Changing Perspective on Data in Designing for Active Environments

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ABSTRACT

Smart solutions provide increasing quality and availability of data. This brings new challenges for designers as it offers novel design opportunities and interlaces disciplines. At the same time, physical inactivity is a big societal challenge and dedicated urban planning and design can contribute to more active lifestyles. In this paper, we investigate how user-generated big data can support designers in shaping more activity-friendly and adaptive environments, addressing both timely challenges. Bridging the fields of HCI and urbanism, we introduce two data lenses. The *individual lens* primarily builds on empathic design skills and calls for a highly personal approach. The *collective lens* emphasizes systematic and holistic design skills, focusing on creating overview and surfacing collective interests. Through exploratory data visualizations, using a large dataset from a run-tracking smartphone application combined with public data sources, and a workshop, we investigate how these lenses can yield meaningful insights. We discuss the value of these lenses to the urban design and HCI communities and address the challenges and opportunities that arise at the cross-section of these perspectives.

CCS CONCEPTS

• **Human computer interaction (HCI)**; • **Visualization**;

KEYWORDS

Human-Environment Interactions, User-Generated Data, Data Visualization, Adaptive Environments, Smart Cities

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1 INTRODUCTION

Sedentary behavior and physical inactivity are an increasing public health concern [13, 31, 42]. The majority of people are aware of these health risks, but it remains difficult for them to actually embed enough physical activity in their daily routine [49, 57]. Finding effective ways to encourage people to be more active and to help them to maintain a healthy lifestyle is thus a critical endeavor for researchers, practitioners, and governing agencies [49, 67, 86].

There is growing evidence that the design of urban environments is contributing to physical inactivity and underlying health concerns [27, 52, 71]. In the field of urban design and planning, the topic of designing 'healthy places' is well-researched, both in relation to general health conditions [10, 19, 36, 55] and to physical activity [30, 51, 69, 71]. Over time, design recommendations and guidelines have been developed to help guide this process. Regarding physical activity, these guidelines often include mixed land uses to preserve a human scale and ensure proximity of facilities, improved pedestrian and bicycle infrastructure and high-quality places for sports, play and leisure activity [1, 30, 82]. Despite this body of knowledge showcasing the benefits of 'healthy places' and providing guidance on how to build these, other matters, such as convenience and vehicle flow, seem to have taken priority in designing urban areas [18, 36, 39]. As a result, urban areas are often arranged in ways that are more likely to have negative health implications. While through their design, these environments have the potential to contribute significantly to physical activity levels [15, 19, 71].

Next to increased awareness for the design of healthy cities, we see a distinct shift towards 'smart city' technologies and design. 'Smart Cities' are defined as being or containing 'smart environments', building on data to optimize processes and sustainability. This data flow is used to learn and address the challenges that come with urbanization and population increase through Information and

Communication Technologies (ICT) and related technologies [75]. Smart cities aim to advance performance, efficiency, sustainability, to connect the physical, social, business, and ICT infrastructure [6, 41], and to increase and maintain quality of life [59, 75].

This transition towards technology-enhanced environments creates a bridge between the urban design and HCI domains. HCI in turn evolves to the realm of physical space through the ongoing shift towards Human-Environment Interaction (HEI) [77, 79]. In this field of research, technology is increasingly integrated in the environment and is thus both more omnipresent and less noticeable. Through their embedded technology, these smart environments provide new interaction possibilities. This offers potential for more adaptive environments that can be dynamically tailored to the user and their context, based on the wealth of data it can collect. In view of creating places that not only enable, but even encourage a healthy lifestyle, it is worthy to note that a tailored approach is a significant element in persuasive technology [12, 29, 47]. Environments that can adapt to accommodate users individually therefore have an increased potential to inspire healthy active behavior.

The ambition to move from static to interactive and adaptable environments has considerable implications for how these spaces are being designed [78]. No longer are static one-type-fits-all solutions required that can withstand changes of many variables over time. Instead, designers can now think about how environments can be made to adapt to circumstances like weather conditions, specific scenarios of use, the users themselves or the temporality of people's experiences. Data plays an instrumental role in these smart environments as it is the fuel to drive such solutions [50]. However, data as a dynamic enabler is not yet a standard topic of attention in the urban design field. While data is increasingly used for analytical purposes, the opportunities it presents to play a key role as a design material [50] throughout the process are still mostly untapped.

With this work, we investigate how both fields can leverage each other's strengths as we study how both a collective and an individual perspective on data are valuable when designing for adaptable environments.

2 RELATED WORK

Designing healthy environments has a longstanding history in urbanism [34, 55, 56, 87]. Smart city and -environment developments introduced a technology and information layer to that, which bridges it into the HCI space. Within the HCI community, an opposite parallel trend is also clearly visible in the growing body of research on Human-Environment Interaction (HEI) [77, 79]. The transition from 'artifact' to 'environment' has several implications for the dimensions of user experience. For example, transitioning from usability to comfort or from short-term relationships with products to durable and immersive experiences [3]. Following the narrowing gap between these two design fields, our objective is to bring perspectives from these communities together in our exploration of how user-generated big data can be valuable in designing for adaptive active environments. To do so, we outline different uses of data in urbanism and in human-computer interaction.

2.1 Data in Urban Design and Planning

Next to their use of data and technology to optimize processes and sustainability, smart cities are characterized by being inclusive and able to adapt to the behavior of their inhabitants [9, 66]. This makes human- and user-centered design approaches for future cities highly relevant and extremely important [77, 78]. In order to design these inclusive 'cities for all', being aware of the real citizens' use of the public space is therefore essential [66], making crowd dynamics a popular research topic in the field of urban design and planning [8, 22].

As such, people have become an important resource in the process of creating this new generation of cities [37, 66]. Through visiting living lab areas, sharing their data or other forms of conscious or unconscious involvement, the inhabitants of these cities provide valuable input for governments and urban architects alike [38]. On-site sensor kits for single point measuring give clear insight in a specific situation without requiring active participation of citizens, while richer, more complex data can be collected by aggregating user-generated data. This data, collected through apps or wearable technology from many different users, can provide relevant insights about the population in general [68].

As this data is connected to specific people or objects, it enables more longitudinal observation. This allows urban architects to understand complex behavioral patterns such as specific transport streams or activity behavior, eventually supporting informed decision-making for urban planning and design [68, 84].

In most cases these user-generated big data sets focus on specific topics (e.g. cycling data), but smart systems expand on this by integrating a wealth of additional data of varying type and source to find meaningful patterns [35]. We note that data is currently being used dominantly for analytical purposes, informing design and decision making as evidence or by driving predictive models [4, 44].

Visualizing these data collected from citizens can be a powerful tool to both get and communicate such insights [20, 40, 74]. Earlier work on the value of visualizing user-generated urban activity data to assist urban planners in creating healthy or active environments found this approach promising, but additional data or details may be needed to make effective use of the sensor data [9, 24].

2.1.1 *Reflection.*

Big data has come to play a more important role in the urbanism practice, with new ways being explored to capitalize on the stream of data coming from smart city solutions. When creating new policies or spatial designs, planners, policymakers and designers typically consider and value the general trends, patterns and averages provided by the aggregated data [61]. Traditionally, this approach makes a lot of sense. Since there would be only one static and lingering space (or policy) that affects many people, the focus lies on 'the average person' so that the design is likely to be suitable for most. But if the definition of a 'smart' city is that it is not static, but can adapt to its resident's behavior [9], involving only the 'average' citizen in the design process seems a little short sighted. We argue that if cities and environments grow to be adaptable, they should be able to adapt on a more personal or individual level. Data plays an important role in enabling this adaptability. As it is essential for digital technology to register, learn from and respond to human behavior, we need data to both understand and help shape human behavior in urban environments.

