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Contextualizing sensor data: integrating user voice in data-driven design

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ABSTRACT: Data-driven design increasingly relies on sensor data, yet these thin measurements often lack the experiential context needed to explain why events occur or what users feel and need. This limits their value for human-centred design. Passive and active contextualisation are introduced to describe how meaning is produced through inference and user participation. A real-world case study using See.Sense cycling data from Melbourne shows how combining thin and thick data produces more situated understanding and actionable design insight.

KEYWORDS: data-driven design, user-centred design, sensor data, thick and thin data, active travel

1. Introduction

Data-driven approaches are increasingly shaping design practice across sectors, from product and service innovation to urban planning and mobility (Creswell & Creswell, 2017; Fetters et al., 2013). Advances in sensing technologies, connected devices, and digital platforms have enabled the large-scale collection of quantitative information about people, environments, and devices. These passively obtained datasets, such as sensor readings, digital logs, or location traces, are precise, continuous, and scalable. However, despite their objectivity, such data remains ambiguous for design. They describe aspects of what happens but not why, capturing patterns of behavior or interaction without access to the lived experiences, motivations, or contextual circumstances that produce them (Fritz & Dermody, 2020).

For design researchers and practitioners, this creates a recurring gap between measurement and meaning. Large-scale quantitative data can offer broad, systematic evidence about what is happening, but without context it provides limited support for interpretation or creativity. Lee & Ahmed-Kristensen (2025) describe the need to combine thin data, such as that from sensors, with thick data, such as qualitative data from observations or interviews, when discovering user needs or designing to influence behavior. A sensor may indicate that an interaction occurred or that something changed, but it cannot account for the complete human, social, or environmental conditions behind these events. Without contextualization, data remains difficult to translate into actionable design-relevant insights about user needs that can meaningfully inform design decisions or guide innovation.

Addressing this gap requires the inclusion of qualitative accounts of user voice and experience alongside passively collected data. User-contributed accounts can explain or challenge what the quantitative data appears to show, revealing how meaning and motivation shape observable behavior. While the value of combining thin and thick data has been widely discussed for design and human-machines interaction, here the focus is on how contextualization operates as an interpretive practice within data-driven design. The need for such contextualization is particularly evident in domains where sensor-based data increasingly informs planning and decision-making, including active travel, healthcare, and smart energy systems. In these contexts, large-scale measurements can reveal patterns of use, risk, or demand, but can lack the experiential explanations that make those patterns actionable for design. Here See.Sense provides an illustrative example within urban mobility, their smart bike lights collect sensor data on ride dynamics such as location, braking, and swerving, while a companion app enables riders to submit

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reports and comments. This combination of passively captured measurements and actively contributed accounts offers a situated case through which to examine how user voice enriches sensor-based datasets. By analyzing the relationship between sensor data and user-voice data, the discussion aims to show how contextualization transforms quantitative readings into design-relevant insight. Empirically, it draws on See.Sense data from Melbourne to illustrate how perception reports complement and extend sensor measurements, showing alignment where they corroborate one another and revealing factors beyond the reach of sensors where they diverge. These moments of convergence, absence, and mismatch are treated not as errors to be resolved, but as interpretive prompts that support design reasoning.

The findings are positioned within the D^3 (data-driven design) framework, showing contextualization as the bridge between discovering patterns in data and defining what those patterns mean for design (Lee & Ahmed-Kristensen, 2025). Rather than producing prescriptive solutions, contextualized data supports design exploration, hypothesis generation, and reflection. In active travel and infrastructure design, this allows designers to engage with perception, safety, and lived experience, informing the prioritization of cycling networks, junction layouts, street reallocations, and safety and behavior-change initiatives shaped by public perception. Consequently, interpreting data becomes a collaborative design activity requiring alignment among the stakeholders shaping urban mobility.

Taken together, the paper repositions contextualization as an interpretive design practice rather than something applied after analysis. Building on this shift, it proposes a distinction between passive contextualization (spatial and temporal) and active contextualization (experiential and social) as a vocabulary for describing the interplay of thin and thick data in design. A real-world case then illustrates how bringing sensor data into dialogue with user voice generates situated insights that support and inspire data-driven design.

