk". This study is being conducted by Virginia Pastore from the TU Delft. The purpose of this user research study is to understand which are the central factors of thermal comfort and how thick detail urban climate research can be integrated with big (blue) data. The study will take you approximately 30 minutes to complete. The data collected will be used for academic purposes, including a master's graduation project, potential publication, design application in the development of a research support tool/platform, and educational use within TU Delft. We will be asking you to take notes about your thermal comfort during a walk in Rome (Quartiere Trieste), and consequently to answer some questions about the data you just collected. This user's activity is anonymous and does not involve the collection of personally identifiable information. Any data collected during the interviews (such as audio recordings) will be stored securely and will be accessible only to the researcher; only an audio transcript will be included in the appendix of the final thesis report. All data will be anonymized and handled in accordance with data protection regulations. This study does not involve open data sharing of individual responses; only aggregated and anonymized results may be used in publications or presentations. Your participation in this study is entirely voluntary and you can withdraw at any time or decide to not answer to some questions. For questions or more information, please contact: Virginia Pastore (Master's Student, TU Delft) Abhinav Singh (Responsible Researcher) / abhinav.singh@tudelft.nl																																								
EXPLICIT CONSENT POINTS PLEASE TICK THE APPROPRIATE BOXES <table border="1"> <thead> <tr> <th></th> <th>Yes</th> <th>No</th> </tr> </thead> <tbody> <tr> <td colspan="3">A. GENERAL AGREEMENT – RESEARCH GOALS, PARTICIPANT TASKS AND VOLUNTARY PARTICIPATION</td> </tr> <tr> <td>1. I have read and understood the study information dated 03/08/2023, or it has been read to me. I have been able to ask questions about the study and my questions have been answered to my satisfaction.</td> <td>☐</td> <td>☐</td> </tr> <tr> <td>2. I consent voluntarily to be a participant in this study and understand that I can refuse to answer questions and I can withdraw from the study at any time, without having to give a reason.</td> <td>☐</td> <td>☐</td> </tr> <tr> <td>3. 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Study contact details for further information: Abhinav Singh																																								

C.2 Printed Maps (P0, P7-P12)



C.3 Transcripts

Translated from Italian by the researcher and edited for clarity.

Participant 0

Date: 04/08/26 | Time: 12pm | Degrees: 34°C

Part 1 – Description of the Walk (written notes)

- It's a thermal neutral start since I'm coming from home, where the air conditioning is on.
- I always take this route because there are usually more trees lining the narrow streets, providing shade, and there's more of a breeze.
- As I walk by here, a little water drips on my head, someone is definitely watering the plants on their balconies. That's something that's never happened to me in the Netherlands. I think plants there are mostly inside, at least in Delft.
- I'm walking under some refreshing shade provided by the trees; it's easier to breathe here.
- This stretch of road is quite uphill, and I'm struggling to walk in this heat.
- Suddenly, I feel an intense wave of heat coming from the right; I turn around and see that it's the exhaust fan from a restaurant's kitchen in the square. Wow, what a blast of hot air is coming out, it's filling this whole section of the street (you can't see it clearly in the photo, but it's behind the stone wall).
- Here, still on the right, is the entrance to a covered parking garage, and as I walk past it, I can really feel a nice cool breeze coming from inside.

Participant 7

Date: 04/08/26 | Time: 1pm | Degrees: 35°C

Part 1 – Description of the Walk (audio transcripts)

- I'm starting the walk in a fairly neutral mood; I arrived here by car.
- I decide to head down Via Chiana because it's a downhill stretch, and there's usually more shade on the right side of the road, so I cross over.
- This stretch of road is completely wet, probably because someone watered the plants on the balconies, or maybe they dumped buckets of water to wash dog urine off the asphalt. Either way, the result is definitely refreshing; it feels better walking over it, even if the air is more humid.
- I've decided to take a walk through the narrow streets; maybe I'll find some shade there. I'm crossing this little square, which is completely open and has no trees, it's really hot here.
- I'm heading down toward Corso Trieste, partly because the road is downhill, and partly because Corso Trieste is definitely a wider and cooler street.
- There it is, it's full of trees here. I cross the street and continue straight ahead to Piazza Istria.

