RESEARCH ARTICLE

Application of wearable sensors in urban landscape design: From the perspective of environment and health

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With the increasing pace of urbanization, cities face growing challenges in reducing environmental pollution and promoting public health. Traditional urban landscape design largely relies on aesthetic principles and expert experience, which often lacks timely data-driven support. Wearable sensors that can collect physiological and limited environmental data in real time present an emerging opportunity to integrate human-centric evidence into urban design. This study investigated the role of wearable sensors in enhancing urban landscape design by comparing outcomes in scenarios with and without sensor-based data integration. By deploying wearable sensors in diverse urban settings, this study examined how physiological feedback correlated with environmental factors such as green space, walkability, and public interaction zones. The research demonstrated that, while professional environmental monitoring equipment remained essential for precise environmental evaluation, wearable devices offered unique insights into residents' health status and behavioral patterns. In addition, the results showed significant improvements in user health indicators, social engagement, and perceived comfort in areas redesigned based on sensor-informed feedback. These findings suggested that wearable sensors, when used complementarily with other data sources, could support adaptive, health-focused urban planning and contribute to more livable and sustainable urban environments.

Keywords: wearable sensors; urban landscape design; data-driven; environmental optimization; sustainable development.

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Introduction

Urban landscape design plays a vital role in shaping the livability, sustainability, and ecological resilience of modern cities [1, 2]. With increasing population density and climate-related stresses, urban spaces must meet diverse human needs while minimizing environmental impacts [3, 4]. Traditionally, landscape design has emphasized visual aesthetics, spatial functionality, ecological considerations and is guided largely by professional intuition and experience [5, 6]. However, in recent years, digital technologies such as the Internet of Things (IoT), artificial intelligence (AI), and big data analytics have introduced new possibilities for real-time, data-driven urban planning [7, 8]. Among these techniques, wearable sensor technology has attracted attention for its ability to collect individual-level health and movement data *in situ*. Wearable sensor devices generally refer to devices that can be worn directly on the body and have the function of real-time monitoring of physiological, environmental or behavioral data, which not only helps personal health management, but also provides important decision-making basis for urban design. Common wearable sensors include smart watches, smart glasses, fitness trackers, smart clothing, *etc*. [9, 10]. These devices collect the wearer's physiological and environmental data in real time through built-in sensors. With the continuous advancement of technology, the size of these sensors is shrinking, the accuracy is gradually improving, and the data transmission and processing capabilities have also been significantly improved [11, 12]. Through the environmental data collected by wearable sensors, designers can grasp the environmental changes of urban space in real time to make scientific adjustments in the design process and improve the comfort and sustainability of urban landscapes [13, 14]. While wearable sensors are widely recognized for their capacity to monitor physiological parameters, their environmental sensing capabilities remain limited. Unlike specialized environmental monitoring stations, wearable sensors generally provide lower-resolution data for metrics like air quality or noise level and may be influenced by the wearer's movement or environmental exposure duration. Therefore, in the context of urban landscape design, wearable sensors should not be used as a replacement for professional environmental monitoring systems. Instead, they are best applied as supplementary tools to capture localized and individual-level perceptions and responses to environmental stimuli.