2. Passive quantitative data and their limits

The growing accessibility of digital sensing has positioned passive das, information gathered without active user input, as a central resource for data-driven design. Such data are generated through sensors, Internet of Things (IoT) networks, mobile applications, and digital logs, and are valued for their precision, continuity, and scalability, providing designers and researchers with new ways to observe patterns of use, environmental conditions, or system performance (Creswell & Creswell, 2017; Fetters et al., 2013). Examples range from sensors in homes or workplaces that record temperature or energy use, to wearable devices that log activity or physiological signals, and digital systems that trace interactions with interfaces or services. While these forms of data enable detailed observation of real-world behavior, their design value remains limited when interpreted in isolation and without accompanying contextual understanding.

As a result, designers often rely on additional models, assumptions, or tightly specified conditions to interpret what passive measurements signify. In human–computer interaction, interaction logs can map frequency and sequence but do not reveal user motivations, intentions, or emotional responses (Fritz & Dermody, 2020). Similarly, in environmental design, sensor networks may report occupancy, movement, or light levels, yet cannot indicate whether occupants feel comfortable or secure (Ceccarini et al., 2022). Research shows that measures of comfort (e.g., pressure points, ergonomic fit) and emotional response (e.g., vase geometry) cannot predict user experience on their own and only gain meaning when interpreted within specific usage (Perez Mata et al., 2017; Stavrakos & Ahmed-Kristensen, 2016). These examples show how thin data excels at detecting change and pattern, but struggles to support interpretive, empathetic, or generative design reasoning without complementary experiential context provided by thick data.

A further limitation concerns the partiality of data production itself. Although passive data often appears objective, it is the result of specific design and measurement decisions that determine what is captured and what is excluded. Dourish (2017) describes data as being "cooked" through choices about what to measure, how frequently to measure it, and how it is recorded. For instance, an activity tracker may prioritize sleep duration, heart rate, or step count while neglecting the psychological, social, and environmental factors that shape how wellbeing is experienced. When such metrics are treated as complete representations of human activity, they can produce a form of design blindness, reducing complex experiences to quantitative proxies that obscure relational, emotional, and cultural dimensions of use (Gomez Ortega et al., 2023). In product-service and service design contexts, performance indicators such as efficiency, engagement time, or completion rates may therefore overlook issues of trust, inclusion, agency, or fairness that are central to user experience.

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These limitations suggest that contextualization is not a corrective step applied after analysis but an interpretive process through which data becomes meaningful. Without participatory or reflexive approaches that surface how data is framed and produced, design risks reproducing the assumptions embedded in its own measurement systems. Consequently, approaches that rely on decontextualized inference, including the use of generative artificial intelligence as a substitute for qualitative interpretation, lack the sociocultural grounding required for situated understanding (Jowsey et al., 2025). This perspective emphasizes the interpretive process required to translate passive measures into forms that are meaningful for design inquiry, positioning user voice not as supplementary evidence but as a means of interrogating, extending, and sometimes challenging what sensor data appears to show. The challenge, therefore, is not only to gather more data, but to understand how thin and thick data can be meaningfully combined through contextualization to reveal the realities of human experience for design.

3. Contextualizing passive data

In design research, contextualization allows quantitative information to become design material by moving from recognizing patterns to interpreting the situations, practices, and experiences from which they may arise. Within the D³ framework, contextualization plays a pivotal role between the "Discovering" and "Defining" stages (Lee & Ahmed-Kristensen, 2025). During discovering, designers identify patterns or anomalies within datasets, and during defining, they interpret these findings to generate insight and future design opportunities. Contextualization therefore functions as the bridge between recognition and understanding, moving data from description to interpretation.

3.1. Passive contextualization: spatial and temporal

Passive contextualization occurs when systems automatically capture contextual information alongside sensor readings. In most sensor-based datasets, the analytical focus lies on identifying change, detecting peaks, troughs, or deviations that signal something of interest has occurred. Spatial and temporal metadata then provide the first layer of meaning by locating and sequencing those events, effectively answering the questions of where and when they happened.