Part 2 – Platform walkthrough(audio transcripts)

R: Does this match what you felt during the walk?

U: Sort of. I see the map is almost entirely orange around here, so it doesn't really tell me much on its own. But of course it was 35 degrees everywhere. That little open square I crossed, with no trees at all, is shown just very slightly darker than the streets around it, but honestly it felt way hotter than that subtle difference would suggest, it really felt like an oven standing there. And then Corso Trieste is shown exactly the same orange as everywhere else, but that's not true at all, that street felt noticeably cooler to me, probably because it's wider and there's more air moving through it. The map doesn't pick up on either of those things properly.

R: And the shadow one, ShadeMap?

U: That one's more accurate, honestly. It shows the shade on Via Chiana pretty much where I actually walked through it. But obviously it doesn't know about the wet patch on the ground from the watering, that made a subtle difference to how I felt, and the map has no way of showing that I guess.

Participant 8

Date: 04/08/26 | Time: 3pm | Degrees: 36°C

Part 1 – Description of the Walk (audio transcripts)

- I'm already feeling pretty hot when I set out, it's 3 p.m. and the heat is oppressive, and I've already walked all the way from my house because my sister has the scooter today.
- Usually, to get to Piazza Istria, I always go this way and then turn left and go straight ahead, because it seems like I get there faster; it feels less tiring than zigzagging between the buildings. It's also greener.
- At this point on Via Chiana, there's a large indoor market, full of refrigerators, ice, and ventilation: you can feel an incredibly cool breeze as you walk past it. I'm almost tempted to walk through it to take a shortcut, but there are too many people inside.
- I've reached the end of the street and turn left; I stay on the left side because it seems shadier to me (the sun and the buildings are on my left, so the shade falls on the sidewalk).
- Here I feel a nice blast of cool air coming from the entrance hall of this building; in Rome, building entrance halls are always freezing cold, even more so when the door is closed and you step inside.
- I'm almost at Piazza Istria, and I'm noticing how the vegetation on the ground is completely dry and yellow. This stretch would be much cooler otherwise. It used to be.

Part 2 – Platform walkthrough (audio transcripts)

R: How does this compare to what you experienced?

U: The temperature map is mostly the same shade of orange the whole way, so it doesn't really capture what I felt. Like, there's no way it can show something like the indoor market with all the fridges, or the entrance hall that felt so cold, those are just too small and specific for a map like this I think. And then Corso Trieste, again, it's the same orange as the rest of the route on the map, but it definitely felt more comfortable to walk through than the other streets.

R: And what about near the end, where you mentioned the dry vegetation?

U: Yeah, that's the same problem but the other way around. The shadow map still shows shade there, because the trees and bushes are still physically there, but it doesn't know they're basically dead and yellow now, so they're not actually cooling anything anymore. From the map you'd think that part was fine, but it wasn't, not really. It's also sad to see everything so dry, it used to be such a nice square.

Participant 9

Date: 05/08/26 | Time: 2pm | Degrees: 35°C

Part 1 – Description of the Walk

- I'm starting my walk already drenched in sweat, I arrived by scooter here, and waiting for the light to turn green at traffic lights with my helmet on under the sun is no fun at all.
- I cross the street because there are so many building entrances that cool the air as you walk past them, almost like the air conditioning in stores.
- I've reached Piazza Verbano; it's completely in the sun, and it's scorching hot, but I have to turn right and stay on the sunniest part of the square, otherwise, I'd end up taking a much longer route. Even though I'd be much cooler if I went through the park, it's too far away right now.
- Here's another huge entrance hall, and at the end, lots of trees: I feel much cooler for a second.
- Luckily, on this last stretch of road, the trees are very dense on either side, while in the center where the cars drive the asphalt is boiling. It's definitely better under the trees. There's more shade.

