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Different perspectives are indispensable for public space quality: Exploring the relationship between urban design quality and physical disorder

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Abstract

Public space quality is a multidimensional concept. Urban design quality and physical disorder represent it from the perspectives of design and maintenance, respectively. However, the practical relationship between these two factors remains unclear, raising questions about the necessity of measuring multiple dimensions of public space quality simultaneously. Based on classical studies and theories, this study developed index systems for both factors. Utilizing artificial virtual auditing and deep learning models, including FCN and SegNet, the street visual quality of two Chinese cities was assessed from the perspectives of urban design and physical disorder using extensive street view images. The correlation between these two factors was explored. The results showed that the Spearman correlation coefficients for urban design quality and physical disorder were 0.308 and −0.085 in the two cities, respectively, indicating weak or unclear correlations. Additionally, the fit and explanatory power of the linear and nonlinear regression models constructed were poor, further demonstrating that it is difficult to predict and explain one variable using the other. In the robustness test, the results were further validated by including control variables related to urban vitality, cultural characteristics, and urban development, considering the impact of the distribution of the street view images, drilling down to more granular dimensions and extending the scope of the study to a wider area. The levels of design and maintenance of streets cannot be conflated or substituted, and neither can independently represent the overall space quality alone. Both are indispensable, making it crucial to separately assess and address space quality issues from different perspectives. These results broaden our understanding of high-visual-quality street space and provide references for urban planners and stakeholders in improving street space quality.

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Data Availability Statement included at the end of the article

Keywords
Street view, deep learning, visual quality, neighborhood disorder, public space

Introduction

High-quality public space significantly contribute to urban vitality, social interaction, outdoor activities, and public health (Handy et al., 2002; Ye et al., 2019). Classical urban planning theories indicate that the evaluation of public space quality encompasses various perspectives, such as design, maintenance, and function, signifying that public space quality is a multidimensional concept (Alexander, 1987; Marcus and Francis, 1997).

Recently, emerging datasets such as street view images (SVIs) and advanced techniques like computer vision have enabled new methods to measure the visual quality of street space. In related studies, two types are widely employed. Scholars in urban planning have evaluated the beauty and positivity of public space, focusing on aspects such as safety, convenience, continuity, comfort, and diversity (Hooi and Pojani, 2020; Qiu et al., 2021). The concept of urban design quality (UDQ), as defined and validated by Ewing and Handy, epitomizes this category and is widely used by researchers to assess public space quality from a design perspective (Ewing et al., 2006; Ewing and Handy, 2009). Concurrently, researchers in sociology and public health have employed the concept of physical disorder (PD) to evaluate the poor spatial quality and chaotic order of public space from the perspective of use and maintenance, such as abandoned buildings, graffiti, and litter (Quinn et al., 2016; Ross and Mirowsky, 1999).

Theoretically, the design and maintenance of public space complement each other. A thoughtful design can reduce long-term maintenance costs and needs, while diligent maintenance helps achieve design goals (Alexander, 2018; Carmona, 2021). Previous studies have independently measured urban design quality or physical disorder to represent public space quality, but the relationship between UDQ and PD is unclear in real city streets. It remains questionable whether the two can be substituted or conflated to some extent, as such an evaluation from a single dimension may largely ignore the complexity of public space quality. For example, a well-designed street with high urban design quality does not necessarily mean it is free of physical disorder regarding maintenance issues. Therefore, we examine the correlation between UDQ and PD to understand the relationship between these two different perspectives of public space quality. If the correlation is robust, assessing one aspect of street space quality could to some extent represent the other. If the correlation is weak, it becomes essential to separately assess UDQ and PD in street space. To enhance street space quality, both aspects should be addressed distinctly, with varied measures tailored to different situations to improve visual quality from diverse perspectives. Even if their externalities are similar, they are irreplaceable and need to be analyzed separately.

This study conducts two empirical analyses to address the scientific question: What is the relationship between urban design quality and physical disorder of streets? Firstly, a methodological framework for evaluating street space visual quality based on both UDQ and PD was developed. Secondly, UDQ and PD in Gusu District of Suzhou and the center district of Pingdingshan were assessed using virtual auditing and deep learning with extensive SVIs. Finally, a quantitative analysis was conducted to explore the relationship between UDQ and PD, followed by robustness tests.