2.2 Data in Human-Computer Interaction (HCI)

In HCI, data has become the fuel to drive smart or intelligent systems, as it plays a key role in personalization solutions [60], recommender systems [64], and adaptive interfaces [11]. For a smart system to adapt its behavior meaningfully to the user and their context, it first needs to understand who the user is, or what spatial setting it is in [72, 83]. For that, it needs to collect data that can embody meaningful stories [23]. For example; a smart baby bottle that gives different feeding advice based on the caregiver [14] or an interactive pedestal that can adapt its behavior based on the people in the room and how they are interacting with it [26]. There is ample evidence from the persuasive design community indicating that personalized solutions are more successful in achieving long-term behavioral change [12, 29, 47].

The increasing role of data in these intelligent systems [48] has also inspired new ways of designing. In this new body of work data is often considered as a material to design with [48, 50, 73]. Using that materialistic lens, this work identifies different material qualities of different types of data [7, 53, 54]. Bornakke & Due [16] introduced the now commonly used difference between Thin/Thick and Big/Small data, that each have their own advantages. Big data is valuable because it encompasses data from many different users as a very large and longitudinal scale. At the same time, this data is often thinner as it lacks qualitative richness at and individual level. Small datasets are often more thick, as in-depth qualitative work has meaningfully enriched the data [16].

Work on data-enabled design [50] reasons along similar lines, as it further explores how a data centric approach can help in designing thick small data that can scale to become thick big data [16]. Focusing on details, nuances and people's idiosyncrasies here prevails over generic insights on population-level [54]. This means focusing both on finding denominators as well as focusing on what makes people unique. Data visualizations that aid in this progress therefore also address being able to compare user behaviors, between different moments and between people. In this area of design research, small datasets and explorative data visualizations are typically used to gain highly individual insights because larger datasets are often missing at the front-end of innovation [76].

Next to the focus on data as a material to design with, we see increasing use of data to drive and inform design decisions [48]. Similar to the common approach in urbanism, in these cases data is mostly used to analyze existing or created situations, based on which decisions can be taken. The data that is being used is not the data that drives these systems, but an additional layer of analytics data that gives detailed insights in the situation. These insights are based on what the majority of users prefer, which could limit its' inclusivity and diversity [25]. Different data-design approaches have varied roles for decision-makers. In data-driven design, results from experiments directly drive decisions. In data-informed design, there is a larger role for the decision-maker, who weighs their personal knowledge with the insights provided by the data [48].

2.2.1 Reflection. In order for a smart environment to encourage people to be more physically active, a tailored or personalized approach to this persuasion would likely be most effective [12, 29, 47]. User-generated data offers a unique opportunity here because it holds detailed, often long-term data about user behavior. These behaviors can be contextualized with more environmental data that can also come from other sources. The key is to focus on individual traits and characteristics as this is essential in gaining the empathic understanding that is needed to design systems that can really adapt to people's individual needs. Explorative data visualizations, with high levels of individual detail, have proven to be a valuable tool in this [62, 74].

3 RESEARCH OBJECTIVES

In this paper, we investigate how research in the fields of urbanism and HCI can be combined to create meaningful perspectives on user-generated big data. The urbanism perspective provides reliable insights in general behavior and trends, a large-scale and birdseye perspective [35]. This view is still rather unexplored in HCI literature [2] and introduces challenges of scale and accompanying inflexibility unfamiliar to the HCI community. On the other hand, the more individual and personal perspective that is thoroughly embedded in the HCI mindset is often lacking in the urban design context. This view that is typically adopted on a product or interaction level in HCI may have been impractical in the past for designs of urban scale and lifespan. Smart city developments, however, are likely to benefit from a more personalized view towards data.

We therefore set out to explore how both fields can leverage each other's strengths as we study how both perspectives on data are valuable when designing for adaptable environments. As we feel these views should not be limited to one field or the other, we introduce two lenses that we investigate through a case study.

By introducing a *collective lens* on data, we aim to emphasize the value of the urban population perspective that is needed to design for an adaptive active environment. Topics like socio-cultural patterns, geographic and environmental characteristics, and collective trends could potentially be addressed by this lens. To do that, this lens focuses on aggregates, common denominators, and repetitive patterns. The collective lens could be used to build a solid foundation that benefits the population in general –the collective– when designing adaptive environments.

We introduce the *individual lens* on data to celebrate individual uniqueness. It is a perspective that values detailed knowledge about individual users in order to investigate how people are different and what makes them unique. Being able to capture these idiosyncrasies would be instrumental in further tailoring the adaptive environments to individual needs. The individual lens could be used to investigate individual preferences and patterns, and the role of external factors, to accommodate users on a more personal level and acknowledge them as human, unique parts of the whole.

We deliberately propose the terms *collective* and *individual* instead of *macro* and *micro* or *big* and *small*, to address these perspectives in order to emphasize not only their scale but also the human-centered focus that's at the core of our approach. Similarly, Afonso et al. (2019) also use *collective scale* and *individual scale* when describing ways in which we experience the city, before switching to the terms *body scale* and *city scale* to accentuate interactions with outdoor interfaces [2]. Micro-macro models are used for a wide array of concepts to indicate scale, with micro-level representing the smallest unit of analysis and macro level the largest. These new lenses describe a specific subset of these levels; they articulate a focus on experience, desire and needs of people, either as an individual or as a group. All other entities, both of a tangible and intangible nature, that influence or are otherwise relevant for that purpose are collectively addressed as context.

To investigate the value of these lenses we conducted two studies; We started by exploring the value of both perspectives through a case study of user-generated data from a popular running app. We focused on running as a well-documented example of conscious physical activity taking place in the urban environment, building on the knowledge that environmental characteristics considerably influence running behavior [27]. Through a series of data visualizations, we explored different ways in which urban data can be combined with other data, and how they can be visualized to yield meaningful insights for their respective perspectives. To test the potential of the lenses we then invited other professionals to use them in a design workshop, using the most auspicious visualizations of the first study to present the data for both lenses. Based on these explorations, we discuss the qualities of the collective and the individual lens, the interplay between these lenses, and how designers can leverage them while designing for adaptive environments.

The studies presented in this paper were approved by the Eindhoven University of Technology Ethics Board.

4 STUDY 1: A CASE STUDY OF USER-GENERATED RUNNING DATA

4.1 Research Approach

In our endeavor to explore ways to design a new generation of healthy environments, our focus in this study is on the value of the *collective* and the *individual* lens. Specifically how we can use the data that is collected through smart systems or environments to improve the design or design process of such places.

As a case study illustrating this approach, we use data collected through a running app. Running is popular because people can do it wherever and whenever they want to. As a case study illustrating this approach, we use data collected through a popular running app. The individual and independent nature of running makes it hard to track these sporters in a traditional, centralized research setup where all participants follow a certain route or schedule. However, through increasingly popular personal activity tracking apps and devices, many recreational runners log their own activity; collecting valuable data often over a longer period of time [46]. We analyzed a large set of this kind of user-generated running data through both lenses to find valuable insights for the design of healthy environments.