Part 2 – Platform walkthrough

R: Does the temperature map line up with your experience?

U: Piazza Verbano, yes, actually, that's marked darker than the rest, and that matches exactly how it felt, it was definitely the worst part of the walk for me too. So that part's accurate. The only thing is that of course one side was a little bit cooler because of the shadow, but I don't see a difference in colors on the map. Also on the map of the shaded areas, the shade I remember was a little different; there's a small flower stand here, too, that provides plenty of shade.

R: And the rest of the route?

U: The rest is honestly all the same color, so it doesn't tell me much. Oh, for example, it doesn't show anything of course about the entrance halls I passed, those felt so different from being outside, but obviously the map can't know that. And the last stretch, with the trees on both sides, that was so much cooler than walking in the middle where the cars go, but the map wouldn't show that kind of difference within one street, it's all one color there too.

Participant 10

Date: 05/08/26 | Time: 4pm | Degrees: 34°C

Part 1 – Description of the Walk (written notes)

- It's a mild start, not too hot, but I already know that with this sun, it won't last long. Luckily, I'm not wearing a shirt but a cotton T-shirt.
- I'm walking this way because there are usually more stores open here, and I was hoping to catch a bit of air conditioning as I walked by.
- Actually, everything's closed, it's still lunchtime. The street here is in the shade, but it's still very hot: there are only a couple of trees, but they don't provide any shelter from the sun at all. I think they've been pruned recently, because I remember there being much more shade a few months ago.
- Suddenly, a powerful blast of heat hits me from the left: it's the fan from a neighborhood restaurant.
- I reach the church square, which is completely open and fully exposed to the sun. I continue down toward Corso Trieste, the tree-lined avenue leading to Piazza Istria, and another blast of hot air hits my face, this time probably from the air conditioning unit of a nearby home. It also has a rather unpleasant smell, so I decide to cross the street.
- I've reached Corso Trieste, and as I pass by the barred window of this house, I feel a nice cool breeze rising up to the street. It's pleasant. Now I'll continue straight on to my destination.

Part 2 – Platform walkthrough (audio transcripts)

R: Do these maps reflect what you felt?

U: Kind of, but not really. This part where I said the trees had been pruned, on the shadow map it still shows shade there, because I guess the tree canopy is still technically there, it's just thinner now. So the map says shade, but it didn't feel shaded at all when I walked through it.

R: And the blasts of hot air you mentioned, the fan and the AC unit?

U: Yeah, no, obviously none of that shows up anywhere. That's such a specific, in-the-moment thing, I don't think a map like this could ever really capture that. And this big street here [Corso Trieste] it's shown the same orange as the rest, but it really didn't feel like the rest to me, at this point it was super hot while here there was more air.

Participant 11

Date: 06/08/26 | Time: 1pm | Degrees: 36°C

Part 1 – Description of the Walk (audio transcripts)

- I'm already feeling very hot as I set out; it's 1:00 p.m. and the heat is almost unbearable. There's too much sun on the right here, so I cross the street to the left; I'm walking toward Piazza Verbano.

- As soon as I arrive, I turn right immediately because I want to get out of the square as quickly as possible. It's an open-air oven.
- I walk through the Church of San Saturnino, they're not celebrating Mass anyway so at least I can get some shelter from the heat for a few minutes.
- Now I'm continuing straight toward Corso Trieste; I hope it's cooler than those last two squares, because as soon as I stepped out of the church, I felt insanely hot. At this point there's a cool breeze coming from a door.
- When I reach the end, I cross on a red light, there aren't any cars coming anyway (Rome is empty these days), and besides, it's too hot to stand here waiting; I'd melt.
- I keep walking toward my destination, staying on the right side because I want to get an ice cream at the end to cool off. The air is cooler here, maybe because the street is wider and there are lots of trees.