Literature review

Visual quality of street space

Quality typically denotes a degree of excellence, and in the context of street space, it relates to environmental conditions and the level of service provided. The street space quality has long been characterized by the continuous emergence of related studies and developments in methods, theories, and applications (Hamidi et al., 2020; Plascak et al., 2023; Wong and Wang, 2022). This study focuses on the visually perceptible quality of street space, encompassing both the design perspective of urban design and the maintenance perspective of physical disorder.

Traditional methods of assessing the visual quality of street space include subjective perception assessments via interviews and questionnaires, along with systematic evaluations based on field surveys. These methods are labor-intensive and costly, hindering large-scale measurement efforts. With the advent of Information and Communication Technology (ICT), big data-based techniques for measuring spatial physical features have emerged, utilizing aerial, building, Point of Interest (POI), and traffic data (Hsu et al., 2022; Long and Zhang, 2024; Xu et al., 2024; Zhang et al., 2023a). However, these technologies encounter challenges like insufficient data accuracy and discrepancies between physical features and perceived quality (Jiang et al., 2023; Wan et al., 2022). In recent years, virtual audits through SVIs have emerged as an effective alternative for space quality measurement, offering extensive spatial coverage, rich visual information, frequent updates, and low cost (Fan et al., 2023; Li et al., 2022a; Zhang et al., 2023b). Artificial virtual auditing of SVIs somewhat overcomes limitations related to measurement accuracy and scale (Li et al., 2022b; Quinn et al., 2016). Subsequently, the application of machine learning and deep learning for large-scale automatic processing of SVIs has further enhanced the efficiency and objectivity of audits (Liu et al., 2017; Shen et al., 2018; Suel et al., 2019). The reliability of space quality measurement methods based on SVI auditing has been repeatedly verified (He et al., 2017; Koo et al., 2023; Ye et al., 2019), laying the methodological foundation for our study.

Urban design quality

Urban design quality typically encompasses perceptual characteristics of the built environment, including coherency, comfort, imageability, complexity, openness, and transparency, among other features (Ewing et al., 2006). It is crucial in evaluating public space quality, particularly in street space. Earlier studies on urban design have identified numerous qualities influencing people's perception of urban space, aiming to measure individual environmental perception and understanding of personal value within these spaces (Abu-Ghazzeh, 1997; Nasar, 1990; Sanoff, 2016).

After reviewing and analyzing 51 perceptual qualities from previous studies, the vast majority of which are related to design and aesthetics, Ewing and Handy's seminal study validated five dimensions representing street design quality: imageability, enclosure, transparency, human scale, and complexity (Ewing and Handy, 2009). These are often considered when designing public space. This index system has become widely used in studies quantifying the visual quality of street space. Numerous studies have evaluated street space quality based on these principles (Yin, 2017), analyzing relationships between space quality and factors such as the built environment (Li et al., 2022b), walking behavior (Hamidi and Moazzeni, 2019), crime density (Su et al., 2023), and housing prices (Hamidi et al., 2020).

Physical disorder

Physical disorder reflects deterioration, disorder, and decline in the quality of the physical environment's appearance. In other words, physical disorder expresses problems that occur in the use and maintenance of space, including abandoned buildings, scattered litter, damaged public facilities, and widespread graffiti (Franzini et al., 2008; Sampson and Raudenbush, 1999).

As understanding of street space expands, an increasing number of scholars are evaluating street space quality from the perspective of PD (Snaphaan and Hardyns, 2021). Existing studies have mainly portrayed the phenomenon of PD in terms of architecture (Kronkvist, 2013; Sampson and

Raudenbush, 1999), commerce (Li and Long, 2024; Odgers et al., 2012), greening (Kronkvist, 2013; Rundle et al., 2011), road (Gullon et al., 2023; Hu et al., 2023), and infrastructure (Marco et al., 2017; Quinn et al., 2016). Chen et al.(2023) developed a checklist of physical disorder elements based on an extensive literature review. Then, seven researchers with professional backgrounds in urban planning or architecture conducted field investigations in China and performed a virtual audit with 1000 SVIs randomly selected from 264 cities. Indicators observed in the virtual audit or field investigations were listed in the index system, which contains the five dimensions described above. This indicator system has also been used in existing studies and has verified its validity (Li et al., 2024b; Zhang et al., 2023c).

Data and methods

Study area

This study selects Gusu District of Suzhou (83 km^2) and the center district of Pingdingshan (529 km^2) as two empirical study areas (Figure 1). Suzhou is located in Jiangsu Province, and Pingdingshan is situated in Henan Province in the North China region.