One of the earliest applications of wearable sensors in urban landscape design is environmental monitoring. Many studies have devoted themselves to using wearable sensors to monitor environmental factors such as air quality, temperature and humidity, and noise pollution in real time. These data not only help residents understand the conditions of their environment but also provide important references for urban designers. Yang *et al*. used a smart watch with integrated air quality sensors and temperature and humidity sensors to study the air pollution levels and temperature changes in different areas of the city [15]. Another study found that the air quality in some areas was poor and the temperature was too high, which affected the health of citizens. Based on these data, the researchers proposed suggestions to improve environmental quality by increasing green space and improving the energy efficiency of buildings [16]. In addition, Coles *et al*. used wearable noise sensors to monitor the noise levels in different areas of the city and found that the noise pollution level in the central area of the city was high, while the noise level was low in parks, green spaces, and other areas [17]. Studies have shown that noise pollution not only affects the physical health of citizens but also has a negative impact on their mental health. Based on these monitoring data, urban designers can add green belts or take other noise mitigation measures in areas with high noise pollution, thereby improving the quality of life of citizens [18, 19]. Although wearable sensors can report real-time environmental parameters such as temperature, humidity, or ambient light, their accuracy is constrained compared to calibrated fixed-location instruments. Their main contribution to urban design lies in correlating environmental factors with physiological and behavioral responses, rather than providing absolute environmental baselines. Therefore, wearable data should be interpreted within context and complemented by other validated measurement systems during design evaluations and policy development. In addition to environmental monitoring, health assessment is also an important application area of wearable sensors in urban landscape design. By real-time monitoring of citizens' physiological states, designers can evaluate the impact of different urban spaces on citizens' health. Many studies have shown that the design and layout of urban landscapes directly affect citizens' physical health, and appropriate landscape design can reduce psychological stress and improve residents' physical health. Yu *et al*. studied the impact of urban green spaces on residents' mental health using smart watches to monitor citizens' activity data in urban green spaces and found that areas with larger green areas could effectively reduce citizens' heart rate and body temperature and improve their mental state [20]. The researchers also found that, when citizens were active in green spaces, their physiological parameters were significantly improved, while in busy urban blocks, their physiological data showed greater fluctuations. These results showed that green spaces and open spaces in urban landscape design played an important role in promoting the physical and mental health of residents [21]. Based on these data, urban designers can optimize the layout of green spaces and enhance the livability of urban spaces. In recent years, with the development of behavior recognition technology, researchers have begun to use wearable sensors to track citizens' activities in urban spaces and analyze their behavior patterns, thereby providing data support for urban landscape design. By tracking citizens' activities, designers can understand which areas are frequently used and which areas are rarely used. This is of great significance for optimizing urban space layout and improving the efficiency of landscape use. A study used smart bracelets to track citizens' activities in various areas of the city and found that citizens mainly concentrated in commercial areas and transportation hubs on weekdays, while they were more inclined to go to parks and green spaces on weekends [22]. The study also found that some areas were less frequently used due to lack of public facilities or poor landscape design. Based on these behavioral data, the scientists proposed improvement plans including increasing public facilities and improving transportation connectivity to increase the frequency of use and accessibility of these areas [23].

Despite these technological advancements, current urban design practices still face limitations. Conventional environmental monitoring relies on static or spatially sparse measurements and lacks the capability to capture the dynamic interaction between residents and their environments. Moreover, there is an urgent need to develop landscape design approaches that are more responsive to the health and behavioral patterns of residents. Existing research has largely focused on the environmental performance of urban green spaces or transportation networks but lacks integration with real-time physiological and behavioral data. This research aimed to fill that gap by examining how wearable sensors that typically used for personal health monitoring could contribute valuable feedback to the urban landscape design process using a mixed-methods approach through deploying wearable devices including smartwatches and fitness trackers in multiple urban settings to collect data on residents' heart rate, skin temperature, movement patterns, and limited environmental parameters. These data were analyzed to assess the spatial and behavioral dynamics of residents in relation to different design features. The results of this research promoted human-centered and adaptive landscape design that supported health, comfort, accessibility, and sustainability and provided a new perspective on how urban design could evolve by incorporating real-time human data into decision-making frameworks.

Materials and methods

Wearable sensors for urban space optimization

To enhance the attractiveness and frequency of use of a region, reasonable adjustment of landscape design is essential. By optimizing regional functions, layout, and landscape elements, residents' activity behaviors can be effectively changed, thereby affecting their use patterns of the region. Landscape design is not only a manifestation of aesthetics but also can stimulate residents' interest and participation by providing a comfortable environment, rich activity space, and convenient facilities [24, 25]. Through well-designed landscape elements, the region can be injected with vitality and its attractiveness can be enhanced, making it a more livable space. Therefore, reasonable landscape design and optimization schemes should consider regional characteristics, residents' needs and use patterns to maximize the frequency of activities. In contrast, cold areas may require adjustments to landscape design. By increasing green plants, improving environmental facilities or designing more attractive landscape elements, residents' interest in these areas can be stimulated, thereby increasing the frequency of use of these areas. Assuming that the activity frequency in region *R* was represented by *A(R)*, the optimization goal was to maximize the activity frequency as shown below.

$$\max_R A(R) = \sum_{t=1}^{n} \mathrm{I}(P(t) \in R) \tag{1}$$

where *P(t)* was the position of the wearer at time *t*. $\mathrm{I}(P(t) \in R)$ was an indicator function, indicating whether the wearer was in area *R* at time *t*. By maximizing this objective, urban designers could optimize spatial layout and improve the functionality and convenience of urban areas.