Part 2 – Platform walkthrough (audio transcripts)

R: Does the map data match how you experienced the walk?

U: Mm.. Piazza Verbano I think should be really marked as purple. The temperature I perceived here was definitely too much. Also I don't think there was that much shade in the middle of the square. The new trees they planted for the Jubilee are still young.

R: What about the rest of the walk?

U: Everything else is more or less the same shade, so it's hard to compare it to my walk which felt really different from one point to the next. Like, going into the church for those couple minutes, or feeling that air from the door before I crossed, none of that would ever show up on something like this. And Corso Trieste at the end, that felt clearly cooler than the squares, wider street, more trees, but the map has it as the same color as everywhere else.

Participant 12

Date: 06/08/26 | Time: 3pm | Degrees: 37°C

Part 1 – Description of the Walk (written notes)

- I'm starting my walk already feeling very hot; it's 3:10 p.m. and we're in the middle of the hottest part of the afternoon, but in the summer there's never a moment when I'm not hot.
- I'm heading down toward Via Chiana because I want to stop at the little gift shop, maybe I'll be able to catch a bit of cool air from the AC. I don't need to buy anything; I just want to escape the heat for a few minutes.
- I've just stepped out of the store, the difference between inside and outside is staggering; it's hard to breathe.
- I'm walking past the open window of a house, or maybe a basement, I can't say for sure, and a rush of cool air hits me, but only for a second.
- I've reached Corso Trieste; I stop in the entrance hall of this building to take a sip of water because it's much cooler here. I always carry my water bottle with me when I go for walks around the neighborhood.
- I keep walking straight down Corso Trieste; it's fairly shaded, and it's definitely more comfortable than on Via Chiana. Probably because there aren't any trees at all on the lower part of Via Chiana, and also because at this time of day the sun is shining almost directly down on the street there, whereas here on Corso Trieste there's a bit more shade from the buildings since the sun is to the left and not behind me.
- From this point on, there are no more significant changes in temperature.

Part 2 – Platform walkthrough (audio transcripts)

R: Does this match your experience?

U: Is this the temperature? I see it's pretty orange, it's pretty uniform, so no, not really, it doesn't show a lot of what I felt. Like, here I felt better since I was in the shop, and here I took a picture of the window, obviously that's way too small and specific for something like this to pick up.

R: What about comparing Via Chiana and Corso Trieste?

U: That's actually the clearest difference for me. Via Chiana, especially the lower part with no trees, and Corso Trieste, they're shown as the exact same orange on the map, but they really don't feel the same at all. Corso Trieste was so much more comfortable, more shade, more air. The map just doesn't capture that difference between the two streets, even though it's pretty obvious once you're actually walking through them. Also the top part of via Chiana is completely different from the bottom. The bottom has almost no trees.