Data

The core data used in this study consists of street view images (SVIs). The first step is to simplify the streets. We utilized 2014 road and street data from Amap (https://mobile.amap.com/) to collect SVIs. The dataset was clipped to the study area to derive street segments, excluding highways and bridges to avoid capturing their street-level images. Before obtaining SVIs, the streets were simplified in ArcGIS 10.7 according to relevant research (Long and Liu, 2017). After simplification, 18,322 streets remained, with a total length of approximately 1558 km (an average of 0.09 km per street) in Gusu District of Suzhou, and 9588 streets remained, with a total length of approximately 2435 km (an average of 0.25 km) in the center district of Pingdingshan. The second step is to generate sampling points. Sampling points were placed on the map at 30 m intervals in Suzhou and

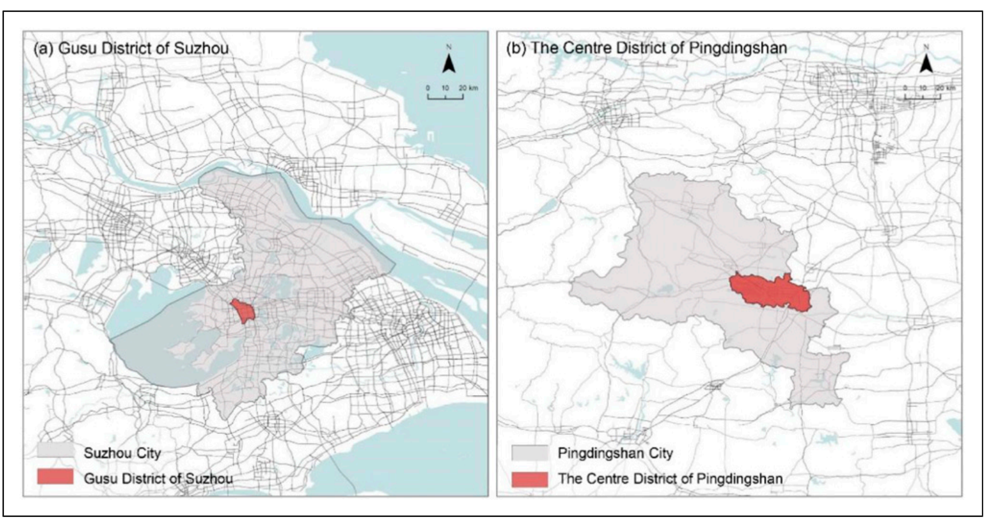

Figure 1. Study area a. Gusu District of Suzhou, b. the centre district of Pingdingshan.

50 m intervals in Pingdingshan. Each point was assigned latitude, longitude, and other parameters to facilitate the collection process. Following street simplification and sampling point generation, the Baidu Maps Application Programming Interface (API) was used to query and download SVIs. Subsequently, with Python support, SVIs were downloaded in four directions (left, right, front, and back) for each sampling point. Ultimately, 139,380 SVIs were collected from Suzhou's Gusu District in 2019 and 65,300 SVIs were collected from the central district of Pingdingshan in 2018.

Methods of UDQ and PD measurement

Methodological framework

The methodological framework for this study is illustrated in Figure 2. First, index systems were constructed to evaluate street space visual quality from two perspectives: urban design quality and physical disorder (Figure 3). Next, the quality of SVIs in the two empirical study areas was evaluated using manual scoring on a virtual audit platform and deep learning techniques. Based on the evaluation results, we conducted a correlation analysis. Finally, the robustness of the results was tested across four aspects.

Urban design quality

Based on Ewing's urban design quality theory and related studies (Ewing et al., 2006; Ewing and Handy, 2009), we constructed a space design quality evaluation index system encompassing five dimensions: imageability, enclosure, transparency, human scale, and complexity (Figure 4). In the experiment conducted in Gusu District of Suzhou, a virtual audit platform from existing research was used for manual scoring (Li et al., 2022b). We invited three volunteers with professional backgrounds in urban planning or architecture, and after training them using the scoring guide, we asked them to manually score the SVIs using the virtual audit platform. An interrater evaluation was also conducted to ensure the reliability of their scoring (see the "Manual scoring process" in the Supplementary Material for more information). The results were then aggregated at the street level through sampling points. If at least one UDQ indicator belonging to a certain dimension appears in the four images of a sampling point, the score for that dimension at that sampling point is 1, and if none appears, it is 0. The overall UDQ score of a sampling point is the sum of its five dimension scores, which range from 0 to 5 (Equation 1). The mean of the scores for all points on a street for a given dimension is the score for that street on that dimension (Equation 2), while the mean of the overall UDQ scores for these points is the UDQ score for the street (Equation 3)