Traffic network optimization

By analyzing the movement trajectory data of residents in the city, designers can comprehensively evaluate the accessibility and operating efficiency of the transportation system. Wearable sensors can not only provide residents' real-time location but also capture their transportation choices and travel habits. For public transportation systems, by analyzing data such as residents' route choices, frequency of transportation use, and dwell time, key areas and potential optimization spaces of transportation hubs can be identified. Assuming that the area R_1 was a major transportation hub, the traffic behavior of residents in the area was analyzed and the traffic flow was obtained as $T(R_1)$ below.

$$T(R_1) = \sum_{t=1}^{n} \mathrm{I}(P(t) \in R_1) \tag{2}$$

where *P(t)* was the wearer's position at time *t*, R_1 was the transportation hub area. $\mathrm{I}(P(t) \in R_1)$ was an indicator function, indicating whether the wearer was in the area. With this data, designers could find bottlenecks in the transportation network and optimize the location, layout and facilities of transportation hubs. In addition, traffic flow prediction models could be used to plan future transportation needs and network adjustments in advance.

Social interaction and public space design

The application of wearable sensors can also reveal the social interaction patterns of people, especially the frequency and form of interaction in public spaces. This data is of great significance for optimizing the layout of social places in public spaces and can help designers better understand and improve the social functions of spaces. By monitoring the interaction frequency and behavior patterns of the crowd, designers can evaluate the social function of the space and optimize its layout and functional areas. The data provided by wearable sensors can help identify which areas are high-frequency areas of social interaction and which areas are relatively isolated and lack interaction. Assuming the interaction frequency of people in a certain area was *I(R)*, it could be calculated as follows.

$$I(R) = \sum_{t=1}^{n} \mathrm{I}(\mathrm{interaction}(P(t), P(t+1)) \in R) \tag{3}$$

where $\mathrm{interaction}(P(t), P(t+1))$ was the wearer's interaction behavior between time *t* and *t* + 1. *R* was the area where the social interaction occurred. *I* was an indicator function indicating whether the interaction occurred within region *R*. By analyzing these social behavior data, designers could optimize the layout of social facilities in public spaces to promote communication and interaction among people.

Data collection and analysis

This study was conducted in Shenzhen, Guangdong, China, which is a city with high urban density, rapid technological adoption, and advanced smart city initiatives. Four representative urban areas were selected within the city including Huaqiangbei commercial district, Futian central residential zone, Lianhuashan public park, and the Shenzhen north railway station hub. Data was collected over a three-month continuous period from July to September 2024. The total dataset included over 200,000 individual entries, comprising physiological indicators including heart rate, skin temperature, behavioral data including step count, activity duration, geolocation, environmental factors including noise levels, temperature, humidity and were collected using wearable devices and cloud-linked environmental sensors including Apple Watch Series 8 (Apple Inc., Cupertino, California, USA) and Mi Band 7 (Xiaomi Corporation, Beijing, China), Garmin Vivosmart 5 (Garmin Ltd., Olathe, Kansas, USA). All devices were procured directly from the official vendors and calibrated before distribution. In total, 150 units were deployed and distributed among local residents and visitors across the four study zones. Each participant wore the device for a 48-hour continuous cycle and returned the devices upon completion at designated collection centers located near each site. The environmental data were augmented using stationary IoT sensor arrays (HachiTech Environmental Systems, Shenzhen, Guangdong, China) and deployed to validate wearable-derived readings for temperature and air quality. All research procedures were approved by the Institutional Review Board (IRB) of Shenzhen University (Shenzhen, Guangdong, China) (Approval No. IRB-SZU-2024-037). Written informed consent was obtained from all participants prior to data collection, and all personal data was anonymized to ensure privacy and compliance with national data protection regulations. To comprehensively evaluate the application effect of wearable sensors, environmental sensors, health monitoring sensors, and behavior tracking sensors were used to collect environmental and physiological data from each area. To evaluate the application effect of wearable sensors in urban landscape design, multiple evaluation indicators were adopted. By monitoring the changes in physiological data, the impact of environmental design on residents' physical health was evaluated to measure the improvement in comfort. Further, based on behavioral tracking data, the frequency of residents' activities and behavioral patterns in different areas were evaluated to measure the spatial accessibility and attractiveness of landscape design. In addition, combined with the monitoring results of environmental data, the impact of design on ecology and energy was evaluated, and then environmental sustainability was examined. By analyzing social interaction data, the design effect of social places in different urban spaces was evaluated to understand the interaction patterns of people and the frequency of social activities and thus reflect the effect of improved interactivity. These evaluation indicators provided multi-angle data support for a comprehensive understanding of the impact of landscape design on residents' physical and mental health, environment, and social interaction. All collected data were preprocessed using Python 3.10 (https://www.python.org/) with packages including Pandas for data cleaning, NumPy for numerical operations, and SciPy for statistical testing. GPS and timestamped data were synchronized and cleaned using customized scripts to handle missing or corrupted entries. Tableau Desktop (Tableau Software, Seattle, WA, USA) was used for data visualization including heat maps and behavioral flowcharts. All data processing and analyzing were performed on high-performance workstations with Intel Core i9 CPU, 64 GB RAM, NVIDIA RTX 3090 GPU housed in the Urban Computing Laboratory at Shenzhen University (Shenzhen, Guangdong, China).