For the collective lens, we start with an urban perspective, exploring how we can use data to enrich that perspective; looking for new or more details, specific information of certain areas or other valuable insights. Next, we adopt an individual lens, looking at the same data from a different perspective. Rather than looking at general trends, here we look at what makes specific users unique, stand out from the crowd, and how we can use exactly these insights in the design of (adaptive) environments.

The exploration of the lenses was a highly iterative process. The process and insights are merged into one section to accommodate the documentation of that process.

4.2 Dataset and Data Visualization Tools

For our study we used a dataset collected by EnergyLab's popular Dutch running app, called *Start2Run* in Belgium [32] and *Hardlopen met Evy* in The Netherlands [33]. These apps primarily target novice runners yet are also used by runners with more experience. They can either be used to track any run or to provide training schedules and audio guidance during runs. Both apps are identical apart from country-specific branding.

The dataset contains detailed GPS trails (approximately 5-meter accuracy) of 1,490,145 runs, collected between 2012-2016, and for each run a set of summarizing metadata, including a run- and user-id, start time, duration, distance, average speed, effective time (time of the run minus pause time) and, if applicable, training-id (relating to a specific training program provided by the app). For privacy reasons, the dataset was de-identified by removing all personal data and by removing the first and last coordinates from each trail to mask start and end location.

We use explorative data visualizations to uncover patterns and gain insights into user behavior [62, 74]. After processing and cleaning the dataset, we visualized it using a combination of visualization tools. Early explorations made use of the d3.js [17] visualization library. As this gave performance issues with the vast amount of data we transitioned to the use of open-source mapping platforms MapBox [58], TileMill [28] and later the webGL powered Deck.gl [81]. For the visualizations for the individual lens we again used d3.js. As we could select a limited number of users, data size was less of an issue here.

4.3 Exploring the Collective Lens

4.3.1 First map-based data explorations. To emphasize the urban and macro approach of this lens we started our explorations with map-based visualizations. Our first one (Figure 1) was a map that visualized the starting point of each run from the Start2Run app on the Belgian map.

This gave first insight into the geographic spread of our data, and already clearly articulated more and less densely populated areas. The map covered a large area, arguably even beyond what urban planning and design is usually concerned with.

As a next step, we added a few color filters to the interactive visualization, allowing us to filter on the time of the day (i.e., morning, afternoon, evening), the day of the week, and the month of the year. This showed how people were less likely to run on the beach in December than in May and that there was often more activity on a Sunday morning than on other moments during the week. Although it was good to see general assumptions being confirmed by the data, there were not many novel insights. We concluded that this data visualization was zoomed out too far to meaningfully capture our collective lens.

4.3.2 Understanding (un)popular places. In new visualizations, we zoomed in further to the level of an area that made sense to address from an urban planning and design point of view, including cities, neighborhoods, or smaller areas. At city level, it became eminent

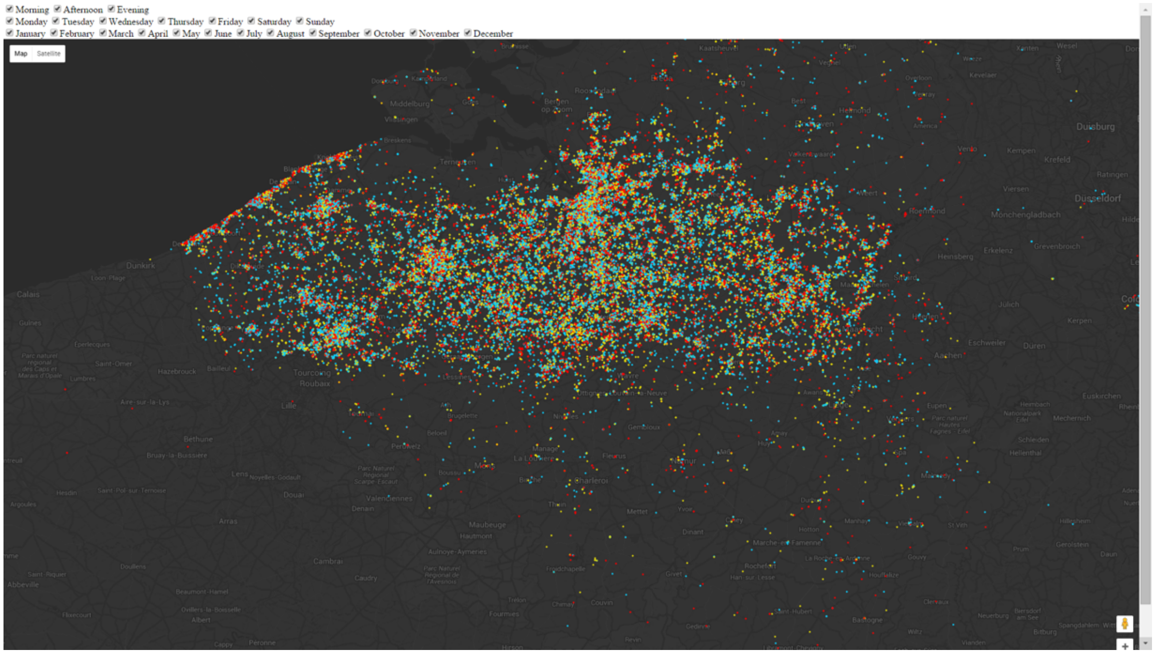

Figure 1: A map visualization showing the starting location of all Start2Run runs in Belgium. Colors indicate time of day; red: morning, yellow: afternoon, blue: evening. Filters can be used to change the meaning of the colors (i.e., 'day of week', or 'month of year').

that we needed more granularity than only the starting location of each run, as that said little about popular running areas; only where people started their activity. On this scale, we therefore added the full run trails to the map.

Figure 2 shows all GPS trails of runs in the city center of Amsterdam, the Netherlands. Brighter colors and wider lines indicate more activity in those places. This revealed clear hotspots and coldspots, indicating what routes and areas were popular for running, and which were avoided.

Previous research [27, 68] indicated that areas with green or water added to the attractiveness of running routes. To visualize this, we mapped runs on maps that showed land-use types. Figure 2 shows how popular running locations in Amsterdam map onto different environments. This clearly illustrates not only that green or water environments are popular running locations, but also shows which parks are preferred over others.

By only showing or coloring runs with specific characteristics in the metadata, such as a certain distance or average speed, we sought to reveal more patterns. We also compared runs at different times to see if patterns change over time, e.g., morning vs. evening runs, weekday vs. weekend day runs or runs per season (Figure 3).

4.3.3 Understanding environmental qualities under different circumstances. As we explored this dataset with a focus on gaining actionable insights for the design of healthy, or more specifically 'runner-friendly' environments, our interest was mainly in environmental characteristics that can be influenced by design [27, 52, 85]. In light of our explorations, we visited more and less popular areas in different cities to investigate what made them different, realizing that not only the environmental characteristics but also context has an important impact on running behavior [43]. Considering the significance of this influence when researching running behavior, we also included this in our study. Context, being a collection of circumstances, we defined by specifying several measurable aspects of it that are likely to influence running behavior.

We merged existing datasets with our running dataset, to give each run the following additional attributes; Weather data (e.g. temperature, rainfall, wind) – dataset from Weather Underground [80]; Neighborhood data (e.g. real estate value, build year) – Dutch dataset from the national bureau of statistics [21] and Light or dark – based on daily sunrise-sunset calculations.

