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Prioritizing Environmental Attributes to Enhance Residents' Satisfaction in Post-Industrial Neighborhoods: An Application of Machine Learning-Augmented Asymmetric Impact-Performance Analysis

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Abstract: Post-industrial neighborhoods are valued for their historical and cultural significance but often contend with challenges such as physical deterioration, social instability, and cultural decay, which diminish residents' satisfaction. Leveraging urban renewal as a catalyst, it is essential to boost residents' satisfaction by enhancing the environmental quality of these areas. This study, drawing on data from Shenyang, China, utilizes the combined strengths of gradient boosting decision trees (GBDTs) and asymmetric impact-performance analysis (AIPA) to systematically identify and prioritize the built-environment attributes that significantly enhance residents' satisfaction. Our analysis identifies twelve key attributes, strategically prioritized based on their asymmetric impacts on satisfaction and current performance levels. Heritage maintenance, property management, activities, and heritage publicity are marked as requiring immediate improvement, with heritage maintenance identified as the most urgent. Other attributes are categorized based on their potential to enhance satisfaction or their lack of immediate improvement needs, enabling targeted and effective urban revitalization strategies. This research equips urban planners and policymakers with critical insights, supporting informed decisions that markedly improve the quality of life in these distinctive urban settings.

Keywords: post-industrial neighborhoods; historic built environment; residents' satisfaction; gradient boosting decision trees; nonlinear association

Citation: Ji, X.; Shang, F.; Liu, C.; Kang, Q.; Wang, R.; Dou, C. Prioritizing Environmental Attributes to Enhance Residents' Satisfaction in Post-Industrial Neighborhoods: An Application of Machine Learning-Augmented Asymmetric Impact-Performance Analysis. *Sustainability* **2024**, *16*, 4224. https://doi.org/10.3390/su16104224

Academic Editor: John Carman

Received: 18 April 2024
Revised: 14 May 2024
Accepted: 14 May 2024
Published: 17 May 2024

1. Introduction

During the urbanization and industrialization phases, numerous factories emerged in urban areas, catalyzing the growth of industrial communities with well-managed residential zones for workers and their families [1]. However, as major cities transitioned into the post-industrial era, shifting from manufacturing to service sectors, traditional industries began to wane. This transition prompted many industrial enterprises to relocate to the outskirts or other regions, leaving behind a landscape peppered with abandoned factories and giving rise to post-industrial neighborhoods [2]. In cities like Detroit, USA, and Manchester, UK, this shift not only transformed the urban landscape but also prompted significant socio-economic restructuring, leading to both challenges and opportunities for urban renewal and heritage preservation. Similar trends have been observed in China, albeit at a later stage, with cities like Shenyang embodying the complex interplay of industrial legacy and modern urban development.

The post-industrial neighborhoods represent the dynamic evolution of urban landscapes, transitioning from bustling industrial hubs to areas beset with economic and social challenges [3]. With the decline in manufacturing and the shift towards a service- and technology-oriented economy, these communities faced hardships such as economic downturns, job losses, and urban decay. The once stable and prosperous life, guaranteed by industrial jobs, diminished, deeply impacting residents typically from working-class backgrounds as they navigated this transformed environment [2].

The residential quality in post-industrial neighborhoods has emerged as a critical concern in urban studies. Residents commonly face housing inadequacies [4] and substantial barriers to accessing essential services [5,6]. Developed under the constraints of limited economic resources and policy frameworks of their industrial inception, these neighborhoods now feature high-density construction misaligned with the evolving needs of modern urban dwellers [7]. The once vibrant industrial environments have become physical manifestations of economic and social decline, underscoring the urgent need for comprehensive redevelopment to meet the community's current needs [8,9].

Alongside physical deterioration, these neighborhoods are grappling with acute social challenges. Poverty, eroding social cohesion, and a pervasive sense of community neglect have become increasingly evident [10]. The demographic shift, driven by deindustrialization and the migration of the working-age population, has resulted in a predominance of vulnerable groups, including the elderly, the economically disadvantaged, and the less educated [11]. This shift has significantly dulled community vitality, adding complexity to the socio-economic landscape of these areas [12].

Furthermore, in urban regeneration projects, widespread demolition and construction practices have significantly disrupted the cultural fabric of these communities [13]. This approach often replaces residents' familiar living environments with uniform neighborhood landscapes, while elements of industrial heritage within the urban setting are frequently neglected, abandoned, or even demolished. Such changes hinder residents' ability to connect with the area's industrial past, eroding their sense of cultural identity and belonging. This transformation impacts not only the physical landscape but also disrupts the continuity of the community's collective memory, an essential component of cultural sustainability in urban settings.

In recent years, there has been an increasing acknowledgment of the need to revitalize these neighborhoods, focusing not only on economic but also on social and cultural aspects [14]. A key element of this revitalization is the emphasis on heritage preservation and the conservation of the urban context [15,16]. These strategies are vital in enhancing residents' satisfaction by reconnecting them with their history and providing a sense of continuity and identity [17,18]. Moreover, preserving the unique urban fabric of these neighborhoods and integrating new developments with sensitivity ensures that revitalization efforts respect the past while addressing contemporary needs.

Leveraging urban renewal as a catalyst, the enhancement of residents' satisfaction through improved environmental quality is crucial [19]. The environmental quality in post-industrial neighborhoods is multifaceted, encompassing the physical built environment, social dynamics, and heritage conservation. Despite the extensive array of research on residential satisfaction [20–22], focused studies on post-industrial neighborhoods are limited. These neighborhoods differ from conventional residential areas in both inherent characteristics and specific challenges. Therefore, a deeper understanding of how various attributes of post-industrial neighborhoods impact residents' satisfaction is essential. This gap in knowledge hinders informed urban design and decision-making in this unique kind of built environment. Addressing these factors is pivotal in transforming these neighborhoods into thriving, sustainable communities that respect their industrial heritage while embracing a prosperous future.

Drawing on data from Shenyang, China, this study utilizes machine learning-augmented asymmetric impact-performance analysis (AIPA) to identify and prioritize the key attributes of post-industrial neighborhoods that significantly contribute to enhancing residents' satisfaction. Our method outperforms traditional approaches that typically rely on linear regression models. These conventional methods may overlook complex variable interactions, leading to potential misestimations. By employing gradient boosting decision trees (GBDTs), our approach adeptly manages multicollinearity and captures intricate, non-linear interactions that are often missed by linear models. Additionally, the AIPA enhances our methodology by providing a visual and intuitive representation of attribute impacts, categorizing them based on their asymmetric effects on satisfaction. This comprehensive approach not only enhances the precision of identifying key factors but also guides planners and policymakers in effectively prioritizing attributes for development, ensuring a strategic allocation of resources.

This research aims to address several critical questions: (1) what is the role of historical urban conservation in elevating residents' satisfaction within post-industrial neighborhoods? (2) which attributes are most influential in determining residents' satisfaction? (3) how do these attributes exhibit asymmetrical associations with residents' satisfaction levels? (4) which specific attributes should be prioritized for targeted improvements in post-industrial neighborhoods? This investigation seeks to provide insights into the nuanced relationship between various neighborhood attributes and residents' satisfaction. By focusing on the asymmetric impacts, this study aims to guide urban planners and policymakers in making informed decisions that can effectively enhance the quality of life in these unique urban settings.

The subsequent section, Materials and Methods, begins with a detailed examination of the attributes in post-industrial neighborhoods that potentially influence residents' satisfaction. It then outlines the methodological approach adopted for this study, followed by a description of the survey areas and the data collection procedures. The Results section highlights key findings from both the gradient-boosting decision trees (GBDTs) and asymmetric impact-performance analysis (AIPA). In the Discussion section, we examine the limitations of this study and explore the policy implications of the findings. This paper concludes by summarizing the research and emphasizing the critical insights derived from this investigation.

2. Materials and Methods

The cultural landscape represents the amalgamation of environmental attributes and cultural groups [23]. Within this context, the post-industrial landscape emerges as a pivotal category of cultural landscape, serving as a dynamic arena for human activities and underscoring the symbiotic relationship between people and their surroundings. The concept of satisfaction assumes critical importance in the discourse surrounding the person–environment nexus.

Empirical inquiries into the interactive dynamics between individuals and their environment frequently manifest within the ambit of satisfaction studies. Campbell's model [24] postulated that overall satisfaction is an aggregate of contentment across various life domains. Given that post-industrial neighborhoods encapsulate the urban milieu inhabited by individuals, the satisfaction of residents within these areas can be conceptualized as a component of overall life satisfaction [25].