C.4 Pictures

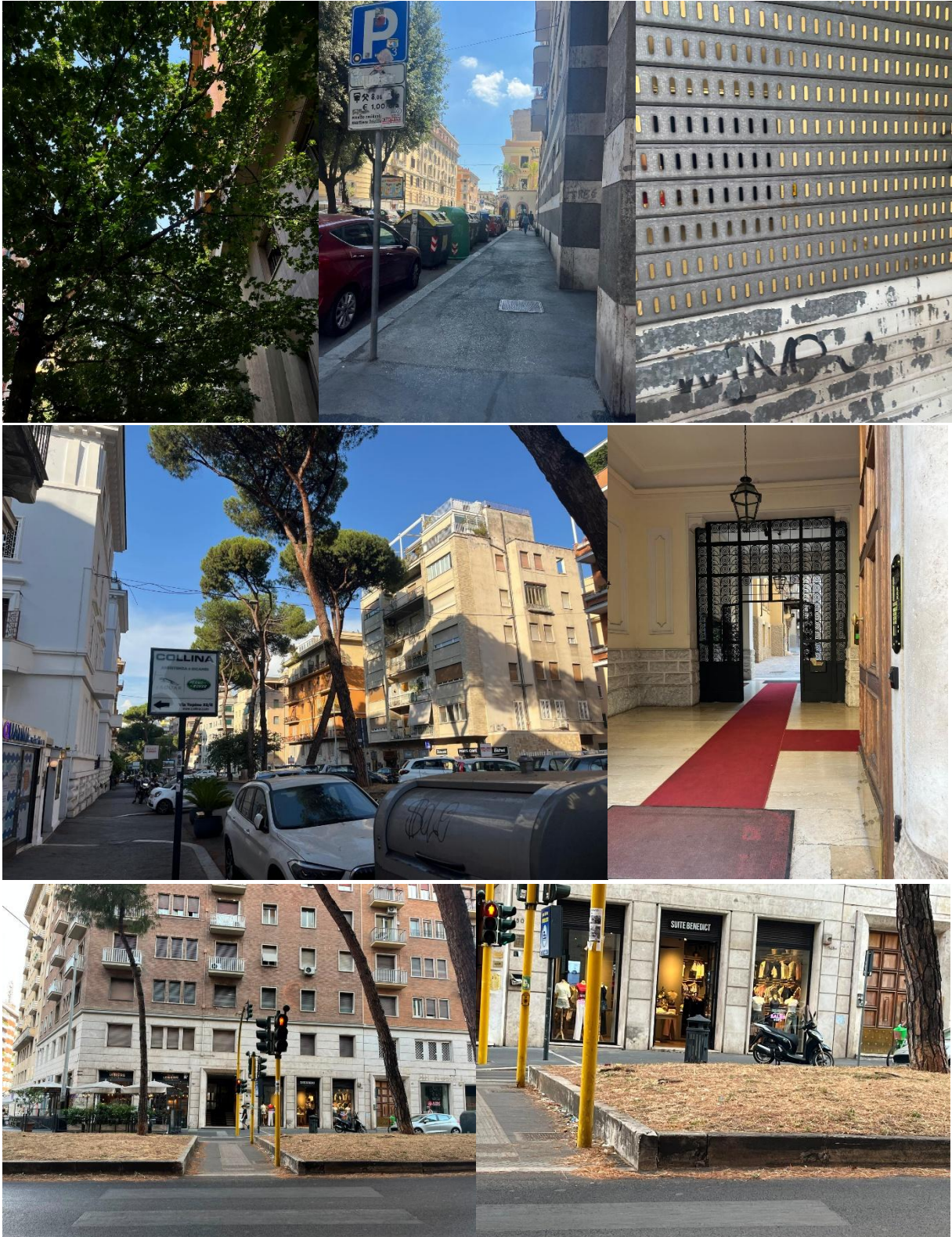
P0:



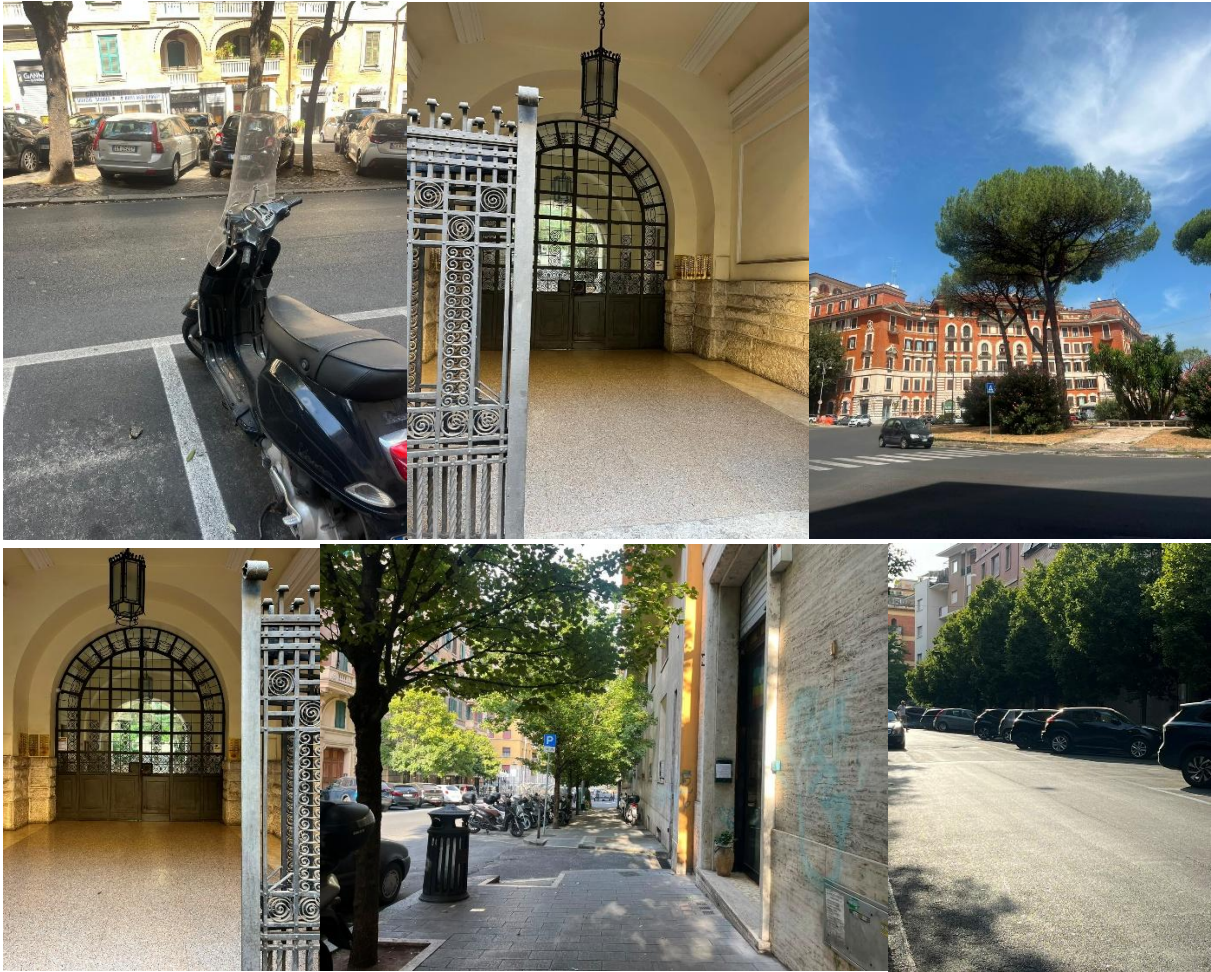
P7:



P8:



P9:



P10:



P11:



P12:



D. User Testing Protocol (V2 & V3)

Structured think-aloud session protocol used during the digital prototype evaluation.

1. Framing (30 seconds)

Telling the participant that the tool is being tested, not them: there are no right or wrong answers, and they should think out loud as they explore.

2. Free exploration, think-aloud (3–4 minutes)

Opening the homepage and observing without giving guidance.

- Does the participant understand what the site is about from the homepage text alone, before touching the map?
- Does the participant discover the hover interaction and the legend on their own, or do they get stuck?
- Asking afterward: “Before I say anything, what do you think this map is showing you?”

3. Guided tasks on points tied to the participant’s own walk (5–6 minutes)

Pointing to two or three specific dots matching the participant’s own transcript and asking:

- “What does this dot’s color tell you, before you click it?”
- After clicking: “Does what you see here match what you remember feeling when you walked it?”
- “Does anything here surprise you, or contradict what you remember?”

4. Legend/categorization check (2–3 minutes)

- “Can you tell me, in your own words, what the four colors mean?”
- “Did you notice the legend on your own, or did you need to be told it was there?”

5. Closing (2-3 minutes)

- “Did this help you understand anything about this spot that the heat map alone wouldn’t have told you?”
- “Was anything confusing or unclear?”