This enabled a new set of visualizations that indicated different patterns depending on these attributes. Making separate maps for daylight and nighttime runs (Figures 4 and 5), for instance, clearly showed places without streetlights going from very popular during daytime to deserted after sunset, demonstrating the impact of public lighting (a). More remote areas, such as nature areas with few dwellings, were however also almost exclusively used during daylight hours (b), regardless of the presence of streetlights. This indicates that during the day, both urban and rural areas can be popular for running, while after nightfall the runners tend to stay in an area that is not only well lit but also sufficiently inhabited.

Applying a similar approach when merging the GPS trails with other contextual data, such as weather (rain or dry, wind conditions), comparing runs in the rain to runs when it is dry clearly shows that far fewer runs take place in the rain, but it also shows other preferred routes in both cases. Zooming in on a coastal city, the Hague, NL, we saw that alongside the beach (Figures 5 and 7), for

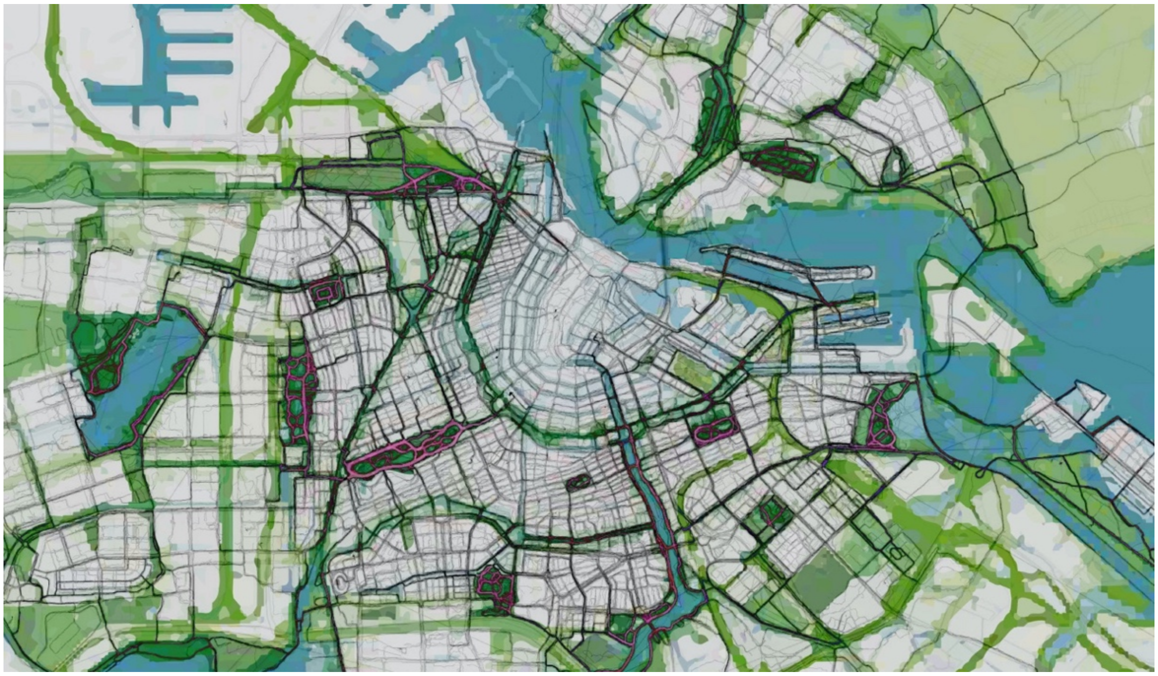

Figure 2: Run data merged with environmental land use data in Amsterdam

Figure 3: A visualization of all GPS trails in Eindhoven, NL. Different colors represent different seasons.

instance, there are many runs when it is dry and almost none when it is raining (c). But at the same time, there are other areas where the weather conditions do not seem to make a difference.

Through these map-based visualizations we explored how different environments are used for running. The introduction of more contextual data allows for easy identification of divergence between environments, based on the circumstances. For example, the preferred paths shifted when it rained or when it was dark. Our collective lens made us focus on the urban population scale, instead of on individual users. This directed our attention towards environmental characteristics that were popular for running in the general population. However, even at population level, we still

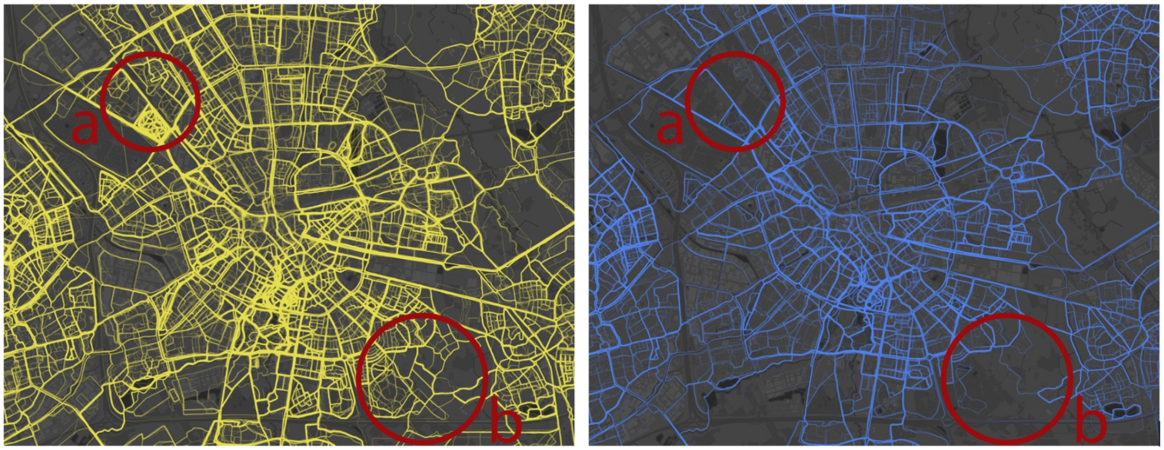

Figure 4: and 5: GPS trails of runs in Eindhoven grouped by *daylight* and *after nightfall*. Circles a and b highlight some of the major differences between these circumstances.

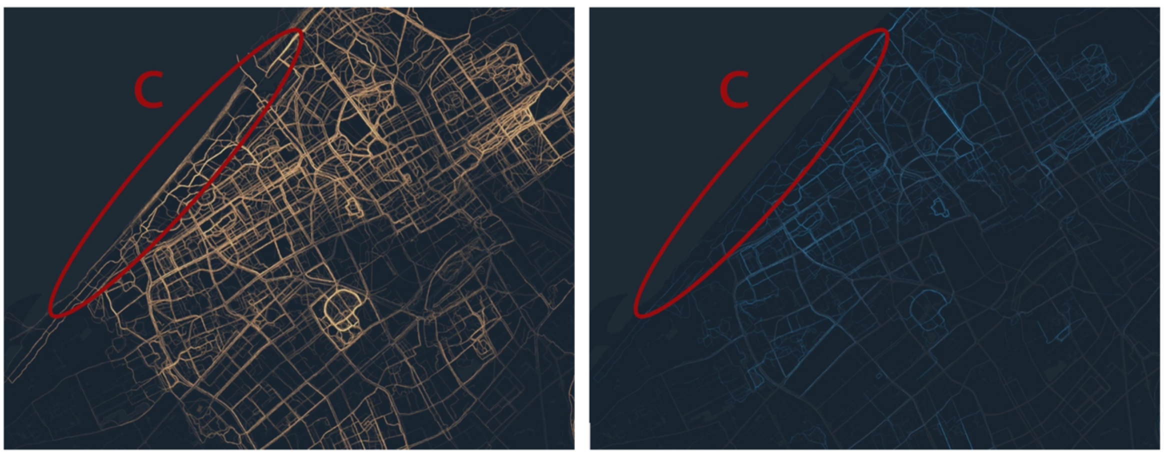

Figure 5: and 7: GPS trails of runs in The Hague, grouped by *dry* and *during rain*. Shape c indicates the difference in popularity of the beach.

see variation on preferences based on circumstances. The claim that green and blue environments are so popular among runners remains true overall (Figure 2), but Figures 4–7 also show that some nuance to this statement is in order. Some places indeed remain popular no matter what, but others vary greatly in popularity based on weather, (day)light or other circumstances.