For example, an environmental sensor may record a drop in temperature, and associated coordinates or timestamps reveal that it occurred outdoors at dusk. This contextual information helps infer possible causes, such as overnight cooling or equipment exposure. Similarly, a sharp deceleration detected by a mobility sensor may be located at a junction late at night, suggesting a potential interaction between visibility and driver behavior. Spatial and temporal data add structure and constrain interpretation but rarely reveal causation. In some areas of design, such as predictive maintenance, this thin, passive data can be sufficient, but when the goal is to understand people and their experiences, additional thick contextual insight is required to interpret these measurements (Lee & Ahmed-Kristensen, 2025).

Comparable limitations appear across design domains. In smart-building systems, occupancy or air-quality sensors can highlight fluctuations that appear significant yet offer little insight into the routines or practices that produced them (Ceccarini et al., 2022). In digital services, usage logs may show bursts of activity but cannot distinguish between genuine engagement, confusion, or technical fault. Across these cases, passive contextualization supports discovery by surfacing patterns, but designers must still seek further context to define what those patterns mean.

3.2. Active contextualization: experiential and social

Active contextualization addresses how situations are experienced and why they matter. It introduces human interpretation into data through direct contribution or participation, capturing experiential dimensions such as perception, emotion, and evaluation, as well as social dimensions including interaction, shared practices, and norms (Gaver et al., 1999; Gomez Ortega et al., 2023). By capturing how people perceive and explain the situations that quantitative measures describe, active contextualization connects data to lived experience and the broader world.

Within the D³ framework, active contextualization complements the strengths and limitations of thin data across the discovering and defining stages. Passively collected sensor data is highly effective for identifying patterns, anomalies, and points of interest at scale, indicating where something notable happens, how frequently it occurs and under what conditions. These strengths make thin data well-suited for surfacing opportunities or problem areas that designers may not otherwise observe. However, the same properties that make thin data powerful for pattern detection limit its ability to reveal why those

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patterns are meaningful to people. Active contextualization therefore contributes the experiential and interpretive insight required to understand the significance of measured events.

Active contextualization can take many forms, including prompts that invite users to reflect on detected events, diary studies that pair logs with personal accounts, or participatory mapping practices in which datasets are annotated with observations. In each case, data shifts from an objective record toward a situated interpretation. The See.Sense system offers an example of this process, cyclists can link perception reports to specific sensor events or locations, describing moments of discomfort, obstruction, or perceived risk. These qualitative contributions supplement the quantitative record by turning mechanical events into accounts of safety, comfort, visibility, and trust. Similar approaches appear in smart-home research that combines energy-use data with household interviews, or in wellbeing studies where biometric readings are complemented by self-reported reflections (Hargreaves et al., 2018). Across these cases, thick data grounds thin measurements in experience, allowing designers to explore why events occur and what they signify.

3.3. Bridging interpretive gaps

Even when both passive and active contextualization are applied, ambiguity often remains. Designers must therefore employ additional strategies to connect data-driven observation with design understanding. These strategies are not discrete techniques but iterative and situated practices that are throughout the design process, supporting the transition from discovering to defining and beyond.

One approach is user-voice integration, which embeds opportunities for users to contribute reflections or annotations at the point of data capture. In-app comment tools, wearable prompts, or feedback typologies allow users to link events to their own interpretations, ensuring that patterns are explored as co-constructed experiences (Fritz & Dermody, 2020). A second approach is triangulation with additional contextual data, such as weather conditions, traffic flows, or demographic information, which can help distinguish physical, behavioral, and systemic influences within the dataset (Hong et al., 2023). Participatory sense-making further enables designers and stakeholders to interpret data collaboratively through workshops or co-analysis sessions (Gomez Ortega et al., 2023).

Finally, context-aware interfaces can support real-time reflection by recognizing situational cues, such as location, motion, or device state, and inviting interpretive input. This dynamic feedback closes the loop between data collection and user meaning. Together, these practices illustrate that contextualization is not a single analytical act but an ongoing design process. Through successive layers of interpretation, data moves from pattern to explanation, and from measurement to material for design reasoning.

4. Case study: See.Sense - Melbourne

This case study demonstrates how combining quantitative sensor data with qualitative user voice supports interpretive reasoning in data-driven design. Rather than evaluating system performance or producing generalizable findings, the case is used to demonstrate how contextualization operates in practice, showing how human experience and interpretation can transform sensor data from measurements into design-relevant insight. The focus is on how patterns, alignments, and ambiguities between data sources function as prompts for reflection and exploration in active-travel design.