An environment's efficacy is contingent upon its acceptance and utilization by its inhabitants [26]. This underscores the significance of understanding residents' perceptions and sentiments regarding their living spaces [27]. Effective urban management necessitates prioritizing the creation of habitable and satisfying urban spaces [28]. Given that urban residents actively contribute to the shaping of their environment, prioritizing their satisfaction becomes paramount in urban planning and management [29].

2.1. Influential Attributes in Posting-Industrial Neighborhoods Affecting Resident Satisfaction

Recent scholarly work has comprehensively charted the evolution and progression of social research pertaining to residents' satisfaction [30,31]. This body of work in the literature has not only scrutinized residents' satisfaction but has also elucidated its various correlates. The research indicates that residents' satisfaction is influenced by an amalgam of both objective and subjective elements [32–34]. It identifies a confluence of personal [35] and social factors, in conjunction with the physical attributes of the living environment, as key determinants impacting residents' satisfaction [36–38].

The quality of the built environment, encompassing aspects like building density [36,39], vegetation coverage [39], environmental design [39], tranquility [40], housing and utility infrastructure, as well as activity spaces [41], plays a pivotal role in shaping residents' satisfaction. It is posited that enhancements in these aforementioned facets of the living environment have the potential to augment the comfort experienced by residents, thereby positively influencing their subjective well-being.

Beyond the physical structure of neighborhoods, the availability and quality of neighborhood services and transportation infrastructure significantly influence residents' satisfaction. Lovejoy et al. (2010) [40] identified a connection between neighborhood satisfaction and factors related to the service environment, including location and accessibility to various amenities. Similarly, research by Yazhuo Jiang et al. [42] highlights the role of service facilities such as parking, childcare, and daily shopping provisions in shaping residential satisfaction.

Zhou Yao et al. (2020) [43] contended that residents' satisfaction is influenced by a multitude of environmental factors, one of which is the natural environment. Kaplan's research [44] supports this view, indicating that the inclusion of diverse natural elements positively impacts residents' satisfaction. The interplay between the function and structure of the landscape and human perception and satisfaction has been corroborated by numerous scholars [45–47], underscoring the significance of natural elements in shaping residents' experiences.

Certain environmental factors indirectly influence residents' satisfaction through the social environment. Critical elements, including community cultural activities, neighborhood relationships, and family dynamics [48], are acknowledged as significant determinants of residents' satisfaction. Friedman et al. (2012) [49] elucidate that both perceived neighborhood safety and social cohesion are positively correlated with life satisfaction. This finding underscores the substantial impact of social factors in the context of the environmental framework on residents' overall well-being [49].

Moreover, the post-industrial neighborhood is distinguished not only by its intrinsic neighborhood characteristics but also by its historical built environment, which plays a critical role in determining the relevant influencing attributes. In this context, attributes related to urban conservation and heritage revitalization demand attention. Factors such as the preservation of historic urban fabric, visual connections within the area, maintenance of heritage sites, accessibility to these heritage locales, and the reuse of heritage properties are essential considerations in understanding the impact of these environments on various outcomes [50,51].

Acknowledging the absence of a standardized scale to measure the effects on residents' subjective perceptions of the built environment in post-industrial neighborhoods, this study established a bespoke set of dimensions and attributes. This tailored framework amalgamates elements from the domains of built environment satisfaction, residential well-being, and the fundamentals of urban planning, conservation, and rejuvenation. To devise and hone this measurement scale, a focus group was assembled, encompassing two experts in heritage preservation and urban planning, alongside five undergraduate students with a focus in urban planning. This collective endeavor led to the selection of 23 attributes, organized into six distinct dimensions. These are thoroughly outlined in Table 1, serving as the foundation for further analysis.

Table 1. Description of the historic-built environmental attributes selected by the focus group.

Dimensions	Variables	Description	Related Empirical Studies
Walkability	Density	Indicates the compactness of building arrangements and impacts the sense of spatial openness or congestion in the environment.	Hur, Nasar and Chun, 2010 [36]; Cao, 2016 [39].
	Diversity	Reflects the mix of functional uses within the area, indicating the variety of living needs that the environment can accommodate.	Tara Smith et al., 1997 [52].
	Design	Assesses the impact of urban physical design on street accessibility and connectivity.	Tara Smith et al., 1997 [52].
Environmental Quality	Greenery	Indicates the presence and accessibility of green elements within the living area, including trees, shrubs, and flowerbeds.	Tara Smith et al. [52], 1997; Bruce, 1994 [39]; Cao, 2016 [39].
	Amenities	Reflects the availability and accessibility of environmental facilities, such as parks, playgrounds, and community centers within the living area.	Cao and Wang, 2016 [22]; Zhou Yao et al., 2016 [43].
	Crowdedness	Reflects the level of pedestrian and vehicle density, indicating the extent of space utilization in urban areas.	Ji X et al., 2024 [51].
	Traffic Volume	Indicates the level of vehicle traffic flow in the surrounding areas.	Cao and Wang, 2016 [22].
	Noise	Indicates the general noise levels within the living area, impacting the urban living experience.	Cao and Wang, 2016 [22]; Hamersma et al., 2014 [33]; Huang and Du, 2015 [39]; Lovejoy et al., 2010 [40].
	Tidiness	Reflects the level of upkeep and cleanliness in the environment, focusing on whether areas are clean or cluttered.	Cao and Wang, 2016 [22].
	Detractors	Presence of significant nuisances or visually displeasing elements that are considered intolerable by residents.	-
Infrastructure and Management	Public Space	Indicates the adequacy of public spaces for activities, assessing their availability within the living area.	Tara Smith et al., 1997[52]; Yu Dong et al., 2023 [41].
	Infrastructure	Reflects the quality of essential municipal facilities, including plumbing, heating, electricity, etc.	Yu Dong et al., 2023 [41].
	Street Furnishings	Indicates the adequacy of environmental facilities such as benches, lighting, and bins in the neighborhood.	Cao and Wang, 2016 [22].
	Property Manage	Reflects the effectiveness and quality of property management services within the living area.	Yu Dong et al., 2023 [41].
Urban Conservation	Historical Scene	Reflects the preservation of the historic urban structure or urban fabric, indicating the extent of changes in the surrounding historical scenes.	-
	Heritage Preservation	Reflects the conservation of historic architectures in the area, particularly focusing on the preservation of old buildings.	-
	Heritage Maintenance	Reflects the upkeep and preservation efforts for existing old buildings, maintaining historical integrity in the area.	Cao and Wang, 2016 [22]; Ji X et al., 2020 [50].

	Visual Connection	Reflects the visual accessibility of heritage elements or landmark landscapes, indicating the extent of visual connectivity to historical heritage in the area.	Ji X et al., 2020 [50].
	Order	Reflects the harmony and continuity between old and new structures, representing the overall character and aesthetic coherence of historic urban areas.	Ji X et al., 2024 [51].
Heritage Reuse	Heritage Accessibility	Reflects the ease of access to historical buildings and sites, indicating the navigability and approachability of historic locations in the area.	Cao and Wu, 2019 [53]; Ji X et al., 2020 [50].
	Heritage Publicity	Reflects the extent to which heritage sites are open and accessible to the public, indicating the level of public engagement and accessibility of historical resources.	Ji X et al., 2020 [50].
Intangible Aspects	Activities	Reflects the presence of organized community activities, indicating the level of community engagement and social opportunities within the area.	Yu Dong et al., 2023 [41].
	Neighborhood Harmony	Reflects the degree of harmony in neighborhood relationships, indicating the overall social cohesion and community rapport within the area.	Cao and Wang, 2016[22]; Friedman et al., 2012 [49]; Hamersma et al., 2014 [33]; Lovejoy et al., 2010 [40];

2.2. Analysis Techniques for the Priority Assessment of Attributes

Given the finite nature of planning resources, identifying the critical factors contributing to residents' satisfaction is of paramount importance to planners. It is recommended that decisions regarding the allocation of resources be informed by a systematic evaluation of attributes' priorities [54].