4.4 Exploring the Individual Lens

The objective of the individual lens is to provide an emphatic focus that helps in understanding who people really are, what their needs are, in light of their running behavior. Through this lens we look in the data at what makes different people similar but also what makes them particular. Being able to find these individual uniquenesses in the data is ultimately a key enabler for further personalizing adaptive environments.

The first set of individual visualizations is derived from the available collective visualizations. Instead of overlaying the data of all users in a region, we now filter on a specific user and create separate visualizations for them. Figure 6a and 8b show the trails of two different users. We randomly selected 250 users (with the requirement of having completed at least 5 runs), whose trails were visualized to be visually compared. The focus here was not so much on characterizing a specific user, but rather on what makes an individual singular. We searched both for uniqueness and commonalities.

These visuals gave clear insight in individual behaviors. The fact that we could compare a good amount of different users allowed us to spot first patterns. Based on their speed and distance, we often saw more experienced runners prefer straight paths without turns. Instead of creating a limited number of profiles and trying to assign these to users, we explored different personality traits and explored how we could identify these. For example, some users could be characterized by always running the same route (Figure 6a), with only minor deviations, where others would hardly attend the same location twice to explore new terrains each time (Figure 6b).

Figure 6: Individual GPS trails of users with (a) mostly same route; and (b) many variations in route.

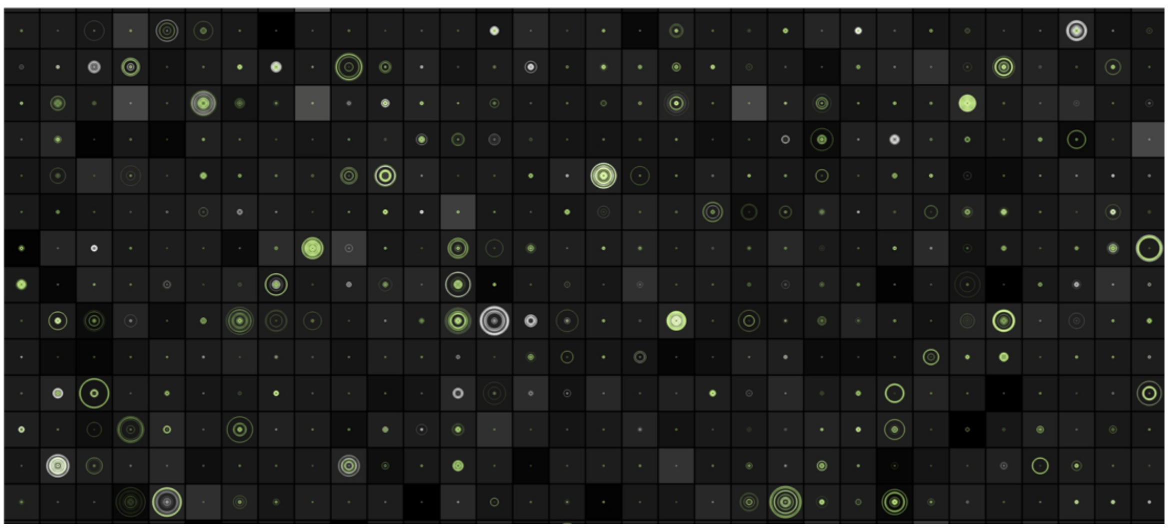

Figure 7: Overview of Individual runs, each square represents 1 user, each circle a single run. Time between runs is shows in space between separate circles.

Also differences in recreational runners and performance runners would often surface by their route choices. Interesting to note is that many of these patterns triggered more questions than they provided answers. In an ideal setup, we would be able to reach out to these people to better understand *why* they behaved in a certain way, but given the de-identified dataset it was not possible to track activities back to individuals.

As these map-based visualizations had a clear focus on geospatial mapping of behavior, they missed behavior patterns that related to time. We could, for instance, not use these visualizations to understand if people only ran in nice weather or stuck to their weekly routine no matter what. To further zoom in on individual behavioral patterns, while again being able to compare and find interpersonal differences, we developed an extensive visualization in which individual users would be represented. A subset of this visualization is shown in Figure 7.

This figure shows all runs of a single user as circles in a square. Within this square the image also shows the distribution of these runs over time (from center to edge), like the annual rings of a tree, allowing us to quickly spot patterns concerning run frequency. The color of each circle indicates whether each run was part of the app training program (green) or not (white). Finally, the background color provides an indication of the average speed of all runs of that user combined (a lighter background represents higher average run speed). This visualization provides quick insights in individual user's performance and training pattern, while still providing an overview to compare many users at the same time.

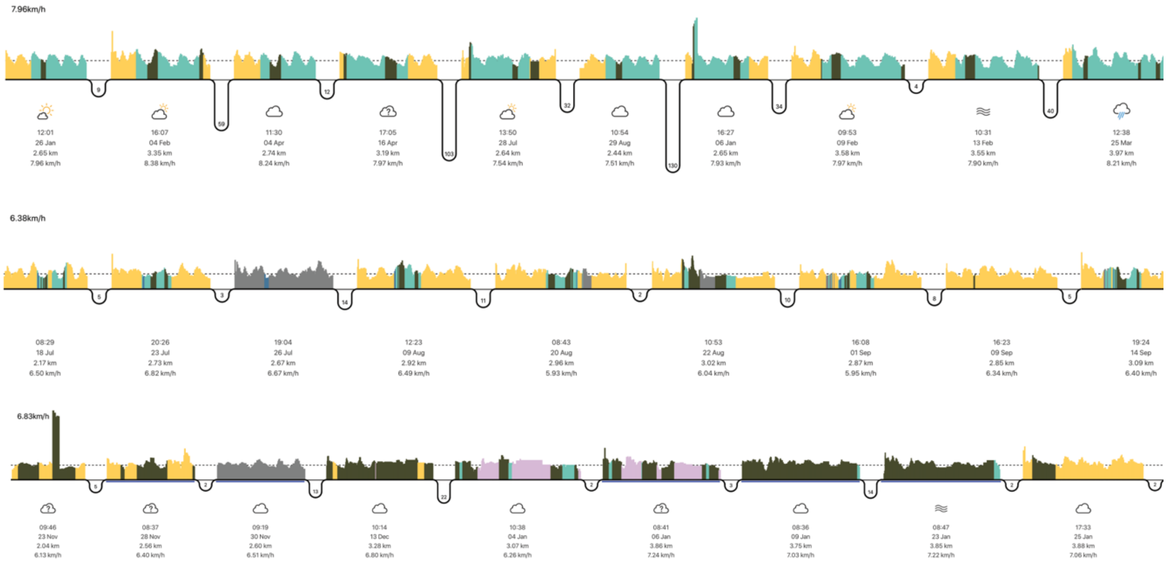

Figure 8: Individual data of 3 users over time; showing environment type (color), time, weather, distance and average speed (under each run), speed (height), overall average speed (top left and dashed horizontal line), days between runs ('dip') and if at night (blue line)

The differences between squares clearly advocate how different personal routines are, yet they also show patterns in how users temporarily stop running and come back later. Rings hardly come up in isolation, showing that people who renew their running ambitions often manage to get beyond the first few runs, while being challenged to sustain that for a longer period. Their patterns are likely to give good insight in motivational strategies and can help to identify people that are motivated in similar ways. This overview (Figure 7) illustrates that treating all these users as one 'average' person, will not do justice to this variety.