4.1. Data and what sensors reveal on their own

The See.Sense smart cycling lights record motion-based indicators such as GPS location, braking intensity, swerving amplitude, surface vibration, and stop frequency, creating a detailed dataset of ride dynamics (See.Sense, 2025). The analysis presented here draws on a sample from a larger dataset collected in Melbourne, Australia. This sample includes approximately 12,000 spatially averaged ride points describing typical riding conditions, 110 abnormal events marking sharp braking, swerving, or vibration spikes, and 81 rider perception reports containing location-tagged comments. The data represents a short period of data collection and is used to examine how insight emerges through the interaction of sensor data and user voice, rather than to generalize about the entire cycling network.

When considered in isolation, the sensor streams capture changes that mark moments when something unusual occurred. Spatial and temporal information locates and sequences these events, revealing clusters of braking, swerving or roughness that may correspond to potential issues in the cycling environment. While this view provides technically precise information about where and when disruptions occur, it remains limited to surface-level description. The data cannot distinguish between

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underlying causes such as infrastructure defects, environmental conditions, sensor artefacts, or interactions with other road users. In this form, the data indicate that a cyclist slowed or swerved, but not why, constraining the interpretive value for informing design.

4.2. What qualitative context adds

Perception reports collected through the See.Sense app take two forms. First, and most relevant here, when the system detects a sensor anomaly, the app prompts the rider to report on the incident. These responses can directly contextualize the sensor data, providing an opportunity to explain what occurred and how it was experienced. Second, riders can submit user-initiated "drop-a-pin" comments, which add experiential context even when no measurable disturbance was detected. Together, these extend the interpretive reach of the sensor data by introducing accounts of perception, meaning, and situation.

4.2.1. Contextualizing sensor anomalies

When riders respond to a detected anomaly, their comments may clarify the event or remain too general to fully explain it, as shown below in Table 1 and Table 2. The interpretations presented are one possible reading of the combined data and are design-relevant hypotheses rather than definitive explanations.

Table 1. Sensor anomalies with context providing perception reports

Location (Lat, Lng)	Sensor Pattern	User Comment	Interpretation
−37.80467, 144.96343	Strong swerve	"Car turned left across the bike lane in front of me almost causing collision."	Clear link between anomaly and vehicle interaction, identifies bike lane-junction issue.
−37.80277, 144.96351	High braking	"Large hole through bitumen of bike lane, centre of lane, northbound near Lincoln Square."	Infrastructure defect explains braking spike, suggests maintenance need.
−37.79819, 144.97031	Elevated swerving	"Several severe ridges and bumps on the northbound cycle lane on Rathdowne St … severe enough to do damage or knock someone off."	Confirms degraded surface as cause, connects anomaly to safety and comfort.
−37.80451, 144.96295	Moderate braking	"In marked green bike lane, car on my right started to move into the lane too early … had to brake to avoid being hit."	Shows modest signal masking high perceived risk, highlights behavioral dimension.

Table 2. Sensor anomalies with ambiguous perception reports

Location (Lat, Lng)	Sensor Pattern	User Comment	Interpretation
−37.80115, 144.96592	Low-level vibration	"Rough surface again here."	Confirms potential discomfort but gives no precise cause or description of surface, limiting actionability.
−37.79985, 144.97002	Mild braking	"Too many cars today."	A broad observation, provides little information regarding the specific event, ambiguous for design insight.

These examples show how user input can transform sensor data into interpretive insight, while also revealing its variability. Detailed comments clarify cause ("car turned left across the lane") or experience ("severe ridges and bumps"), turning ambiguous anomalies into meaningful events. Less specific comments demonstrate that contextualization is an iterative and interpretive process. Designers must still evaluate, aggregate, and curate user input, constructing meaning from multiple forms of evidence.

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4.2.2. Independent user observations

A smaller subset of the reports were not triggered by sensor anomalies. These user-initiated "drop-a-pin" comments broaden the dataset by capturing perceptions of safety, comfort, or social interaction that produced no significant sensor reading.