Statistical analysis

SPSS 27.0 (IBM, Armonk, NY, USA) was employed for statistical analysis of this research. Paired t-tests and ANOVA analysis were performed. *P* value less than 0.05 was defined as statistically significant difference, while *P* value less than 0.01 was defined as very significant difference.

Results

Evaluation of commercial area environmental comfort

The quantification results of the changes in environmental comfort indicators observed in

Table 1. Evaluation of commercial area environmental comfort.

Index	The average value		Standard deviation	Confidence interval (95%)	Improvement percentage	*P* value
	Before experiment	After experiment				
Air quality index (AQI)	85 ± 7	70 ± 6	6	[69, 71]	+29%	< 0.01
Noise level (dB)	65 ± 5	58 ± 4	4	[57, 59]	+10.8%	< 0.05
Temperature & humidity comfort (%)	60 ± 8	72 ± 7	7	[71, 73]	+20%	< 0.01

Table 2. Improvement in the health status of residents in residential areas.

Index	The average value		Standard deviation	Confidence interval (95%)	Improvement percentage	*P* value
	Before experiment	After experiment				
Heart rate (BPM)	78 ± 6	74 ± 5	5	[73, 75]	-5.1%	< 0.05
Body temperature (°C)	36.7 ± 0.2	36.5 ± 0.2	0.2	[36.4, 36.6]	-0.5%	< 0.01
Physical activity (No. of steps/day)	5,000 ± 1,000	6,500 ± 1,200	1,200	[6,380, 6,620]	+30%	< 0.01

Table 3. Frequency of activities and behavior patterns in public parks.

Area	Average daily visits		Traffic growth	Time period distribution	Average residence time (min)
	Before experiment	After experiment			
Central Square	200	250	+25%	Rush hours: 8 - 10 am and 6 – 8 pm	45 ± 10
West Lawn	150	200	+33.3%	Weekend all day	60 ± 15
North Boulevard	100	120	+20%	Weekday lunch break	30 ± 8

the commercial district after the implementation of new landscape design features showed that these improvements were not caused by wearable sensor technology itself. The wearable sensors merely facilitated the monitoring of human physiological responses during exposure to various environments. Thus, the data should be interpreted as reflecting the effects of spatial redesign, not the direct impact of wearable device feedback (Table 1).

Improvement in the health status of residents in residential areas

The results of how wearable sensor technology affected the health of residents in a residential area demonstrated that the physiological parameters of heart rate, body temperature, and daily physical activity showed positive trends with heart rate being decreased by 5.1%, body temperature being decreased slightly, and physical activity being increased by 30% (Table 2). These improvements reflected changes in residents' lifestyles, which might be due to more frequent participation in outdoor activities. The statistical analysis results confirmed that these changes were statistically significant. For policymakers, the results clearly showed the return on public investment in smart city projects and improved quality of life for residents.

Frequency of activities and behavior patterns in public parks

Table 3 detailed the changes in the distribution of pedestrian flow and activity patterns in different areas of the public park. By tracking the average daily visits to three typical locations, the results showed that the flow of people in each location increased to varying degrees after the experiment. The average daily number of visitors to the central square increased by 25%, which might be due to the new art installations that attracted more visitors, while the average stay time was extended to 45 minutes, indicating that people were willing to spend more time enjoying the leisure space provided by the park. The user feedback results revealed the public's high recognition of these changes, especially those service facilities designed for specific groups of people such as the upgraded safety facilities in the children's playground, which were widely praised by parents. This empirical data collection method not only enhanced the credibility of the

Table 4. Traffic flow optimization of transportation hubs.