A myriad of techniques at the attribute level exist for pinpointing areas for enhancement [55,56]. The traditional research in this domain has often operated under the assumption that there is a linear or at least generalized linear relationship between neighborhood characteristics and the satisfaction of residents. This approach typically involves comparing correlation coefficients to gauge the relationship between various neighborhood factors and residents' satisfaction. Yet, this method, focusing solely on bivariate correlations, overlooks the potential interplay between different neighborhood characteristics, potentially leading to a skewed perception of their importance [57]. An alternative approach considers the practical significance of empirical findings by examining the effect size [58].

Nonetheless, emerging research in the field of customer satisfaction [59]—which includes studies within urban planning—challenges the validity of the linear model [50,53]. The evidence suggests that the relationship between neighborhood attributes and residents' satisfaction may, in fact, be nonlinear, which implies that adherence to a linear model could lead to inaccurate estimations and, consequently, a misunderstanding of the actual relationships. Such misestimations could further result in the misallocation of scarce planning resources due to an incorrect assessment of the relative significance of different neighborhood attributes in contributing to residents' satisfaction [59]. Moreover, research into service satisfaction reveals that the relationship between service attributes and satisfaction is asymmetrical [59,60]. This asymmetry has been substantiated by numerous studies [61–64], indicating that the impact of an attribute's positive performance on overall satisfaction can differ significantly from the impact of its negative performance, and vice versa.

The three-factor theory of customer satisfaction, initially put forth by Kano [65] and subsequently refined by various scholars [61,66], posits that satisfaction is a multi-dimensional construct rather than a binary one, where the absence of dissatisfaction does not automatically imply satisfaction [54]. This theory delineates attributes into three distinct categories based on their asymmetric effects on satisfaction: basic, performance, and excitement factors. Basic factors are those whose absence leads to dissatisfaction; however, their presence or surpassing expectations only marginally enhances satisfaction [67]. Conversely, excitement factors are associated with a direct, positive impact on satisfaction, engendering delight without causing dissatisfaction when absent [68]. Performance factors, distinct from the other two, have a symmetric relationship with satisfaction, where their performance level directly correlates with either satisfaction or dissatisfaction [54,69].

In the scholarly realm, various methodologies have been developed to differentiate these three types of factors, such as the critical incident technique [70], the importance grid method, and penalty–reward contrast analysis [71]. The latter, in particular, has gained widespread application. It involves the creation of two sets of dummy variables by recoding the performance levels of each attribute [72], which, after conducting regression analysis on the attributes' impact on overall satisfaction, allows for the identification of the factor structure through the interpretation of two coefficients [68]. These coefficients signify the penalty index (PI) and reward index (RI) for each attribute, aiding in the determination of each attribute's category [73].

Building on this analytical framework, Mikulić and Prebežac [59] introduced the concept of impact range-performance analysis along with impact-asymmetry analysis (IAA), further sophisticating the categorization by identifying five distinct factors: frustrators, dissatisfiers, hybrids, satisfiers, and delighters (Figure 1). This refined classification leverages the degree of asymmetry to provide a more nuanced understanding of how different attributes influence satisfaction, with frustrators and delighters representing the extremes in terms of asymmetry relative to the more balanced impact of dissatisfiers and satisfiers [53].

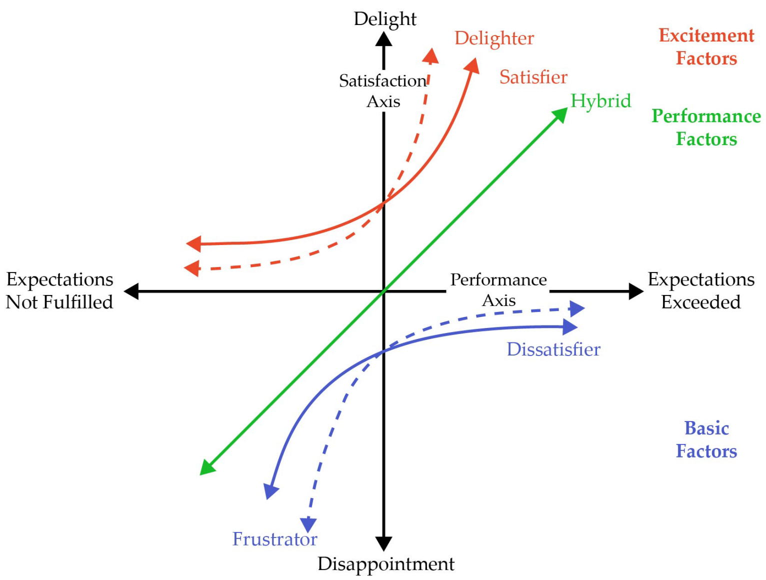


Figure 1. Factors of the impact-asymmetry analysis and their influence on satisfaction.

Caber, Albayrak, and Loiacono [72] developed a technique known as asymmetric impact-performance analysis (AIPA), an advancement that refines and simplifies the impact-asymmetry analysis (IAA) framework. AIPA stands out for its visual clarity and ease of understanding, aspects that are pivotal in enhancing its applicability. Its reliability and effectiveness have been validated through comparisons with impact-performance analysis (IPA), evidencing its utility in discerning areas for improvement [54]. AIPA has found applications across various sectors, including business-to-business engagements and tourism research, where it serves as a tool for prioritizing enhancement initiatives [54,72,74]. AIPA is situated within the framework of penalty–reward contrast (PRC) analysis, which posits that the subpar performance of an attribute results in penalties and dissatisfaction, whereas superior performance yields rewards and satisfaction. Utilizing regression analysis with dummy variables is a cornerstone technique in PRC analysis, facilitating the identification of the attribute structure through the application of the penalty index (PI) and the reward index (RI). This method underscores the criticality of sorting attributes based on their capacity to generate satisfaction or dissatisfaction. This is quantified through the relationship between the RI and PI values. To facilitate the prioritization of attributes, the impact-asymmetry index (IA index) and the range of impact on overall satisfaction (RIOS) are graphically represented on a bi-dimensional matrix, enhancing the strategic focus on attribute improvement [69].

A critical challenge with AIPA is its vulnerability to multicollinearity when using regression with dummy variables, an issue often encountered in studies of the built environment [67,75,76]. To mitigate this problem, there has been a pivot towards integrating machine learning techniques with impact-asymmetry analysis (IAA) [53]. In our study, we embraced this innovative direction by applying gradient boosting decision trees (GBDTs) to assess the significance of various attributes. A comprehensive description of the methodology and operational mechanics of GBDT is provided in Appendix A. This method excels in navigating the complex interrelationships among variables and is particularly effective in addressing multicollinearity concerns [75,77]. Given its non-linear nature, GBDTs as a method is adept at uncovering complex and non-linear interactions that are beyond the reach of traditional linear regression models. Moreover, it surpasses in predictive accuracy and demonstrates resilience against overfitting. This makes GBDTs exceptionally well-suited for our investigation into the nuanced factors that affect residents' satisfaction, aiming to unveil the detailed web of influences with greater precision and reliability [78,79].

Furthermore, GBDTs illuminate the relative significance of independent variables, a key aspect for informed planning and decision-making. The emphasis is increasingly on the practical significance rather than merely statistical significance, recognizing that the real-world impact of a variable is determined by its effect size rather than just its statistical detectability. This distinction becomes particularly relevant in large sample sizes, where even negligible effects might attain statistical significance, underscoring the importance of discerning the genuine influence of variables [80,81].

In our study, we innovatively combined GBDTs with AIPA to enhance the analysis of attribute importance and prioritization. This dual approach leverages the strengths of each method: on one hand, the GBDTs method is utilized to ascertain the relative significance of attributes, providing a robust framework for understanding complex variable interactions and their effects. On the other hand, the AIPA matrix serves as a strategic tool, bolstering our capacity for making well-informed priority decisions based on the nuanced understanding of penalties and rewards associated with each attribute.

Specifically, we utilized the scikit-learn library (version 1.3.2) within the Python 3.10 environment to develop our GBDT model. This model was precisely calibrated to evaluate the impact of penalties and rewards, reflecting the intricate dynamics influencing attribute prioritization. The process was facilitated by the Jupyter Notebook interface (version 6.4.12), provided through Anaconda, which enabled an interactive and iterative approach to model development and analysis.