Table 3. User-initiated "drop-a-pin" perception reports without sensor anomalies

Location (Lat, Lng)	User Comment	Interpretation
−37.80495, 144.96410	"Felt unsafe after dark, poor lighting on path."	Identifies visibility and perceived exposure issues beyond sensor scope.
−37.80332, 144.96602	"Large truck passed very close, scared me even though speed low."	Reveals psychological risk and social interaction effects unmeasurable by sensors if rider stays stable.
−37.80047, 144.97055	"Lots of pedestrians crossing suddenly, hard to predict."	Indicates shared-space problems absent in metrics.

Although these examples, given in Table 3, fall outside the focus on contextualizing sensor data, they highlight the additional value of enabling user-initiated reporting. Such entries reveal aspects of experience and perceived risk that sensors cannot detect, expanding opportunities for more inclusive and participatory forms of data-driven design.

Together, the examples illustrate how qualitative data can both explain sensor readings and extend the data's reach. This layered understanding establishes richer base for interpretation and design reasoning.

4.3. From contextualized evidence to insight

Bringing sensor readings together with rider comments produces distinct forms of insight that strengthen design reasoning. In some cases, the two data streams corroborate one another. When a cluster of sharp braking or swerving coincides with a comment such as "car turned left across the bike lane" or "large hole through the bitumen," the quantitative and qualitative accounts align to create a picture of cause and effect. These intersections between measurement and experience identify clear sites of risk or discomfort, providing evidence that can inform targeted inspection, maintenance or redesign. They show how the integration of user voice enhances the interpretive specificity of passive sensor data by clarifying what the signal may represent in the real world.

Rider comments can reveal experiences invisible to sensors, such as fear after dark, intimidation from close-passing vehicles, and uncertainty in shared spaces, highlighting human dimensions of mobility beyond motion data alone. These perspectives show that infrastructure must not only function well but feel safe, with perception and trust shaping active travel behavior (Aldred, 2019; Shepherd et al., 2024). From a technical perspective, such mismatches may reflect sensor limitations, timing offsets, or reporting error. While these explanations remain plausible, the value of contextualization lies not in conclusively resolving ambiguity but in making such uncertainties visible and available for design reasoning. From a design perspective, these moments can also be treated as productive prompts for further inquiry. They mark locations where existing measures are insufficient to explain experience and where closer investigation, through site visits, observation, or participatory analysis, may reveal underlying issues not yet captured in the data. Here, ambiguity functions as a design signal, pointing toward areas of complexity that warrant attention and learning.

Across these patterns, contextualization transforms the data from a descriptive resource into a diagnostic one. It allows designers and planners to explore the relationship between measurable disruption and lived experience, identifying how each source extends the other. This progression from observation (detecting anomalies) to explanation (interpreting their meaning through user experience), and finally to application (identifying where further action or inquiry is required) illustrates how contextualization turns passive data into an interpretive resource for design.

This process supports a more nuanced understanding of the cycling environment by connecting physical and behavioral conditions with the perceptions and emotions of those who use the network. By linking what was recorded to how it was experienced, the combined dataset begins to outline design priorities, from surface maintenance and junction safety to lighting and behavioral education. Rather than producing final solutions, contextualized data provides informed starting points for reflection, dialogue, and design exploration.

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4.4. From insight to action

The transition from contextualized insight to practical design application depends on how data is shared and interpreted among the stakeholders who shape urban mobility. To examine this process, four workshops were undertaken with See.Sense and a range of external stakeholders, supported by ongoing meetings with See.Sense that provided additional technical context about their system. Methodologically, these workshops functioned as interpretive sense-making sessions rather than evaluative studies, their purpose was to explore how different stakeholders read, question, and act upon the data, rather than to validate findings or measure outcomes.

The first, a data-led session with nine See.Sense employees, explored how existing sensor and rider-submitted data could create value for cyclists and helped identify relevant external stakeholders. Two subsequent stakeholder-led workshops involved ten and twelve participants respectively from organizations including Active Travel England, Transport for London, local authorities, bike-share operators, and digital-innovation teams. In these sessions, participants examined the types of data See.Sense could collect and, through facilitated activities, identified potential insights for different stakeholder groups along with additional datasets, such as collision records, weather information, or GIS layers, required to support them. A fourth workshop brought together twenty stakeholders from Dublin City Council, bike-share schemes, and smart-city and open-data teams. Here, participants generated their own needs and challenges and explored how See.Sense data, combined with other data sources might address issues such as junction safety or infrastructure prioritization.