$$U_{point} = \sum\nolimits_1^5 D_{point\_i} \tag{1}$$

$$D_{street\_i} = \frac{\sum_1^n D_{point\_i\_j}}{n} (j = 1, 2, \ldots, n) \tag{2}$$

$$U_{street} = \frac{\sum_1^n U_{point\_j}}{n} (j = 1, 2, \ldots, n) \tag{3}$$

where $D_{point\_i\_j}$ is the score of sampling point j on dimension i, where $i = 1, 2, 3, 4, 5$, denoting imageability, enclosure, transparency, human scale, and complexity, respectively; D_{street_i} is the

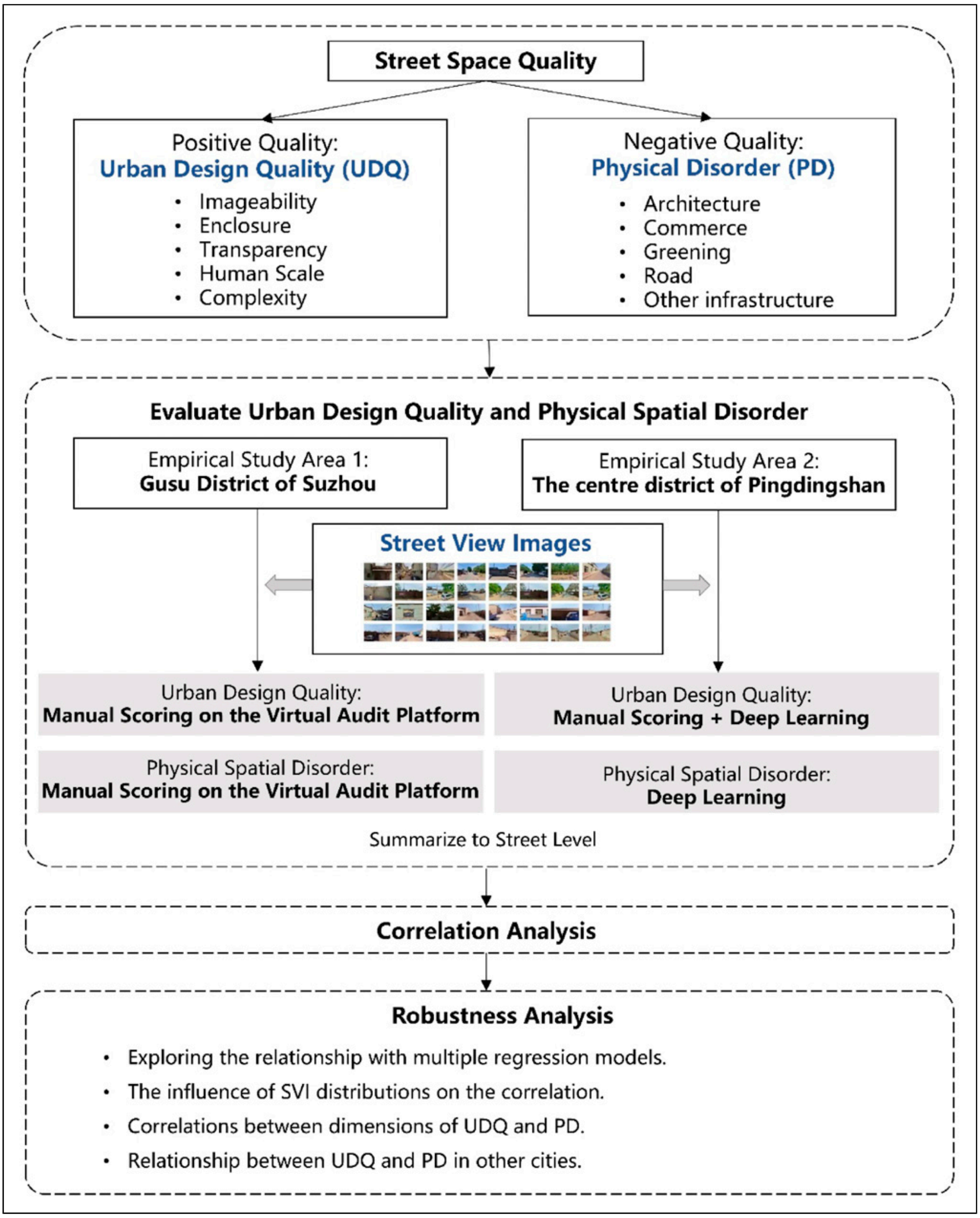

Figure 2. Methodological framework.

score of street on dimension i; U_{point_j} is the overall urban design quality score of sampling point j; U_{street} is the overall urban design quality score of street.