2.3. Data Collection

Data for this study were collected through a self-administered survey conducted in Shenyang from November to December 2023. Shenyang, located in the southern part of Northeast China within Liaoning Province, is the provincial capital and a significant urban center. It stands as a pivotal city within the historical industrial heartland of Northeast China, and played a key role during the First Five-Year Plan. This period marked a significant industrial surge with 58 of the 156 key projects under Soviet assistance situated within the region. Such developments established a robust heavy industry system, positioning Northeast China as a foundational industrial base and a cradle of the nation's industrial emergence. The city's economic growth rates and output became emblematic of "industrialization" and "modernization". Over the years, Shenyang has evolved into a sub-provincial and mega-city, acknowledged as the core of the Shenyang Metropolitan Area. It is celebrated for its rich historical and cultural heritage, which has garnered national recognition. As the driving force behind the revitalization of old industrial bases and a central hub for advanced equipment manufacturing, Shenyang now faces significant urban spatial challenges stemming from rapid economic expansion and extensive urban development. This complex backdrop has shaped numerous industrial communities within the city, characterized by systematically organized residential zones for workers and their families.

Transitioning into the post-industrial era, the once-dominant heavy industry-centric model of the Northeast has seen a decline. This shift has led to the emergence of a significant number of derelict factories within urban spaces, with surviving industries either relocating to peripheral areas or moving to other regions entirely. Consequently, former industrial communities have morphed into post-industrial neighborhoods, confronting various challenges. In Shenyang, Worker's Villages and similar residential zones that once housed industrial workers epitomize these post-industrial communities.

This survey was centered on six post-industrial neighborhoods situated in the core urban areas of Shenyang, specifically within the Tiexi, Huanggu, Dadong, and Shenhe Districts (see Figure 2 for locations). These areas were meticulously chosen based on their illustrative capacity of the urban transition from industrial to post-industrial phases.

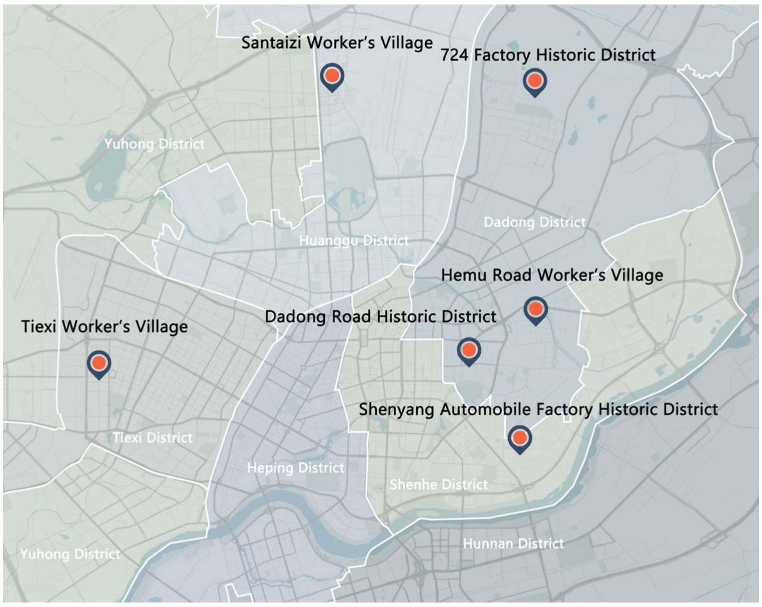


Figure 2. Spatial distribution of the survey locations in the core urban areas of Shenyang.

In the Tiexi District, the Worker's Village, founded in 1952, symbolizes one of the earliest attempts to create a residential community for industrial workers, reflecting the district's legacy in equipment manufacturing. Meanwhile, the Huanggu District's Santaizi Worker's Village, established in the 1950s for Shenyang Aircraft Manufacturing Factory employees, underscores the area's significant contributions to China's aviation industry.

The Dadong District is particularly rich in industrial heritage, hosting the 724 Factory Historic District, which originated in the 1930s as a facility for the Japanese Army before becoming a key site for China's munitions production. Additionally, Dadong is home to the Hemu Road Worker's Village and the Dadong Road Historic District, the latter offering a glimpse into the evolution of China's modern industrial landscape over nearly four centuries. These sites collectively highlight Dadong's role in the development of national industry and urban architecture.

Shenhe District's contribution is marked by the Shenyang Automobile Factory Historic District, inaugurated in 1958. This site played a crucial role in advancing China's automotive industry, notably with the establishment of Jinbei Automobile Co., Ltd., showcasing innovation in the sector and marking a milestone with its entry into the international stock market.

Despite the diverse industrial backgrounds and unique contributions of these neighborhoods to Shenyang's economic fabric, they share common challenges in the post-industrial era. Issues such as deteriorating infrastructure, insufficient amenities, and aging demographics are prevalent, highlighting the need for comprehensive urban renewal strategies.

This study aimed to examine environmental correlates and their impact on residents' satisfaction within post-industrial neighborhoods. To ensure the questionnaire's validity and identify potential biases, it was pretested with nineteen residents from the target neighborhoods. Feedback from these pre-testers informed the necessary adjustments to the survey content.

The survey was carried out by five undergraduate students, who were thoroughly trained on respondent recruitment and survey administration techniques. To maintain data quality and share insights, the survey team convened once every three days, discussing strategies to ensure a balanced representation of respondents across different sex and age groups. The respondents were selected based on their residency within a 500 m radius of the surveyed neighborhoods, ensuring that they were directly influenced by the local environment. To ensure randomness and a comprehensive demographic representation, interviews were conducted at various locations in and around the post-industrial neighborhoods, including residential entrances, open spaces, commercial areas, and transportation hubs, at different times of the day and on various days of the week. To encourage participation, each respondent was offered a box of eggs, valued at CNY 5. Furthermore, to broaden the survey's reach, an online recruitment strategy was also implemented. Posters with a QR code linked to the online questionnaire were displayed on local bulletin boards. These posters included a covering letter explaining this study's purpose. Upon successful submission and validation of their responses, online respondents received a digital "red envelope" with a randomly assigned amount ranging from CNY 5 to CNY 10. A total of 348 questionnaires were collected online and offline, of which 307 were valid.

The questionnaire for this study encompassed questions across three categories of variables: overall satisfaction with the neighborhood environment, perceived neighborhood attributes, and demographic characteristics. Overall satisfaction was gauged through a single item, asking respondents to rate their attitude towards the neighborhood environment on a five-point scale, from "Very Dissatisfied" (1) to "Very Satisfied" (5). The perceived neighborhood attributes, detailed in Table 1, were assessed using a five-point ordinal scale ranging from "Strongly Disagree" (1) to "Strongly Agree" (5). The demographic information gathered encompassed age, gender, work experience, ethnic background, political identity, education level, income, and length of residency, providing a contextual backdrop to the respondents' perceptions and satisfaction levels.

Table 2 outlines the demographic profile of the survey respondents. It shows that a significant portion, over half, either have direct work experience in a local factory or are related to someone who has. Regarding the duration of residency, approximately 41% of the participants have been living in these neighborhoods for over a decade, reflecting the neighborhoods' origins as housing for factory workers. Despite changes over time, many retired workers and their families continue to reside here, contributing to a strong cultural identity and sense of belonging. The educational data indicate that most respondents, approximately 82%, have attained an education level below a college degree, signifying limited access to higher education. Income distribution shows that 70% of the households earn CNY 100,000 or less annually. This, coupled with the finding that over half of the respondents are aged 51 and above, suggests a demographic leaning towards older and potentially economically vulnerable groups, highlighting the need for government intervention to enhance community support and engagement. The sample is relatively balanced in terms of gender distribution. Ethnically, the Han Chinese represent a significant majority at 93%. Politically, the majority, about 79%, identify with the common populace, known as 'The Masses'. The detailed demographic breakdown provided by this sample is particularly relevant for understanding the specific challenges and needs of post-industrial neighborhoods in the context of this study.

Table 2. Sample characteristics (n = 307).