Across all workshops, several themes recurred. Participants emphasized the need for clarity and accessibility in how contextualized data is presented, favoring visual and narrative formats that communicate both quantitative evidence and the rider experience it reflects. User voice was consistently regarded as essential for understanding not only where issues occur, but how they are felt by those affected. At the same time, participants recognized the limits of See.Sense data in isolation and highlighted the importance of integrating it with complementary datasets to gain a full picture of cycling conditions. While designers and analysts may identify technical patterns or correlations, turning these into priorities and interventions requires dialogue with those responsible for implementation. The collaborative interpretation of data therefore becomes a form of participatory design, where multiple perspectives negotiate meaning and determine appropriate action.

In practice, this process helps distinguish between physical interventions, such as resurfacing rough segments, redesigning junction geometry, or improving lighting, and behavioral or policy measures, including awareness campaigns, driver education, or enforcement of lane rules. For instance, repeated reports of close passes may indicate a need for lane redesign, while anomalies aligned with rider comments about “ridges” or “holes” point to targeted maintenance needs.

Through this collective process, contextualized data evolves from a record of performance into an opportunity for collaboration and empathy. By combining the precision of measurement with the insight of lived experience, it enables a more reflective and responsive form of data-driven design, one capable of supporting safer, more equitable, and more engaging cycling environments.

5. Context, interpretation, and method in data-driven design

The See.Sense case demonstrates how integrating sensor and user-voice data transforms raw measurement into meaningful starting points for design. Thin, passively collected sensor data when paired with user accounts, becomes contextualized, enabling interpretations that connect physical events with lived experience.

At the same time, incorporating user voice introduces new methodological and ethical challenges related to representation, bias, and privacy. The process reveals that designing with data is not purely technical but interpretive and situated, shaped by decisions about whose experiences are captured, how they are represented, and how insights are translated into action. These considerations highlight the need to treat contextualization as an integral part of design method rather than as an analytical add-on.

5.1. Whose context counts

The See.Sense analysis showed that user voice can reveal the causes and emotions behind cycling events that sensors alone cannot capture. However, it also exposed inequalities in participation. Most perception reports were submitted by confident and connected riders, while those facing greater accessibility or confidence barriers may be under-represented. This imbalance reflects a broader challenge in

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participatory and data-driven design, where the ability to contribute data is shaped by access to technology, understanding, and confidence (Johnson & Ahmed-Kristensen, 2025).
Contextualization should therefore not be treated as a neutral correction to quantitative data but as an exposure of difference. Recognizing these imbalances enables designers to read data critically and to use them to question rather than reinforce bias. Rather than assuming thick data offers a complete counterbalance to thin data, representational gaps can themselves become diagnostic signals, highlighting where engagement or inclusion needs to be deepened. By communicating these limitations openly, contextualized approaches can foster more transparent and inclusive decision-making.

5.2. Interpretation as design

The See.Sense findings demonstrate that interpreting data is itself a design act. Aligning sensor outputs with rider accounts involved selective choices about which signals to link, how to represent them, and what meanings to draw out. These interpretive decisions shaped how the data could inform subsequent design thinking. While existing work advocates combining thin and thick data, contextualizing information is often treated as supplementary to analysis rather than as an embedded design practice. In this sense, contextualization operates as a form of design reasoning, translating between computational record and human experience to build meaning. The integration of thin data with thick data depends on this interpretive work, which situates quantitative measure within the lived experiences from which they emerge (Policy Lab, 2020).
This approach reflects ideas from data humanism, which emphasizes empathy and reflection alongside precision (Lupi, 2017) and from human-data interaction, which highlights the social and interpretive nature of data use (Mortier & Henderson, 2014). In the See.Sense study, connecting sensor metrics with rider comments grounded the data in everyday experience, shaping what was noticed, which questions were asked, and what possibilities were explored. Interpretation here is not a step that precedes design, but part of design itself. Recognizing interpretation as a design act also highlights the designer's responsibility to balance analytical rigor with sensitivity to the perspectives that data represent.