In the experiment conducted in the center district of Pingdingshan, some indicators were measured using deep learning models to enhance objectivity, while others were scored using the same virtual audit platform as in the Suzhou experiment. Indicators measured by deep learning models included the ratio of walls, the ratio of windows, and color diversity in SVIs. For these ratios, a Fully Convolutional Network (FCN) was used to process street view images into scenes similar to

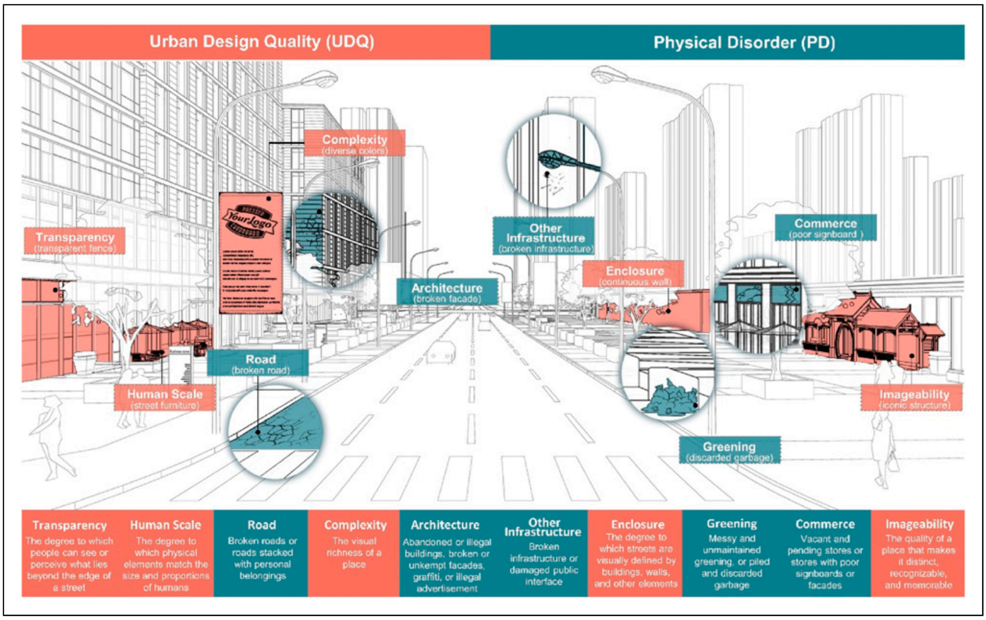

Figure 3. Urban design quality and physical disorder of streets.

those on the MIT ADE20 K website (https://groups.csail.mit.edu/vision/datasets/ADE20K/index.html#Download) (Jia et al., 2022). The ADE20 K dataset includes various scenes related to urban space, facilitating the development of deep learning models to identify walls and windows in SVIs. Based on the model's identification results, the ratio of walls or windows in the SVI was calculated by comparing the total number of wall or window pixels to the total number of SVI pixels. For color diversity, the "colorfulness" model was used to quantify the diversity of colors in the SVI (https://pyimagesearch.com/2017/06/05/computing-image-colorfulness-with-opencv-and-python/). An SVI was scored as 1 in the index system if the "colorfulness" model's output rate was greater than 50, indicating sufficient color diversity, or 0 otherwise.

Physical disorder

We evaluated another aspect of street space visual quality in the study area using a physical disorder index system applicable to Chinese cities, established by related research (Chen et al., 2023). This index system includes 15 items across five dimensions: architecture, commerce, greening, road, and other infrastructure (Figure 5). Similar to the UDQ evaluation, a virtual audit platform was used in Suzhou for manual scoring. In the center district of Pingdingshan, a platform was established to identify PD items using image semantic segmentation with the SegNet algorithm based on a training set. The SegNet algorithm was utilized for automatic calculations (Badrinarayanan et al., 2017), and the training set consisted of annotations from 200,000 randomly sampled street view images in China containing numerous visual examples of all the physical disorder features (Chen et al., 2023). The F2-score and IoU (Intersection over Union) are employed as performance evaluation indicators of the model, with specific results presented in Table S1 in the Supplementary Material. Physical disorder for streets is calculated in a manner similar to urban design quality. The five dimensions and overall PD scores were aggregated to streets through sampling points.