Variable	Value	Percentage
Work Experience [1]	None	47.23%
	Oneself	38.11%
	Family Member	14.66%
Gender	Female	53.42%
	Male	46.58%
Ethnic Groupe	Han	92.83%
	Manchu	5.54%
	Mongolian	1.63%
Political Identity	The Masses	79.15%
	Party Member	14.66%
	League Member	3.58%
	Young Pioneer	2.28%
	Else	0.33%
Education	Primary or below	12.05%
	Junior high	37.13%
	High school	20.52%
	Vocational school	12.38%
	Bachelor	14.98%
	Postgraduate	2.93%
Income [2]	Below 50	39.22%
	50–100	30.39%
	100–150	23.20%
	Over 150	7.19%
Residency Duration	Below 3 years	22.55%
	3–5 years	21.24%
	5–10 years	15.36%
	10–15 years	14.38%
	15–20 years	10.13%
	Over 20 years	16.34%
Age Groups	Under 18	6.84%
	18–30	11.07%
	31–40	9.77%
	41–50	13.03%
	51–60	14.01%
	Over 60	45.28%

Notes: [1] This indicates whether the respondent or any of their family members have previously been employed in a factory located in proximity to the neighborhood. [2] Represents annual household income, expressed in thousands of CNY. In 2023, the average per capita disposable income in China was CNY 39,218, with urban residents in Shenyang earning an average of CNY 51,702. Considering Shenyang's average household size of 2.48, the average household income amounts to approximately CNY 128,221 per year.

Table 3 provides the descriptive statistics for residents' perceptions of built environment attributes and overall satisfaction. Most attributes have mean perception scores above the neutral midpoint of 3, indicating a generally positive perception. The attributes of amenities, property management, historical scene, and activities, however, have mean scores that suggest a lower level of residents' satisfaction. Activities, in particular, received the lowest average score. In contrast, the design and neighborhood harmony attributes stand out with mean scores over 4, reflecting a high level of satisfaction among residents with the physical design and communal harmony in their post-industrial neighborhood.

Table 3. Descriptive statistics of residents' perception of built environment attributes and overall satisfaction.

Attributes [4]	Mean [3]	L	SL	*n*	SH	H [1,2]
Density	3.61	0.65%	12.05%	21.17%	58.31%	7.82%
Diversity	3.88	0.00%	9.12%	8.79%	67.10%	14.98%
Design	4.08	0.33%	2.61%	8.14%	66.12%	22.80%
Greenery	3.27	6.19%	23.78%	17.92%	41.04%	11.07%
Amenities	2.99	15.64%	16.94%	30.94%	26.06%	10.42%
Crowdedness	3.64	1.30%	10.42%	21.50%	57.00%	9.77%
Traffic Volume	3.26	6.19%	19.87%	23.45%	42.67%	7.82%
Noise	3.46	2.94%	14.38%	23.86%	51.31%	7.52%
Public Space	3.38	5.63%	16.56%	19.87%	50.33%	7.62%
Tidiness	3.53	1.95%	13.36%	24.43%	50.49%	9.77%
Infrastructure	3.19	10.10%	21.17%	17.92%	41.37%	9.45%
Street Furnishing	3.58	3.91%	13.03%	15.64%	56.03%	11.40%
Property Management	2.96	11.73%	19.54%	34.85%	28.34%	5.54%
Historical Scene	2.82	17.92%	31.60%	11.73%	27.69%	11.07%
Heritage Preservation	3.11	6.84%	32.25%	11.73%	41.69%	7.49%
Visual Connection	3.68	7.17%	19.22%	8.14%	29.64%	35.83%
Heritage Maintenance	3.13	7.49%	15.96%	34.85%	39.41%	2.28%
Order	3.08	10.10%	19.87%	23.45%	44.63%	1.95%
Heritage Accessibility	3.91	3.58%	5.86%	14.66%	47.56%	28.34%
Activities	2.26	40.39%	16.94%	23.45%	14.33%	4.89%
Neighborhood Harmony	4.05	1.96%	0.65%	16.67%	51.96%	28.76%
Heritage Publicity	3.43	32.25%	1.30%	9.12%	5.86%	51.47%
Overall Satisfaction	3.97	0.65%	2.61%	16.29%	59.61%	20.85%

Notes: [1] Perception and satisfaction levels are represented as: L = low; SL = somewhat low; *n* = neutral; SH = somewhat high; H = high. [2] The percentages in the columns correspond to the proportion of respondents who rated their perception or satisfaction at each level. [3] The "Mean" column reflects the average perceived value for each attribute and the overall satisfaction score. [4] "Detractors" is measured by a binary True/False response and is not included in the table. A total of 20% of respondents identified 'Detractors' as True.

3. Results

3.1. Model Performance

The dataset was partitioned into dependent and independent variables, with categorical variables being transformed via one-hot encoding. This preparation facilitated the initial modeling efforts. For hyperparameter tuning, the BayesSearchCV algorithm, leveraging Bayesian optimization methods from the scikit-optimize package, was employed. This process utilized cross-validation to identify optimal settings. Within the GradientBoostingRegressor class of scikit-learn, the "n_estimators" parameter, which specifies the number of sequential trees to be modeled, was explored within a range of 50 to 400. The "max_depth" parameter, limiting the complexity of the trees, was examined between 1 and 20. The learning rate was evaluated across a continuum, from 0.001 to 0.2. Details on the tuning parameters can be found in the Supplementary Materials section.

BayesSearchCV offers a more sophisticated parameter search capability than GridSearchCV by using probabilistic models to guide the search for the best hyperparameters. This method allows for a more efficient tuning process, particularly in finding a learning rate that balances model complexity with the ability to generalize. The optimal set of hyperparameters identified included a learning rate of 0.1815, max_depth of 1, and a total of 304 trees (n_estimators).

Figure 3 presents the model's deviance plot, which illustrates a robust performance. The training set deviance decreases steeply at the onset, indicating rapid improvement in the model's fit. Similarly, the test set deviance also shows a marked decline, signaling the model's strong generalization capabilities. As the boosting iterations progress, both training and test deviances plateau, suggesting stability in the model's predictions. The absence of an upturn in the test set curve as iterations increase implies that overfitting is unlikely. This pattern indicates a model that effectively captures the underlying trends of the data, while resisting the influence of noise or anomalies specific to the training set.

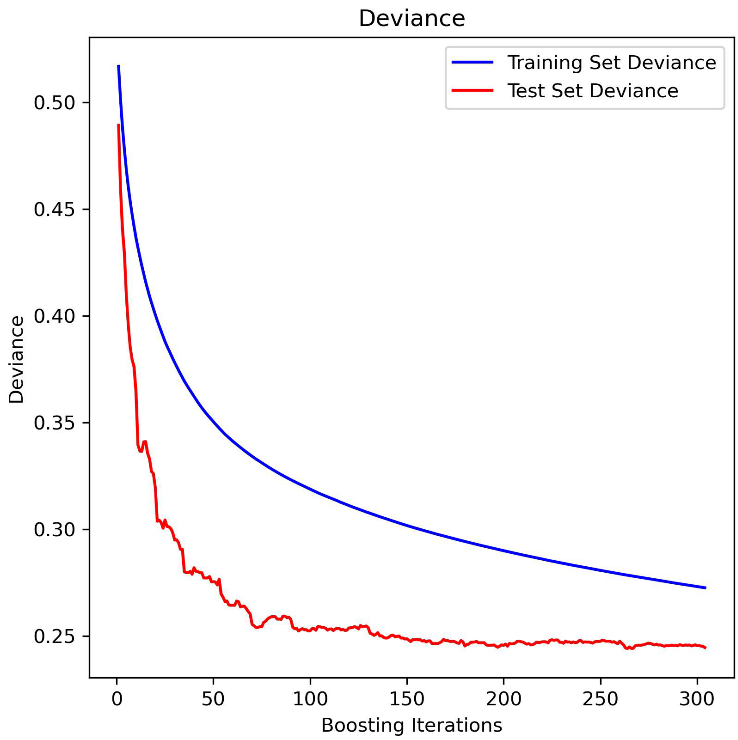


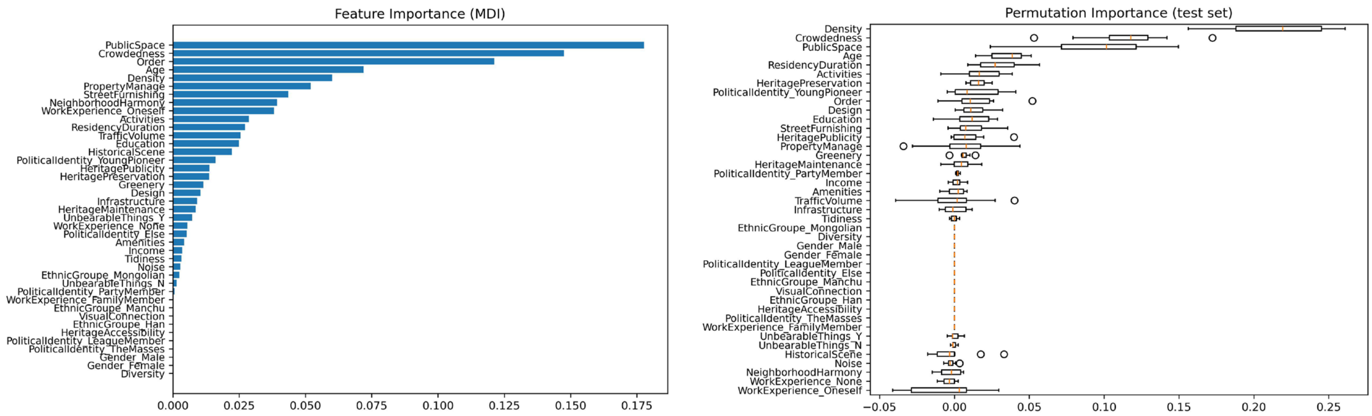
Figure 3. The deviance plot of the GBDT model.