The visualization shown in Figure 7 successfully helped in understanding activity patterns but lacked detail on individual runs. As for the collective lens, we added more contextual data. Next to the attributes that were already added earlier (weather, neighborhood information, light or dark), we also included detailed data about the surroundings. The OpenStreetMap Overpass API [63] provided us with detailed data about the land uses along each running track (e.g. percentage of water, farmland, forest, residential area etc.).

We created a visual overview of individual user data that includes these variables, as well as time and speed progression during those runs, as can be seen in Figure 8. Here, time is displayed on the x-axis, which dips down to indicate the much longer timespan in-between runs, with the number of days passed shown inside those dips (i.e., bigger dip; longer time between runs). Speed is displayed on the y-axis, with the overall average speed shown in digits at the top and as a dashed line in the graph. For each run, the start time and weather information of the run is shown below, with a blue line underneath the run if it took place at night. Lastly, the colors indicate the type of environment, based on the OpenStreetMap land use data. Again, we plotted data for 250 random users with a minimum of 5 runs for visual comparison.

The patterns that start to emerge here show individual progress and environment selection combined with some context characteristics. When used for longitudinal observation, such visualizations could even help to identify influences of context or different environments on user performance, recognize characteristics of a certain type of user or predict behavior. Creating this type of visualizations also allows to quickly spot recurring or deviating patterns, without the need to know exactly what to look for beforehand. For follow-up studies these visuals can also help to quickly select 'interesting' (similar or deviant) users, either based on performance or patterns.

In the context of designing encouraging running environments, this detailed knowledge about individual behavior can be of great value to determine effective strategies. Especially when adopting a personalized approach through adaptable environment technologies, insights in personal routines and preferences can strongly add to their potential to encourage healthy active behavior. An interactive system could for instance guide people towards a longer or shorter route, a specific area, busy or quiet routes, or adjust light hues and soundscape, all based on personal training progress or environment preferences.

Next to learning about personal preference for running times, routes, buildup, or circumstances and translating these into design guidelines, this approach of studying and comparing individual patterns can contribute to our cause in other ways. From a health perspective, it can for instance help to track individual progress or predict oncoming fall-out (either because of injury due to overtraining or motivation loss due to underachieving) [5, 88, 89]. At the same time, it can indicate effective personal training strategies [45] and help to identify unintended use of the application. From a designer's perspective, these are all points of interest. These findings provide inspiration and possible intervention points, presenting both the challenge and opportunity to intervene on a more personal scale. Based on these insights we can use technology to create digital, adaptable, or unique features that inspire users because they fit the type of person they are.

5 STUDY 2: APPLYING THE LENSES IN PRACTICE, INSIGHTS FROM A DESIGN WORKSHOP

To explore the value of the introduced lenses –and data visualizations– when designing active environments, we set up a design workshop. The goal of this workshop was to test how practitioners experience using these lenses, and whether the lenses offer valuable potential to improve their process and the resulting design concepts.

5.1 Participants

We hosted 3 sessions with a total of 21 participants (7 women, 14 men, aged between 22 and 59 years), 7 participants per session. Participants were selected based on their experience with designing active environments; 14 design researchers and practitioners and 7 human movement scientists. All participants had professional and/or personal interest in encouraging physical activity and 8 identified as experienced runners, including 1 running coach. Informed consent was obtained from all participants prior to the study.

5.2 Protocol

The workshop relied on the HME/S2R running dataset and derived data visualizations and consisted of four parts: a warm-up exercise and three rounds of analyzing and interpreting running-related data, in order to design a stimulating running environment (Figure 9). As a warm-up exercise, participants brainstormed the types of data they would like to collect when asked to design a 'perfect running environment' in the city.

Participants were then presented with data visualizations from the collective (round 1) and individual (round 2) perspectives. During both rounds, participants were asked to first describe objectively what they see in the data and then to interpret these findings (subjectively) using a provided worksheet. Based on these insights they then derived design guidelines for a fitting encouraging running environment.

For the collective lens, the same data was presented to all participants, visually showing running data of a city through heatmaps (runs colored by Day/Night, Dry/Rain, Distance, and Speed) and additional charts showing runs per user; average distance, duration, and speed per run; distribution of runs over Day/Night, months and weekdays, weather circumstances and land use (based on OpenStreetMap land use data [7]). This data was analyzed in groups of 2 or 3 participants. For the individual lens, each participant was given the data of a different user through visualizations showing a heatmap with all their running routes (Figure 6) and an overview of their individual combined data over time as presented in Figure 8.

In the last round, both perspectives were combined into final insights and implications for design. Here, we aimed to bring together the different perspectives developed earlier in the workshop and spark discussion where insights or interests do not align. To maximize diverse views in this round, participants were divided into groups of 3 or 4, representing the different groups from round 1 in each new group. Additionally, participants gained varying insights from the individual runners they analyzed in round 2.

The insights and conclusions from each round were recorded on the worksheets. At the end of the workshop participants were asked to reflect on their experience using the different –and combined– lenses and data-visualizations in this design process.

5.3 Results

In total, participants listed 110 types of data they would collect prior to designing a perfect running environment in the city (Table 1). The warm-up exercise shows a distinct preference to collect data from the collective perspective, with area information (34%) and popular running routes and times (26%) expressed as required the most by participants. Only 3 of 110 collected types of data refer to knowledge about individual users. This aligns with typical urban design practice (as described in section 2.1) triggered by the instructions.

Regarding the analysis and interpretation of running-related data, participants were positive about the collective data visualizations, which largely provided their most requested data from the warm-up. They found the visualizations provided a good overview and were easy, intuitive to read. These data-representations helped to *"bring out more information hidden in the data and thus design opportunities"* (P10) and *"made it easier to 'observe' actual behavior"* (P4).

Looking at the design guidelines derived from the collective perspective, we see an emphasis on lighted paths, uninterrupted and connected routes, green routes, and routes providing protection or shelter (e.g., from rain or sun) (Table 2).

Six participants indicated that the individual lens brought in a personal level and inspired realistic user personas. Thirteen appreciated the timeline visualization that offered detailed information while allowing easy pattern-recognition and five noted this provided inspiration and sparked creativity. In addition to the insights into personal behavior patterns, the visualizations of the individual perspective had another interesting effect. By closely examining the data of a single user, the individual perspective strongly inspired empathy and a feeling of connectedness to that user, even though anonymous quantitative data was provided. This helped to create a more detailed persona and encouraged participants to 'fight' for their user's needs in the final round, leading to less common, more creative compromises. Several participants indicated that they enjoyed this personal aspect; the detailed information on one user made them feel connected to this person and therefore the data, which may well contribute to the renewed inspiration and creativity. "*Deep-dive into one person's story caused me to imagine motivations and project myself.*" (P13).