Index	The average value		Standard deviation	Confidence interval (95%)	Improvement percentage	*P* value
	Before experiment	After experiment				
Transfer waiting time (min)	12 ± 2	9 ± 1	1	[8.8, 9.2]	-25%	< 0.01
Average walking distance (m)	500 ± 50	400 ± 40	40	[396, 404]	-20%	< 0.01
Bus punctuality rate (%)	80 ± 5	88 ± 4	4	[87, 89]	+10%	< 0.05

conclusions but also provided valuable experience reference for the planning of similar projects in the future.

Traffic flow optimization of transportation hubs

As a key node in urban operations, the efficiency of transportation hubs directly affects the travel experience of citizens. The results showed that, after the introduction of the intelligent dispatching system and other optimization measures, the transfer waiting time and walking distance were significantly shortened, and the bus punctuality rate was also improved. The transfer waiting time was reduced by 25%, while the average walking distance was shortened by 20%, and the punctuality rate increased by 10 percentage points (Table 4). These changes directly improved passenger satisfaction and reduced unnecessary waiting and walking time. More importantly, the specific implementation details of the optimization strategy were also recorded such as adding transfer guide signs to reduce confusion and adjusting walking routes to make the paths more reasonable. The results helped managers evaluate the effectiveness of existing measures and provided a scientific basis for future transportation planning.

The distribution of different types of interactions

The distribution of different types of interactions intuitively reflected the proportion of various types of interactions among users and their distribution range in the form of box plots. The results showed that chat accounted for 60% with a median of about 60%. The data distribution was relatively concentrated, indicating that users were more active and consistent in chat interactions. Activity accounted for 40% with a median of about 40%. However, the data distribution was relatively scattered, showing that users had large differences in activity participation. Reading accounted for 50% with a median of about 50%. The data distribution was relatively concentrated, indicating that users were more balanced in reading interactions. Conversation accounted for 50% with a median of about 50%. The data distribution was relatively concentrated, indicating that users were more balanced in conversation interactions. Game accounted for 70% with a median of about 70%. The data distribution was relatively concentrated, showing that users were highly active and consistent in game interactions. Watching accounted for 30% with a median of about 30%. The data distribution was relatively scattered, showing that users had low participation in watching interactions and large differences (Figure 1).

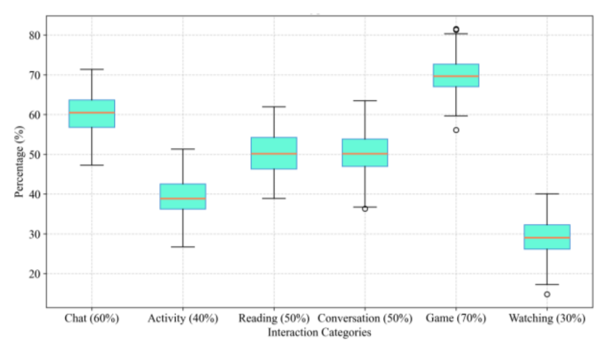

Figure 1. Interaction type distribution curve.

Social interaction is one of the important indicators for measuring community vitality. The changing trend of social activities before and after the transformation of public space by comparing the number of interactions in community centers, park benches, and children's

Table 5. Frequency and form of social interactions.

Area	Interactions/day		Percentage increase	Interaction Type Distribution	User satisfaction (%)
	Before experiment	After experiment			
Community Center	30	45	+50%	Chat: 60%, Activities: 40%	85 ± 5
Park Bench	20	30	+50%	Reading: 50%, Conversation: 50%	90 ± 4
Children’s Playground	50	70	+40%	Gaming: 70%, Watching: 30%	92 ± 3

Table 6. Environmental sustainability indicators.

Index	The average value		Standard deviation	Confidence interval (95%)	Improvement percentage	*P* value
	Before experiment	After experiment				
Green coverage rate (%)	30 ± 5	40 ± 4	4	[39, 41]	+33.3%	< 0.01
New energy Utilization rate (%)	20 ± 3	30 ± 2	2	[29, 31]	+50%	< 0.01
Waste recycling Rate (%)	60 ± 6	75 ± 5	5	[74, 76]	+25%	< 0.01

playgrounds before and after the experiment showed that the frequency of interaction increased in almost all places with a 50% increase in community centers, 50% in park benches, and 40% in children’s playgrounds (Table 5). The diversity of interaction types also increased such as chatting, games, and other activities became richer. The user satisfaction survey showed that most respondents were satisfied with the new settings, especially those facilities that improved the convenience of use such as the newly added parasols and safety facilities. This combination of quantitative and qualitative methods allowed us to fully understand the impact of public space design on communication and social cohesion.