Despite the inherent complexities and potential noise within the data, the model exhibited commendable performance, evidenced by an R^2 value of 0.5260. This level of determination, coupled with a root mean squared error (RMSE) of 0.4946 on the test set, is noteworthy. In urban planning and related fields, an R^2 exceeding 0.5 is often indicative of substantial explanatory power. Such a value implies that over half of the variance in residents' satisfaction can be explained by the environmental attributes of post-industrial neighborhoods included in our analysis.

3.2. Relative Contributions of Independent Variables

Two methods were utilized to assess the relative importance of independent variables in our model: mean decrease in impurity (MDI) and permutation importance. MDI quantifies the extent to which each variable contributes to the homogeneity of nodes and leaves in the decision trees, with the total sum of feature importance equating to 1. Features with higher MDI values are considered to have a greater impact on reducing prediction error. On the other hand, permutation importance is calculated by randomly shuffling each feature and observing the resulting decrease in model performance, which reflects the feature's predictive power and interactions with other variables.

Figure 4 juxtaposes the MDI-based feature importance with permutation importance for all independent variables. Notably, attributes like public space, crowdedness, order, and age exhibit high importance in both measures, indicating their robust impact on residents' satisfaction. This suggests they are not only vital to the model's structure but also significantly influence prediction accuracy. Density and heritage preservation stand out in permutation importance, signaling that residents' satisfaction is particularly responsive to alterations in the density of the built environment and the conservation of historical architecture. Their lower MDI values may imply that these features, while not dramatically altering the model's structure on their own, have a considerable effect on satisfaction when combined with other variables.



(**a**) (**b**)

Figure 4. Comparative analysis of feature importance: (**a**) MDI-based feature importance; (**b**) permutation importance.

In identifying influential attributes for residents' satisfaction, this study implemented a stringent dual-criteria approach. We considered features with an MDI value of at least 0.005, signifying a contribution to the model's predictive power of no less than 0.5%. Additionally, we selected variables exhibiting a mean permutation importance greater than 0.005 to ensure the robustness of our findings. This method guarantees that the highlighted variables are crucial for minimizing predictive uncertainty and possess a demonstrably significant effect on the model's prediction accuracy. Of the 16 key independent variables determined to be significant, 4 are demographic attributes, while the remaining 12 are related to the built-environment characteristics, emphasizing the substantial influence of the physical surroundings on residents' satisfaction. These important variables are comprehensively cataloged in Table 4, which details their relative importance and underscores their varied effects on residents' satisfaction levels.

Table 4. The relative importance of key independent variables in predicting residents' satisfaction.

Categories	Variables	Rank	MDI	Perm Imp Mean [1]	Perm Imp Std [2]
Demographics	Age	4	7.20%	0.029	0.016
	Residency Duration	9	2.73%	0.039	0.020
	Education	10	2.49%	0.015	0.017
	Political Identity-Young Pioneer	11	1.61%	0.015	0.017
Influential Attributes	Public Space	1	17.77%	0.085	0.040
	Crowdedness	2	14.75%	0.125	0.043
	Order	3	12.13%	0.033	0.026
	Density	5	6.01%	0.210	0.049
	Property Management	6	5.20%	0.005	0.020
	Street Furnishing	7	4.36%	0.014	0.011
	Activities	8	2.87%	0.018	0.017
	Heritage Publicity	12	1.38%	0.013	0.010
	Heritage Preservation	13	1.36%	0.013	0.008
	Greenery	14	1.14%	0.007	0.005
	Design	15	1.05%	0.015	0.009
	Heritage Maintenance	16	0.86%	0.008	0.009
Other Attributes	Total of Other Attributes	-	17.09%	-	-

Notes: [1] Perm imp mean refers to permutation importance mean; [2] perm imp std refers to the standard deviation of the permutation importance.

3.3. Asymmetric Impact of Attributes and AIPA Results

In examining the asymmetric impact of attributes on residents' satisfaction, the GBDT model was utilized to predict satisfaction levels for each attribute across three defined performance scenarios: low (scores 1–2), neutral (score 3), and high (scores 4–5). The predicted satisfaction for attributes perceived as low is denoted "*PSl*", for those perceived as high as "*PSh*", and for neutral perceptions as "*PSn*".

Consistent with the approach of Ji et al. (2024) [51], these predicted satisfaction levels under varied perceptual scenarios enable the calculation of the impact-asymmetry (IA) index. This index is crucial within the asymmetric impact-performance analysis (AIPA) framework, allowing for a quantitative assessment of the differential effects that attributes have on overall satisfaction. The equations that form the basis for determining this index are detailed as follows:

$$PI_i = PSl_i - PSn_i, \tag{1}$$

$$RI_i = PSh_i - PSn_i, \tag{2}$$

$$DGP_i = PI_i / RIOS_i, \tag{3}$$

$$SGP_i = RI_i / RIOS_i, \tag{4}$$

$$IA_i = SGP_i - DGP_i. \tag{5}$$

The equations calculate two indices critical for quantifying the asymmetric impact of neighborhood attributes on overall satisfaction. The penalty index (PI) reflects the reduction in satisfaction when an attribute's performance declines from "Neutral Performance" to "Low Performance", and the reward index (RI) represents the increase in satisfaction when an attribute's performance improves from "Neutral Performance" to "High

Performance”. Together, these indices assess the effect of an attribute’s performance on overall satisfaction. By combining the PI and RI for each attribute, the range of impact on overall satisfaction (RIOS) is determined, indicating the total potential influence of the attribute on satisfaction levels.

Additionally, impact asymmetry (IA) is computed to measure the extent to which the impacts of reward and penalty are unbalanced for each attribute. This is performed by comparing its dissatisfaction-generating potential (DGP) and satisfaction-generating potential (SGP). Using the IA thresholds established by Back and Lee (2015) [82], attributes are categorized into five distinct groups:

An attribute is considered a “frustrator” if its IA < −0.7;

A “dissatisfier” if −0.7 ≤ IA < −0.2;

A “hybrid” if −0.2 ≤ IA ≤ 0.2;

A “satisfier” if 0.2 < IA ≤ 0.7;

A “delighter” if IA > 0.7.

Table 5 categorizes the key built environment attributes by their impact on residents’ satisfaction. Notably, three attributes are classified as “hybrids”, indicating a linear association with residents’ satisfaction. Beyond these, the complexity of the neighborhood’s influence is evident, with the majority—nine out of twelve attributes—demonstrating non-linear associations. Specifically, of the twelve influential attributes, four are identified as “satisfiers”, two as “delighters”, and three as “dissatisfiers”. This varied impact reflects the multifaceted nature of how residents interact with and perceive their environment.

Table 5. Factor classification of the key built environment attributes.

Variable	Rank	PI	RI	RIOS	SGP	DGP	IA	Classification	Mean Performance [1]
Public Space	1	−0.08	0.46	0.53	0.86	0.14	0.72	Delighter	3.38
Crowdedness	2	−0.56	0.19	0.75	0.25	0.75	−0.49	Dissatisfier	3.64
Order	3	−0.02	0.37	0.39	0.94	0.06	0.88	Delighter	3.08
Density	5	−0.36	0.15	0.51	0.30	0.70	−0.41	Dissatisfier	3.61
Property Management	6	−0.19	0.26	0.46	0.58	0.42	0.15	Hybrid	2.96
Street Furnishing	7	−0.12	0.40	0.52	0.76	0.24	0.53	Satisfier	3.58
Activities	8	−0.14	0.12	0.26	0.47	0.53	−0.07	Hybrid	2.26
Heritage Publicity	12	−0.12	0.10	0.22	0.46	0.54	−0.08	Hybrid	3.43
Heritage Preservation	13	−0.05	0.14	0.19	0.74	0.26	0.48	Satisfier	3.11
Greenery	14	0.16	0.35	0.51	0.69	0.31	0.38	Satisfier	3.27
Design	15	0.22	0.40	0.62	0.65	0.35	0.30	Satisfier	4.08
Heritage Maintenance	16	−0.31	0.13	0.44	0.29	0.71	−0.42	Dissatisfier	3.13

Notes: [1] Mean performance refers to the mean satisfaction score, calculated as the difference between the perception level and preference level for each attribute.