This increased empathy can also be seen in the design guidelines derived from the individual perspective. There's a clear overlap in main themes with those from the collective lens, with a preference for green and uninterrupted paths. However, we see an increased emphasis on creating attractive and motivating routes. The participant's desire to aid 'their' user is also clear from the phrasing of these guidelines. The collective lens design principles were mostly

Figure 9: Four parts of the workshop; warm-up, the collective lens, the individual lens, combining and discussing

Table 1: Desired data types to address the design challenge

From the collective lens		
popular running routes and times		29
area information		37
environment type	*10*	
green	*5*	
water	*2*	
landmarks/facilities	*4*	
traffic and road lights	*12*	
pollution	*2*	
Surface type	*1*	
weather conditions		5
motivations and barriers		9
other qualitative data		6
runner demographics		21
runner experience levels	*5*	
general health data –including sports participation (4)	*8*	
who is running?	*2*	
From the individual lens		
user's journeys (precise descriptions of user's habits)		1
data from tracking a sample of runners over time		1
running level of user versus other users		1

Table 2: Design guideline themes derived from the collective and individual data visualizations

Themes from the collective lens		Themes from the individual lens	
green	8	green	10
connected and nearby routes	6	connected routes	1
routes for different distance or experience level	4	routes for different distance or experience level	7
shelter/protection	8	shelter/protection	2
lighted paths	11	attractive routes –*including lighting (2)*	10
motivation	8	motivation	19
uninterrupted paths	9	signage and designated routes	5
–*including signage & designated routes (3)*			
data collection & adaptability	4	information sharing & feedback	2
facilities	2	training frequency	6
sustainability	1		
quiet & busy routes	1		

stated matter-of-factly (e.g., *"Design for 'dry running' (covered but green)"* P1). The phrases for the individual lens were more focused on helping the users (e.g., *"This person often runs the same round. A predetermined route can help him to explore other routes and so increase distance."* P19). This difference is underlined by occurrence of the terms 'support', 'help', 'encourage', or 'motivate' in these guidelines; they occur in 18 of 56 guidelines of the individual lens, versus in only 5 of 55 for the collective lens.

Regarding both lenses fostered a deeper understanding of –and even connectedness to– the data and the users that would have been hard to achieve when only using one perspective. Participants appreciated the richness of data that comes from combining them as *"it combines individual stories with the generic perspective"* (P15). Combining these insights, together with the accompanying discussion, led to new insights and more creative design solutions as it "*forced us to regard different viewpoints and user desires which let us address and pinpoint new design opportunities"* (P11). An example here was the need of one runner to also look after their children, resulting in a design for a running track going around a playground.

Though several participants indicated they had to look for some common ground or creative solutions to come to one design in this final stage, none of them encountered different needs or desires that were irreconcilable in one concept. This indicates that the collective and individual needs are often close enough to allow a smooth combination, and that for seemingly conflicting interests creative solutions may still offer a fitting compromise.

Participants indicated that instead of insights into 'the user' this approach gave them insights into a pallet of users, with varying perspectives and backgrounds, while still having a clear overview of how this group behaves as a whole.

Aware of this limitation of the exercise, most participants nevertheless indicated that they missed qualitative data to accompany the objective visualizations, and some wished for demographics and user context for the individual data. Several participants indicated that using an interactive interface instead of static data-visualizations could help to combine different maps for the collective lens or even the individual data compared to the entire population when combining perspectives. This will be valuable to consider in future work and when developing a method.

6 DISCUSSION

In this paper, we explored how user-generated big data can be used to design for adaptable active environments. To do this, we built on research from the fields of urban design and planning and HCI, proposing two lenses to regard this data.

Through the *collective lens*, we aim to emphasize the perspective at population level. This lens provides overview and is required to address active environment challenges at scale and in relation to the existing urban fabric in a holistic way, to make sure collective needs are served by new designs. With the *individual lens* we aim to stress the value of understanding individual needs and behavior. This lens can aid designers and planners to go beyond common denominators, to design adaptive environments that can be tailored to individual interests. We deliberately chose the terms *collective* and *individual* instead of *macro* and *micro* or *big* and *small* to address these perspectives to emphasize not only the scale, but also the human-centered focus that's at the core of our approach.

We explored the value of these lenses and how they could be utilized to aid designing running friendly environments by analyzing a large user-generated dataset through data visualizations. We tested their potential through a workshop series. Specific method development and validation of this process are outside the scope of this paper.

We discuss our insights from using the collective and individual lens in this process and the value of these lenses for designers and toward designing for adaptable active environments.

6.1 The Collective Lens

In our case study, we used the collective lens to consider the data from an urban population perspective, showing overall running patterns and behavior. This perspective provided some clear commonalities that seem to apply to most runners, such as a preference for uninterrupted paths and 'green' or 'blue' areas, matching the findings of Deelen et al. [27], giving insight into favored environmental characteristics for a running environment. The data visualizations also show how such preferred running environments can change with circumstances. We could for instance distinguish different hot-and coldspots between runs in different weather types, runs during the day or after nightfall and differences in running locations over time, based on varying daytimes, weekdays, or seasons.

Instead of providing one recipe of environmental characteristics for *the* perfect running environment, this data shows that several preferences shift based on context. Designers can use this knowledge to expand the runability of a city by creating several different places, each with characteristics that are preferred during other circumstances, such as well-lit, lively places for running after dark or more sheltered routes for bad weather.

Although the maps give a clear indication of preferred environment under certain circumstances, we have to be careful when interpreting only the objective behavioral data. The reason *why* people prefer certain running routes cannot always be derived from the heatmaps. For instance, green areas are obviously popular for running, but is this indeed because there is a lot of green there, or because these areas provide running paths safe from motorized vehicles and uninterrupted by roads or traffic lights unlike anywhere else in a city? When searching for attributes of popular running environments it is important to keep this in mind as it is easy to ignore the impact of all the aspects not covered by the data.

Even though we worked with a considerable dataset, our visualizations and analysis could still not provide conclusive answers to these questions as they still provided a limited perspective. For a better understanding of experiences and the motivation behind these running patterns, future research will have to include more in-depth qualitative data, for example by surveying people in the app after their run about their running motivation and experience. However, this will need to be built into the app before data collection starts.

The size of the dataset that we used played a role in enabling explorations through the collective lens. As it encompassed so many runs from so many people, it gave an accurate view on the popularity of different environments. In Bornakke and Due's framing [16], we clearly used big data for our collective lens investigation. Although this dataset contained little to no qualitative data, we did see high levels of behavioral detail in the data. We argue these qualities of the dataset, combined with our approach in analyzing this data, enabled a shift from thin to more thick data. This way, the collective lens is not simply a big and thin data lens, where the individual lens is a small and thick data lens. The collective lens needs to have good coverage of the topic of interest, but this does not necessarily have to come from a big dataset. The maps of very specific areas with only limited activity exemplify this. Both lenses represent a more human-centered way of looking at the data and as such our explorations on both lenses each describe how the same data could be treated more as thick than thin data.