Figure 4. The index system of urban design quality.

Figure 5. The index system of physical disorder.

Results

Evaluation of UDQ and PD of streets

In the evaluation results of Gusu District, the average UDQ score of streets is 2.39. Simultaneously, the average PD score for streets in Gusu District is 1.04. In the center district of Pingdingshan, the average UDQ score of streets is 3.54. Meanwhile, the average PD score of streets in the center district of Pingdingshan is 0.11. The distribution of streets with high urban design quality and physical disorder varies across the city. Detailed results can be found in Figures S4 and S5 in the Supplementary Material.

The correlation between UDQ and PD of streets

Spearman's rank coefficient was utilized to examine the correlation between UDQ and PD at the street level. Table 1 shows the analysis results for Gusu District of Suzhou and the center district of Pingdingshan. The results show that, although the correlation is statistically significant ($p < .05$), the correlation coefficients in both models are very small, indicating that the relationship between UDQ and PD is extremely weak or unclear, and the ability to explain or predict one variable using the other is limited.

Considering that Spearman's rank coefficient is more effective in measuring monotonic changes, we also aimed to explore the potential linear and nonlinear characteristics between UDQ and PD by constructing a simple linear regression (SLR) model and several commonly used machine learning (ML) models for handling nonlinear relationships, such as Decision Tree (DT) (Ding et al., 2019), Random Forest (RF) (Hatami et al., 2023), and eXtreme Gradient Boosting (XGBoost) (Parsa et al., 2020). The performance of the models is shown in Table 2. The R^2 and adjusted R^2 values for all models are very low, close to 0, which indicates that UDQ has limited explanatory power over PD. Even the best-performing linear regression model was able to explain only 7.6% of the variation in the target variable in Suzhou, and just 0.8% in Pingdingshan. Furthermore, the relatively high values of MAE, MSE, and RMSE suggest significant prediction errors, implying that none of the models are able to effectively predict PD using UDQ.

These findings suggest that there is no strong correlation between UDQ and PD in street space. Excellence in one aspect does not guarantee similar quality in another. For instance, streets exemplifying superb design quality, with attributes like imageability and human scale, may not necessarily be well-organized. Issues such as discarded garbage and unkempt building facades might still be prevalent despite the high design quality, and vice versa.

Robustness analysis

Exploring the relationship with multiple regression models. Initially, to confirm the robustness of the result, multiple regression models were constructed to examine the correlation between UDQ and

Table 1. Correlation analysis results of UDQ and PD.

	Model 1 (Gusu district of Suzhou)	Model 2 (The center district of Pingdingshan)
Correlation coefficients	0.308**	−0.085**
Sig. (2-Tailed)	0.000	0.000
N	22,486	9801

Note. **represents 5% significance levels.

PD, and five control variables related to urban vitality, cultural characteristics, and urban development were added (See Table S2 in the Supplementary Material for details). As shown in Table 3, the results indicate that although the relationship between PD and UDQ is significant, this relationship is weak when assessed in conjunction with the regression coefficients. This finding is consistent with the results of the correlation analysis.

The influence of SVI distributions on the correlation. SVIs are unevenly distributed throughout the city, so not every sampling point contains SVIs. The impact of the quantity of SVI distributions on each street's correlation was examined. In Gusu District of Suzhou and the center district of Pingdingshan, 73.2% and 61.3% of streets, respectively, feature only one effective sampling point with street view images. The maximum number of effective sampling points per street reaches 36 in Gusu and 26 in Pingdingshan. Streets were categorized into three groups based on the number of effective sampling points, and the correlation between UDQ and PD was analyzed for each group. The finding reveals that correlation coefficients between UDQ and PD remain low, irrespective of the number of SVIs on the street (Table 4).

Correlations between dimensions of UDQ and PD

Correlations between the dimensions of UDQ and PD were assessed. The results show that there is no strong correlation between the dimensions of UDQ and PD in Gusu District of Suzhou and the

Table 2. The performance of linear and nonlinear regression models.

Study areas	Models	MAE	MSE	RMSE	R^2	Adjusted R^2
Gusu district of Suzhou	SLR	1.185	1.206	1.104	0.076	0.076
	XGBoost	1.319	1.476	1.177	0.076	0.075
	RF	1.812	1.755	1.567	0.061	0.060
	DT	2.823	2.715	2.659	0.035	0.033
The center district of Pingdingshan	SLR	1.955	2.036	2.099	0.008	0.008
	XGBoost	2.012	2.365	2.228	0.006	0.006
	RF	2.568	2.783	2.756	0.006	0.005
	DT	3.321	3.116	3.059	0.002	0.002

Table 3. Results of regression models.