The AIPA matrix depicted in Figure 5 offers visual guidance for prioritizing attributes in the context of post-industrial neighborhood renewal. Attributes are plotted in the matrix using their impact asymmetry (IA) values on the vertical axis and their performance means on the horizontal axis. The grand mean of performance across the twelve evaluated attributes establishes a reference dividing line between zones of “Low Performance” and “High Performance”. Color-coded regions within the matrix intuitively signal varying levels of priority for improvement. Utilizing this matrix, planners and policymakers can craft nuanced strategies for targeted enhancements tailored to the specific needs of post-industrial communities.

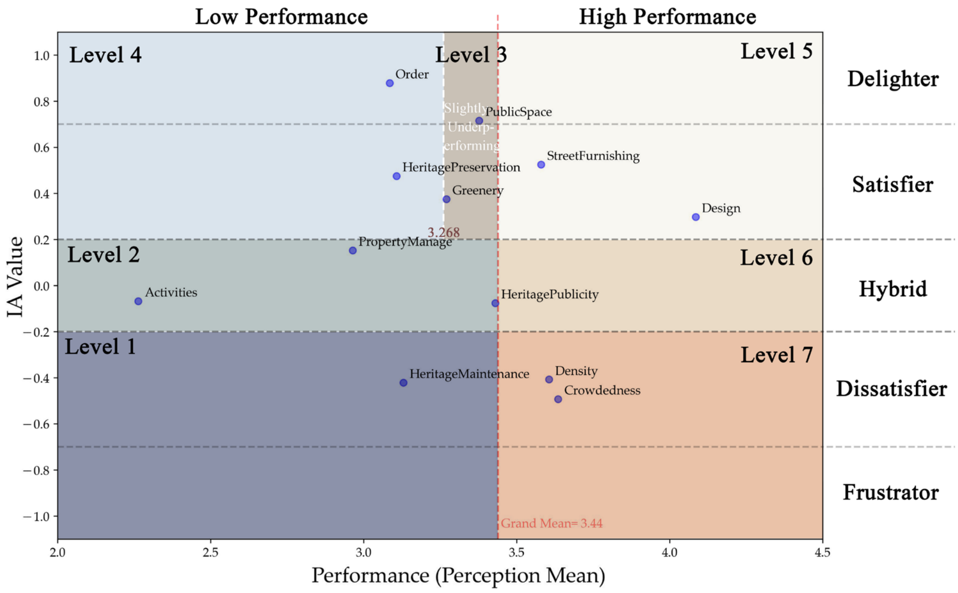


Figure 5. Factor classification results on the AIPA matrix.

The AIPA matrix delineates seven levels of attribute improvement priorities based on each attribute's classification and current performance:

First Priority (Level 1): Attributes classified as either frustrators or dissatisfiers with low performance receive the highest priority. Their inadequacies are directly linked to residents' dissatisfaction, and therefore, their improvement is critical.

Second Priority (Level 2): Hybrid factors showing low performance are next in priority. Their linear relationship with satisfaction means that any underperformance directly contributes to dissatisfaction, necessitating timely improvements.

Third Priority (Level 3): Slightly underperforming delighters and satisfiers fall into the third priority tier. Even modest efforts to enhance these attributes (as indicated within the brown zones of Figure 5) can lead to significant improvements in performance and satisfaction.

Fourth Priority (Level 4): Delighters and satisfiers with low performance are assigned fourth priority. Elevating their performance from low to high can profoundly and positively influence residents' satisfaction, warranting more extensive improvement actions.

For high-performance attributes, the priorities are adjusted accordingly:

Fifth Priority (Level 5): High-performing delighters and satisfiers are given a lower priority, yet they remain important due to their positive asymmetric impact on satisfaction.

Sixth Priority (Level 6): High-performing hybrid factors, due to their linear impact on satisfaction, are ranked just below, as further improvements might yield diminishing returns.

Seventh Priority (Level 7): Frustrators and dissatisfiers with high performance are deemed lowest in priority. While their adequacy is beneficial, the level of satisfaction they provide may not justify the effort required for further enhancement.

Table 6 outlines the prioritization of built environment attributes for enhancements in Shenyang's post-industrial neighborhoods, sorted by their potential impact on residents' satisfaction and the urgency of improvement needs.

Table 6. Prioritization of built environment attributes for post-industrial neighborhood improvement in Shenyang.

Categories	Priority Levels	Attributes [1]
Immediate Need for Improvement	First Priority	Heritage Maintenance (0.86%)
	Second Priority	Property Management (5.20%) Activities (2.87%) Heritage Publicity (1.38%)
Potential for Enhanced Satisfaction	Third Priority	Public Space (17.77%) Greenery (6.01%)
	Fourth Priority	Order (12.13%) Heritage Preservation (1.36%)
	Fifth Priority	Design (6.01%) Street Furnishing (4.36%)
	Sixth Priority	-
No Need for Improvement	No Priority	Crowdedness (14.75%) Density (6.01%)

Notes: [1] Within each priority level, attributes are listed in order of their relative importance (MDI), indicated by the values in parentheses.

The "Immediate Need for Improvement" category includes four attributes across the first and second priority levels that require urgent attention. Heritage maintenance, with the highest immediacy, underscores the urgent need to preserve the historical fabric of these neighborhoods. The effective management and organization of property management and activities are also essential and warrant prompt improvements. Additionally, the role of heritage publicity is highlighted, indicating the importance of engaging the public in heritage conservation initiatives.

In the "Potential for Enhanced Satisfaction" category, six attributes from the third to fifth priority levels are identified as having room for improvement that could lead to increased residents' satisfaction. The emphasis placed on public space and greenery indicates the residents' desire for better-quality public areas and the integration of natural elements into the urban landscape. The significant roles of order and heritage preservation are also recognized, pointing to their impact on maintaining the historic character of the neighborhoods. The assigned importance to design suggests that the physical layout of the urban environment, including street accessibility and connectivity, is a priority. Furthermore, the attention to street furnishing indicates the value residents place on environmental facilities.

Lastly, the "No Need for Improvement" category reveals that attributes such as crowdedness and density currently meet residents' satisfaction levels, implying that the existing spatial arrangements and density are adequate. These elements, while integral to the residents' quality of life, do not demand immediate improvements.

4. Discussion

Revitalizing post-industrial neighborhoods is essential not only for reconnecting residents with their historical roots and fostering a sense of identity but also for significantly enhancing environmental quality and living conditions. This study explores the impact of neighborhood attributes on residents' satisfaction within these communities, leveraging machine learning-augmented asymmetric impact-performance analysis (AIPA) to identify and prioritize the attributes that notably enhance residents' well-being. Such insights are vital for urban planners and policymakers to effectively improve the multifaceted environmental quality of post-industrial neighborhoods and to make informed, strategic decisions.

While previous research has utilized established methodologies such as importance-performance analysis (IPA), the three-factor theory [61–66], and impact asymmetry analysis (IAA) [53,59], these methods have limitations, including susceptibility to multicollinearity in regression analyses. Our study advances this research by integrating gradient boosting decision trees (GBDTs) with IAA to pinpoint the relative significance of neighborhood attributes. This foundation enables the novel combination of GBDTs with AIPA, refining our analysis of attribute importance and prioritization. The AIPA matrix, with its intuitive visualization, takes into account the types of attributes and their current performance levels, facilitating more nuanced and data-driven decisions for neighborhood enhancement.