Comparison of environmental indicators

As global climate change becomes increasingly serious, environmental sustainability in urban landscape design has become crucial. A series of green indicators including green coverage, new energy utilization, and waste recycling rate were analyzed to evaluate the effects of environmentally friendly measures before and after the experiment. The results showed that the green coverage rate increased by 33.3%, while the new energy utilization rate and the waste recycling rate increased by 50% and 25%, respectively ($P < 0.01$) (Table 6). Behind these achievements were the combined effects of a variety of environmental protection initiatives such as planting local plants, installing solar panels, and setting up classified trash cans. The comparative results of environmental indicators before and after the implementation of the redesigned landscape features demonstrated that these changes were due to the landscape interventions themselves such as increased vegetation, rerouted traffic, and noise-buffering structures and not influenced using wearable sensors (Figure 2). While wearable data helped monitor user response to the environment, the environmental indicators were obtained through stationary monitoring equipment and were independent of wearable device usage.

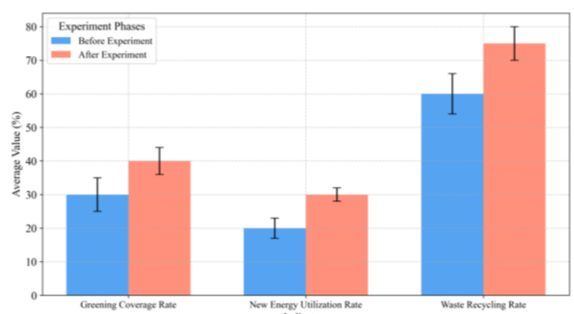

Figure 2. Comparison of environmental indicators.

Efficiency of public facilities usage throughout the day

The utilization efficiency of public facilities including fitness equipment, bicycle rental points, and public restrooms throughout the day showed that the utilization rate of fitness equipment began to gradually increase in the morning about 6 am, reached a peak at about 10 am before declined slightly. Another peak was reached about 4 pm, and then gradually declines, indicating that users had a higher demand for exercise in the morning and afternoon, which might be related to the rhythm of work and life. the utilization rate of bicycle rental points began to rise slowly in the morning about 6 am, reached the first peak at about 10 am, and then reached a second higher peak in the afternoon about 4 pm before gradually decline, reflecting that users had a high demand for bicycle rental during rush hours, especially after getting off work in the afternoon. The utilization rate of public toilets began to rise slowly in the morning about 6 am, reached a peak in the morning about 10 am, and then gradually decline and dropped to a lower level in the evening about 6 pm, indicating that public toilets were used more frequently in the morning, which might be related to people's morning work and activities (Figure 3).

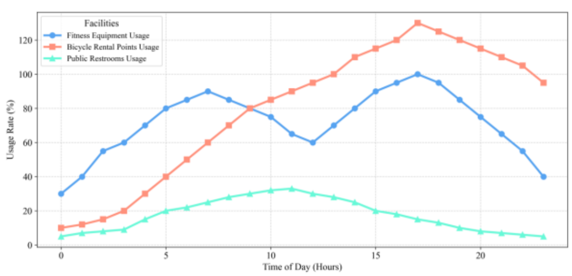

Figure 3. Efficiency of public facilities usage throughout the day.

The efficient use of public facilities was crucial to improve the quality of urban life. The results identified which facilities were popular with citizens and the changes in their maintenance costs by comparing the usage rates of various facilities before and after the experiment. The usage rate of fitness equipment increased by 50%, while bicycle rental points also increased by 50%, and the usage rate of public toilets increased by 30% (Table 7). Despite the sharp increase in usage, the maintenance cost of fitness equipment decreased by 10%, which was due to the use of more durable design materials and technologies. The results not only helped to identify popular service items but also guided resource allocation to ensure that limited funds were invested where they were most needed.