Variable	Gusu district of Suzhou		The center district of Pingdingshan	
Urban design quality	0.275***	0.218***	−0.091***	−0.087***
Density of human activity		0.037***		0.018*
Density of restaurants		−0.016*		−0.011*
Density of historical sites		0.097***		−0.020
Changes in functional density		−0.220***		−0.091***
Population growth rate		−0.165***		−0.012**
Dependent variable	Physical disorder			
N	9542	9542	3275	3275
R^2	0.076	0.125	0.008	0.057

Note. The standardized coefficients (Standardized Beta) are listed in the table. ***, **, * represent 1%, 5%, and 10% significance levels, respectively.

Table 4. Correlations between UDQ and PD in streets with different number of sampling points.

	Gusu district of Suzhou	The center district of Pingdingshan
Streets with 1 sampling point	0.315**	−0.053*
Streets with 2 sampling point	0.285**	−0.107**
Streets with 3 or more sampling points	0.321**	−0.119**
N	2697	1670

Note. In order to avoid the influence of sample size on the correlation coefficient, the two groups with the larger sample size were randomly sampled so that their sample size was consistent with the smallest group. ***, **, * represent 1%, 5%, and 10% significance levels, respectively.

center district of Pingdingshan (Figure S6 in the Supplementary Material). This lack of strong correlation further substantiates our findings.

Relationship between UDQ and PD in other cities

To further validate our findings, we randomly selected 100 sampling points in each of 20 Chinese cities, downloaded their latest street view images, used the same methodology as in the Pingdingshan experiment to measure UDQ and PD and evaluated the correlation between the two. The results are shown in Figure S7 in the Supplementary Material, where correlation coefficients between UDQ and PD in all cities do not exceed 0.3, and they all show a low correlation, verifying the independence of UDQ and PD.

Discussion

To the best of our knowledge, this study represents one of the first endeavors to investigate the correlation between urban design quality and physical disorder. Prior research on quantifying public space visual quality typically focuses on a single perspective or employs both subjective and objective methods for quantification (Chen and Biljecki, 2023; Ho et al., 2021; Zhu et al., 2021). However, few studies have concurrently measured UDQ and PD in street space or concentrated on the interrelationship between these two aspects. This study's principal contributions are two-fold: first, it establishes a methodological framework for evaluating street space quality from both UDQ and PD perspectives, utilizing artificial virtual audits and deep learning techniques with extensive street view imagery; second, it reveals that the correlation between UDQ and PD in street spaces is not significant. They should not be conflated or substituted for one another, nor should either be used as the sole criterion to gauge space quality.

Potential factors affecting urban design quality and physical disorder

Theoretically, the design and maintenance of public space complement each other. However, as our findings show, this is difficult to achieve in practice. This is because the design and maintenance of public space are also influenced by various factors, such as political management, user groups, cultural characteristics, and resident attitudes. For example, Suzhou, one of our study cities, includes the National Historical and Cultural City Conservation Area, where top-level policy has unified the requirements for urban design styles. This has resulted in a significantly higher number of landmarks and historic buildings. The more prominent the historical style of the area, the higher its urban design quality. However, older buildings and higher tourist density increase the pressure on spatial management and maintenance, likely leading to more severe physical disorder.

Pingdingshan, the other city in our study, is a resource-based industrial city without a strong emphasis on historical landscape creation and tourist attraction. Here, urban design quality and physical disorder show a very weak negative correlation. This difference may also explain the contrasting correlation results of UDQ and PD in the two study areas (The relevant content is analyzed in more detail in the potential factors affecting urban design quality and physical disorder section in the Supplemental Material). Furthermore, short-term spatial changes can influence the UDQ and PD phenomena we observe. For example, during special festivals or events, streets may be decorated, thereby enhancing urban design quality. Fewer street disorder problems are likely to be observed after regular daily garbage collection times. These factors also affect the relationship between UDQ and PD in the short term.