Adding more data to enrich the running set also showed to be valuable in gaining more contextualized insights [14]. It did not directly produce characteristics of popular running environments but was instrumental in understanding how environments were used differently under different circumstances. Combining these insights, the collective lens provided us with a valuable perspective on how current environments are commonly used by runners, which environments are popular under which conditions and how popular and unpopular running environments co-exist. This way, this lens provided valuable insight into commonalities within the running population that could serve as a strong foundation for designing adaptive environments.

6.2 The Individual Lens

Looking at the data through an individual lens, we visualized and clustered data of single users to learn more about their specific routines. Rather than only serving en masse to show averages and overall trends, we find that this information about individual behavior truly adds a new and underexplored dimension to the data. Since a population is built up of many individuals, views may diverge or even conflict on how and which environmental features influence personal exercise experiences. It is important to recognize and explore this variation in order to gain a better understanding of how adaptive environments could tailor to individual users [43]. Instead of grouping people into clusters (i.e., personas) we focused on assigning multiple possible behaviors and personality traits to each user (e.g. always sticks to their route). This reversed approach was key in honoring their uniqueness. Building data visualizations that allow for easy comparison between many individuals played an important role in this.

The individual lens provides large-scale insights in individual and personal data. While this approach is gaining traction in HCI research, this lens is not typically adopted in an urban design process. But there too, it has valuable potential. It holds possibilities to create subgroups of users based on commonalities, but more importantly it shows where and how people are exceptional, differing from the mass. These deviations and the unique, personal stories they encompass, are where both designers and health professionals can find inspiration and possible intervention points through the data.

From our workshop we learned that while the data presented in the collective lens was found valuable as it provided a comprehensive overview and general insights, it was the individual lens that inspired a true sense of connectedness with the data through the imagined other. This shows that regarding this type of personal data not only adds details, but a new depth to the data and the story it tells. It sparked empathy and creativity, and so added to the potential and scope of the considered design solutions. This is where data becomes part of the design process, when instead of imposing boundaries it enables new ways to motivate behavioral change, especially when technology allows for more and more personalization in these interventions. Therefore, the individual lens can play a key role in enabling our environments to adapt to highly personal needs and intentions, and in doing so make these environments a better fit to a larger group of people [9].

6.3 Towards Designing for Adaptable and Active Environments

Through the collective and the individual lens we presented a way to focus both on the urban population perspective that took into account planning and policy challenges, and the personal perspective that celebrated individual uniqueness. Both perspectives play a key role in designing for adaptable environments, covering a strong foundation based on collective values, while being able to adapt to the individual people interacting in it, under different circumstances.

Considering our aim to create stimulating running environments, considering how best to persuade people to move is essential. For effective 'mass persuasion', looking at individual users and personalizing the design is likely to be more effective than a one-size-fits-all intervention [12, 29, 47]. Looking back at our dataset, our findings also indicate that running behavior changes when circumstances vary. This suggests that next to advantages for persuasive qualities, an 'ideal' running environment should also be able to adapt to those circumstantial changes.

Following the current developments in human-environment interaction, 'smart' environments are increasingly equipped with the means to register these changes [37, 77]. Actually enabling them to adapt to this is still less common practice, but very much within reach of current technology [70]. Since such adaptable environments would support a system that is both personalized and persuasive, they hold significantly more 'persuasive power' than systems that are only one or the other [12, 47]. This adaptability is most likely to be achieved through a digital layer, offering its designers another advantage. While the physical environment is very costly and time-consuming to alter, a digital layer can be controlled and adjusted easily, even remotely. This allows not only for more interactivity and a more personalized space, but also for quick and easy design iterations, introducing the iterative design process to the domain of urban design [70].

An interesting discussion point in the creation of these adaptable environments is who or what gets preference when needs or desires from the different lenses do not align. Such differences in what constitutes the preferred environment can occur in several ways, based on simultaneous users with contrasting preferences, but also between a user's desire and 'what is good for them'. Even conflicting views on ideal behavior or use of the space between its users and designers or policy makers could lead to disagreement. Next to being 'smart' enough to recognize its different users, stakeholders, and their preference in the first place, for such cases the environment will also need clear rules on how to behave and what form to take. With possible conflict of interest between the collective and individual, here again, we see the need for consideration of data through both lenses in order to address such situations appropriately. Since varying circumstances and multiple simultaneous, possibly conflicting preferences make for a highly complex context, the quick and remote adjustment opportunities provided by a digital HEI layer could be beneficial in such an environment.

While building on HCI foundations and developments to create these adaptable environments can be a valuable asset to urban design, the urban environment is significantly different from traditional computing spaces and communities. We introduced two lenses to look at data as a way to help close this gap between disciplines. Understanding the design holistically –the small parts, the overall design, how those relate to each other and their context– requires abstract, conceptual and representational thinking [62]. Where Shneiderman's classic Visual Information-Seeking Mantra '*Overview first, zoom and filter, details on demand*' [74] clearly advocates a top-down approach, understanding and applying large amounts of data to observe existing and new behavior patterns requires and approach that is neither top-down nor bottom-up [62]. We therefore suggest switching lenses continuously throughout the design process, to acknowledge the importance of both the detailed properties of interfaces, interactions and personal experiences as well as a broad overview that pays attention to collective needs, context and long term implications [2].

A successful approach asks for a blend of many disciplines, from architecture and urban planning to sociology and psychology to computer science and engineering [65]. The development of the next generation of smart and adaptable healthy places crucially calls for a close collaboration between these disciplines. The collective and individual lenses provide a step towards that bridge, offering a user-centered approach for data and insights to be shared between disciplines.

6.4 Implications for Practice and Future Work

Designers have increasing access to big datasets that hold potential value for their work. This paper provides two lenses that can help designers in regarding such data in a comprehensive way, as they include both individual and collective perspectives. With blurring boundaries between fields, this study shows the value of including interdisciplinary skills in the design team, such as adding data visualization experts.

The case study of data exploration and workshop have shown potential of using both –and combined– lenses in the design process. In future work, we will further investigate how using these lenses affects the design process and/or the derived design decisions and best practices to integrate this. This includes developing a method to help designers and other project stakeholders look at their data through both lenses. We can use this to set up a larger experiment to better understand how people perceive their value, especially in a real-life active environment design challenge. Here, we can also address several limitations of the workshop setup; adding qualitative information and offering participants (interactive) access to the raw data. Additionally, we aim to gain more insights in: a) what type of data (lens, datatype and data visualization format) is the most insightful for specific stakeholders within the design project team; b) what insights do different professionals get from looking at the same data?; c) how do they handle conflicting interests between the individual and the collective lens?

7 CONCLUSION

In this paper, we investigated the challenge designers face as they are confronted with increasing amounts of data through a case study of creating activity-friendly environments, addressing two timely challenges. Introducing a collective and an individual lens to regard data, we demonstrated the value of both perspectives for such a design challenge. Our explorations showed how these lenses can be used to drive data visualizations that yielded significant insights on different levels, yet also gave insight into the qualities of these lenses. Illustrated through the workshop, the lenses proved to be a valuable instrument for analyzing collective needs, while also telling detailed stories about the individual. Thereby, this research provides an important step towards use of user-generated data in designing for adaptive active environments. Through this work, we additionally hope to inspire design researchers and practitioners and invite the community to reflect on the use of data in design projects and fuel the discussion about how best to adapt to this.

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The authors report there are no competing interests to declare.

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