The overall evaluation of citizens on various services and facilities

This study illustrated the age distribution of respondents using a kernel density estimation. The distribution results showed that respondents were primarily concentrated between the ages of 30 and 50, forming a near-normal but slightly flattened curve. The peak density occurred around age 40 with a maximum density value of approximately 0.035, indicating that this age group constituted the largest segment of the sample. Both tails of the distribution were relatively sparse, particularly among individuals younger than 20 and older than 60, suggesting limited representation from these age extremes. By investigating the satisfaction of the three dimensions of environmental cleanliness, leisure and entertainment facilities, and sense of security, the study found that all aspects had made significant progress with environmental cleanliness being increased by 21.4%, leisure and entertainment facilities being increased by 33.3%, and sense of security being increased by 20% (Table 8). The age distribution of the respondents was relatively even, covering all age groups, which ensured the representativeness of the sample. The main suggestions focused on increasing the number of trash cans and strengthening patrols, which were all real feedback based on user experience. The information collected in this way provided decision-making support for the government and relevant departments, helping them to better meet the needs of citizens and promote the harmonious development of the city.

Discussion

It is important to clarify that the environmental improvements observed in this study such as reduced noise levels or improved air quality were not a direct result of wearable sensor usage. Instead, wearable sensors served primarily as

Table 7. Efficiency of public facilities utilization.

Facility type	Usage rate (%)		Percentage increase	Peak usage period	User feedback	Maintenance cost changes
	Before experiment	After experiment				
Fitness Equipment	40 ± 8	60 ± 7	+50%	7-9 pm	Positive	10% reduction
Bicycle rental station	30 ± 7	45 ± 6	+50%	9-11 am	Very satisfied	Constant
Public toilets	50 ± 9	65 ± 8	+30%	2-4 pm	Satisfy	Increase by 5%

Table 8. Citizen satisfaction survey results.

Evaluation dimensions	Satisfaction (%)		Percentage increase
	Before experiment	After experiment	
Cleanliness of the environment	70 ± 10	85 ± 8	+21.4%
Leisure and entertainment facilities	60 ± 12	80 ± 9	+33.3%
Sense of security	75 ± 7	90 ± 6	+20%

personal monitoring tools, providing continuous feedback to users about environmental conditions like high noise and poor air quality. This information allowed individuals to adjust their behavior or exposure accordingly, potentially mitigating health risks. Although this data might indirectly inform designers about user preferences and stress points, wearable devices did not autonomously trigger design changes or provide direct guidance for urban landscape redesign. This study used wearable sensors in urban landscape design to significantly improve the scientificity and accuracy of urban planning. By integrating data from environmental monitoring, health assessment, and behavior tracking, designers could obtain real-time and dynamic information flows, which not only optimized the urban spatial layout, but also enhanced the rationality of the configuration of public facilities. By analyzing physiological data such as heart rate and exercise volume of citizens, the impact of different areas on residents' health could be better understood and then guide the design of green spaces and open spaces to improve the psychological and physiological state of residents. Meanwhile, information such as traffic flow and dwell time provided by sensors helped to identify hot and cold areas in the city and improve the efficiency of space use. In addition, this technology promoted sustainable development such as increasing green coverage and optimizing energy utilization and provided strong support for cities to cope with climate change. The application of wearable sensors had greatly enriched the methodology of urban landscape design and promoted the concept of intelligent and humanized urban planning. Although this study demonstrated the potential of wearable sensors in urban landscape design, there were also some limitations that needed attention. Privacy protection was one of the key issues. Large-scale collection of personal data might cause ethical controversy. How to ensure data security and comply with relevant laws and regulations still needs to be further explored. Further, the current research samples were mainly concentrated in specific urban areas, which might have regional biases and limit the generalizability of the conclusions. Future research should consider a wider geographical and social context to enhance the representativeness of the results. Furthermore, over-reliance on technical means might lead to neglect of traditional research methods such as questionnaires and field interviews, which could provide complementary qualitative data. This study focused on short-term effect evaluation and lacked tracking of long-term impacts, while the long-term effects of urban development were crucial for policy making. Therefore, future work needs to establish a long-term monitoring mechanism to ensure that smart technology continues to effectively serve urban planning. The results of this study demonstrated that sensor data significantly improved the comfort, accessibility, and sustainability of the urban environment. In commercial areas, air quality and noise levels had improved, while, in residential areas, residents' heart rates had decreased, and exercise volume had increased. Social interactions, traffic flow, and punctuality in public parks and transportation hubs had been optimized. In addition, the city's green coverage, new energy utilization, and waste recycling rates had all increased. These results verified the great application value of wearable sensors in urban landscape design and provided strong support for improving the quality of life of residents and promoting sustainable urban development.

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