Implications for improving the street space quality

As emphasized in several classical urban planning theories, design and maintenance are two key components in the creation of public space, and the absence of either can jeopardize the sustainability of the space (Gehl, 1987; Lynch, 1964). To create high-quality street space, it's crucial not only to emphasize superior urban design quality, but also to focus on urban management and maintenance issues such as discarded garbage, damaged building facades, and broken roads, which contribute to undesirable physical disorder. Additionally, varying measures need to be adopted based on different coupling situations of UDQ and PD. For instance, if a street has high urban design quality but serious physical disorder issues, the focus should be on enhancing space detail management and maintenance to reduce physical disorder. Specific measures might include regular trash removal, greenery planting, and repairing damaged buildings, roads, and public facilities. Administrative departments ought to devise systematic policies for street space maintenance. In contrast, if the urban design quality of a street is low but there is no physical disorder, the focus should be on enhancing the overall urban design. Specifically, optimizing spatial design along street interfaces can improve street space transparency and enclosure. The addition of street furniture, such as seating, signage, and flower beds, can be beneficial. In general, improving street space quality necessitates attention to both UDQ and PD, addressing each separately.

Possibilities of using remote sensing data

Street view imagery, widely utilized as an effective data source for auditing urban space, offers several advantages over traditional survey methods, including extensive coverage and high measurement efficiency (Fan et al., 2023; Li et al., 2022c; Zhang et al., 2023b). However, the temporal fineness of commercial SVIs is limited, and it is often difficult to obtain continuous-time street views at the same location (Biljecki and Ito, 2021; Zhang et al., 2024). Meanwhile, the information observed from SVIs is only from the pedestrian viewpoints of the main streets that are favorable for image acquisition, which leads to the omission of visual information from other locations and viewpoints in the city. Some innovative studies have proposed the use of self-collected SVIs to measure spatial qualities with temporal dynamics. Li et al. (2024) assessed multi-year changes in physical disorder by combining self-collected and commercial SVIs. Other scholars used images captured by wearable cameras to assess individuals' exposure to physical disorder at different times of the day (Li et al., 2022c).

In addition, we believe that remote sensing technology can also help address the limitations of SVIs. Satellite remote sensing imagery provides an aerial view of the city and captures different visual information compared to SVIs. Satellites such as Landsat, Sentinel, and MODIS provide free or low-cost continuous satellite images over many years. Studies have been conducted to use satellite images to detect urban slums (Kohli et al., 2016; Kuffer et al., 2016). Grubesic et al. suggest that UAVs (Unmanned Aerial Vehicles) can be used to detect physical disorder (Grubesic et al., 2018). UAVs are capable of capturing remote sensing images with higher resolution compared to satellite images. We compared remote sensing images and street views (Figure S8 in the Supplementary Material) and listed the UDQ and PD indicators observable from them (Figure S9 and Table S4 in the Supplementary Material). We believe that future research may benefit from integrating a diverse array of data, combining street view images with remote sensing images, and measuring urban spatial quality from multiple perspectives over an extended period of time. This approach can facilitate the acquisition of more comprehensive perspective information, thereby enhancing our understanding of urban space.

Limitations and future steps

Several limitations must be considered when interpreting the results of this study. Currently, certain UDQ indicators still depend on manual virtual audits. Although rigorous manual audits are adhered to, manual methods of measuring street space quality inevitably introduce subjective evaluations. This approach also limits the efficiency of measuring the visual quality of street space. Future research will continue to explore the full automation of street spatial quality measurements to improve the efficiency and objectivity of urban space quality evaluation, and the use of more types of data to address the limitations of SVIs. The association between UDQ and PD is still very much in need of broader and deeper assessment. Mining more control variables and using better measurement methods to expand the understanding of public space quality from more perspectives will be the next goal.

Conclusions

This study explores the relationship between urban design quality and physical disorder in streets to affirm the necessity of assessing public space quality from multiple perspectives simultaneously. Focusing on case studies in Gusu District of Suzhou City and the central district of Pingdingshan, we developed a methodological framework incorporating massive street view images, virtual audits, and deep learning to assess the visual quality of street space in terms of urban design quality and physical disorder, and explored their correlation. The results indicate a lack of strong correlation between the two. This implies that although both urban design quality and physical disorder represent street space quality and have similar externalities, they cannot substitute for or be conflated with each other. Evaluating space quality from a single perspective may overlook its complexity and even result in biased assessments. This result broadens our understanding of high visual quality street space from diverse perspectives and calls for us to assess and enhance public space quality across multiple perspectives simultaneously. The association between UDQ and PD needs to be assessed further, with the inclusion of more control variables and the use of better measurements for an accurate and in-depth portrayal to expand the understanding of public space quality. This will offer valuable insights and references for researchers and urban planners,

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Data availability statement

Data sharing not applicable to this article as no datasets were generated or analyzed during the current study.

Supplemental Material

Supplemental material for this article is available online.

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