5.3. Ethics, privacy, and accountability

Integrating experiential data with sensor records introduces important ethical responsibilities. As the reports are tied to time and location, they may reveal sensitive aspects of people's routines, emotions, or identities. Under the principle of contextual integrity, data practices must respect contributors' expectations and consent (Nissenbaum, 2004). Participants may be willing to share data to improve infrastructure or safety, but not support surveillance, enforcement, or commercial gain (Polonioli, 2022). Transparent governance is therefore essential, ethical data-driven design depends on clarity about how information is collected, stored, and shared (Kapp, 2022). Participation should remain voluntary and informed, contributors should retain control over how their data are used, and the outcomes should support learning and improvement rather than monitoring or sanction. The representation of findings also matters, visualizations and summaries should situate individual contributions within a collective account, rather than isolating them as items for scrutiny. Seeing interpretation as a collaborative and value-driven process helps maintain trust in participatory data systems and reinforces accountability within data-driven design practice.

5.4. Ambiguity and reflective interpretation

One of the key methodological insights from the study is that ambiguity is not necessarily a weakness of the data but a productive feature of complete process. Instances where anomalies lack comments, or where comments appear without measurable change, expose the limits of current sensing and invite further exploration. These gaps point to the complexity of lived mobility, including factors such as lighting, visibility, social interaction, or perceived risk that are difficult to quantify.
Embracing ambiguity turns uncertainty into a resource that encourages designers to question assumptions, seek missing perspectives, and combine data, field observations, and discussion. Understanding emerges through iterations of comparison, critique, and collaboration rather than through linear processes. Rather than acting as analysts who extract meaning from neutral data, designers become interpreters who work between technologies, participants, and contexts. This position reinforces the need for continual questioning of what can be seen and sensed, and what remains missing.

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5.5. Methodological implications

From the See.Sense study and discussions, it becomes clear that when designers work with passive sensor data, quantitative and qualitative information should not be treated as separate phases of analysis. Instead, they function as interdependent materials that evolve through iterations of discovery, contextualization, and reflection. Interpretation should not be the final stage of analysis but an ongoing practice that links observation, experience, and imagination.

The findings emphasize participatory sense-making in contextual data interpretation. Through dialogue among designers, planners, and users, data becomes a shared resource rather than a static input, keeping human experience central and frames interpretation as a collaborative process.

The study suggests that data is most valuable when it acts as prompts rather than prescriptions. The role of data in design is not to dictate solutions but to prompt reflection, dialogue, and exploration (Gall et al., 2023; Gaver et al., 1999; Shepherd et al., 2024). generative materials that invites designers to ask new questions, imagine alternatives, and navigate uncertainty with empathy and curiosity. Together, these reflections point toward a practice of contextualized data-driven design in which measurement provides precision, user voice gives meaning, and collaborative interpretation connects the two.

While the examples presented here are interpreted manually at a small scale, the approach is not intended to rely on close reading of individual comments alone as datasets grow. At larger scales, contextualization would depend on aggregation, clustering, and participatory filtering of user voice, using qualitative input to guide where attention and further investigation are directed, rather than requiring exhaustive interpretation of every individual contribution.

6. Conclusion

Quantitative data such as those produced by the See.Sense sensors captures movement and change with precision, but alone this thin data can lack the interpretive context needed to explain cause, intention, or experience. When combined with qualitative perception reports, the same data acquires depth and meaning, providing accounts of lived experience.

The See.Sense case demonstrates how contextualized data can transform measurements from sensors into a resource for design. Sensor anomalies identified points of braking, swerving, or vibration, while rider comments revealed the conditions and emotions behind them. Together, these data created insights that neither could supply alone, exposing both the physical and felt dimensions of risk, safety, and comfort in the cycling environment. This integration enabled design prompts ranging from maintenance and junction layout to behavioral and policy measures that support confidence and awareness.

More broadly, the study illustrates how contextualization provides a foundation for reflective and participatory data-driven design. The process of interpreting and integrating diverse forms of data is not just a technical procedure but a creative act that connects evidence with empathy. Treating thin and thick data as complementary materials positions data as a human-centered design resource, inviting designers, policymakers, and communities to engage and to treat data as prompts for dialogue and imagination.

The future of data-driven design lies in its capacity to combine precision with perception and analysis with experience. Extending this approach to other domains of design will require systems that support ongoing feedback, collaborative interpretation, and transparent data governance. When integrated through ethically grounded processes, the result is an approach to data-driven design that remains technically rigorous while also being socially responsive and human-centered.

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