This study acknowledges several limitations. First, the sample selection is subject to potential bias, as it may underrepresent residents who spend most of their time at home, possibly skewing variable representations. Second, given the specific socio-economic backdrop of the post-industrial neighborhoods under study—ones that evolved during the Northeast's industrial heyday but now face economic downturns—the applicability of our findings to other contexts is not assured. The tension between the high demand for neighborhood renovation and limited financial resources in these areas compounds the complexity, and the results, along with the suggested policies, may not be directly transferrable to regions with different economic statuses or cultural narratives. Furthermore, despite an exhaustive literature review and the inclusion of numerous attributes, the potential for overlooking certain factors remains. Notably, the focus group used to develop our measurement scale, while diverse, was limited in size. Future studies could enhance the robustness of research findings by expanding the focus group to include a wider range of experts from various fields and backgrounds, further minimizing the risk of oversight. Another challenge lies in precisely ranking the attributes, especially when considering delighters and satisfiers that perform poorly or well, along with high-performing hybrid factors. The priority order proposed should be considered a guide rather than a definitive ranking. Additionally, the thresholds defining attribute categories are pivotal—altering these cut-off points could lead to reclassification of attributes and thus, different prioritization in management strategies. Moreover, the dual-criteria method for variable selection may carry its own set of limitations. By establishing a minimum MDI value of 0.005 and a mean permutation importance above 0.005, there is a risk of excluding variables that possess lower yet still meaningful impacts [51]. Hence, attributes with mean permutation importances marginally below our threshold might still influence residents' satisfaction in subtle but significant ways. For instance, the prior research has underscored the significance of acoustic aspects [83,84], particularly focusing on human perception and response to sound. While traffic volume and noise were considered in our analysis, they did not emerge as pivotal attributes. However, it is important to recognize that these factors can subtly yet significantly influence residents' satisfaction. Finally, this study's non-random sampling strategy, while effective in capturing a broad spectrum of perceptions within Shenyang's post-industrial neighborhoods, may limit the generalizability of our findings. Future research could enhance these insights by employing random sampling to assess whether our results can be extended to other urban contexts.

In urban renewal projects, modern methods are commonly utilized to enhance living conditions, directly impacting residents' satisfaction. However, relying solely on these methods without incorporating historical conservation can lead to significant cultural and social losses, such as a diminished sense of identity, loss of collective memories, and erosion of local characteristics. These losses can adversely affect residents' satisfaction by disconnecting them from their cultural and historical context. The past research has underscored the influence of historical urban preservation on residents' satisfaction, highlighting elements such as heritage maintenance [22,50] and heritage accessibility [50,53] as significant factors. Building on these findings, our study delves into the role of historical urban conservation in post-industrial neighborhoods. It takes into account attributes related to urban conservation and heritage reuse, including historical scene, heritage preservation, heritage maintenance, visual connection, order, heritage accessibility, and heritage publicity. The applied machine learning-augmented asymmetric impact-performance analysis reveals heritage maintenance, heritage publicity, order, and heritage preservation as critical influences on residents' satisfaction. Their combined MDI importance, amounting to 0.1573, shows that these attributes are integral, contributing to about 15% of the model's structure. This underlines their substantial role in the model's decision-making process and corroborates their significance in boosting satisfaction within post-industrial neighborhoods. These results affirm that initiatives in urban conservation and heritage reuse are significant contributors to enhancing satisfaction among residents of post-industrial neighborhoods.

In determining which attributes are most influential, our analysis identified 16 significant independent variables. Among these, four were demographic attributes, while the remaining twelve pertained to the built-environment characteristics, stressing the profound effect of the physical surroundings on residents' satisfaction. In line with earlier findings [50,53,76], our study also found asymmetrical associations between various attributes and residents' satisfaction levels. In this study, about three-quarters of the most significant attributes, such as public space and crowdedness, have an asymmetric impact on residents' satisfaction in post-industrial neighborhoods. Specifically, heritage maintenance, crowdedness, and density are identified as dissatisfiers that, when underperforming, markedly decrease satisfaction but offer only marginal satisfaction gains when performing well. On the other hand, attributes like public space, order, street furnishing, heritage preservation, greenery, and design act as satisfiers or delighters, significantly boosting satisfaction when present and performing well, yet their absence does not inherently cause dissatisfaction. This nuanced interplay between different attributes and satisfaction confirms the complex dynamics observed in prior studies [85].

The AIPA matrix offers nuanced insights into the prioritization of improvements for post-industrial neighborhoods in Shenyang. The matrix positions heritage maintenance as an attribute requiring immediate improvement, with its dissatisfaction-generating potential (DGP) of 0.71 illustrating the substantial negative impact its poor performance can have on residents' satisfaction. This places it at the forefront of our improvement priorities, echoing the emphasis on heritage preservation underscored by Cao and Wang (2016) [22] and Ji et al. (2020) [50]. To address this, strategies should focus on elevating protection levels from inadequate to effective, avoiding excessive measures that may yield diminishing returns.

In the realm of community management, deficits in property management are evident, characterized by an absence of professional services and a lack of clarity in rights and responsibilities. This often leads to a reluctance among residents to pay service fees, thereby perpetuating a cycle of deteriorating management quality and increasing dissatisfaction—a pattern highlighted by its classification as a hybrid factor [41]. This cycle suggests an urgent need for improvements in professional services and clearer delineation of responsibilities to break this cycle and foster residents' satisfaction. Activities and heritage publicity, also identified as hybrid factors, indicate an additional need to bolster community engagement and enhance the accessibility of historical heritage.

Both greenery and heritage preservation are classified as satisfiers, performing below the grand mean. To further differentiate the priority levels of each attribute, we applied a 5% threshold below the grand mean performance for more precise classification. Attributes that slightly underperform—falling into this category—are placed in the third priority tier, termed the low-hanging fruit zone. Modest efforts to enhance these attributes can lead to significant improvements in performance and overall satisfaction. The AIPA matrix places greenery and public space in the low-hanging fruit zone. Historically, post-industrial neighborhoods have not prioritized green and recreational spaces, but as resident demands for such amenities increase, focusing on enhancing greenery and public space becomes ever more essential in addressing dissatisfaction and improving quality of life [47].

The matrix further reveals that order, a delighter with low performance, and heritage preservation, a satisfier with low performance, offer opportunities for satisfaction enhancement. However, their improvement, while beneficial, is not as critical as for those attributes directly linked to dissatisfaction. This aligns with their categorizations, suggesting that while investment in these areas can increase satisfaction, it is not imperative for immediate action.

Design, recognized as a satisfier, suggests that the current satisfactory performance in street accessibility and connectivity in post-industrial neighborhoods is adequate. Nonetheless, there is potential for further enhancement, particularly in areas lacking robust physical design. Street furnishing, also a satisfier, underscores the importance and satisfactory performance of environmental facilities, resonating with findings from Feng and Lin (2017) [58].

Crowdedness and density, while situated in the "No Need for Improvement" category for post-industrial neighborhoods in Shenyang, present a nuanced case. As high-performing dissatisfiers, perceptions of these attributes are subjective and vary widely; the same level of density may be deemed crowded by some while acceptable by others. Furthermore, both attributes possess a significant dissatisfaction-generating potential (DGP over 0.7), indicating that their low performance could lead to substantial dissatisfaction. Therefore, despite their current classification suggesting no immediate need for enhancement in Shenyang, this does not diminish their overall importance. In different contexts or individual experiences where crowdedness and density are perceived as insufficient, they may become critical factors to address. This highlights the importance of contextual and subjective assessments when determining improvement priorities in urban environments.

Guided by the insights from the AIPA matrix, the focus for urban planners should be to prioritize enhancements in heritage maintenance, property management, activities, and heritage publicity within post-industrial neighborhoods of Shenyang. Targeting these 'Immediate Need for Improvement' attributes will significantly boost residents' satisfaction. The subsequent layer of priority should address the 'Potential for Enhanced Satisfaction' category, which encompasses public space, greenery, order, heritage preservation, design, and street furnishing. With the relative scarcity of public spaces and greenery in contrast to the growing resident demand, strategies to expand these amenities are essential. Planners can consider designing multifunctional open spaces in underutilized neighborhood areas to provide residents with immediate access to recreational and green spaces, which is anticipated to contribute greatly to improving residents' satisfaction. Conversely, attributes such as crowdedness and density are categorized as 'No Need for Improvement' since they currently align with residents' satisfaction levels and therefore do not require immediate intervention.

This study uncovers a more diverse structure of influential attributes in Shenyang compared to those in Harbin as identified by Dong et al. (2023) [41]. The previous research has predominantly focused on satisfaction studies within traditional residential areas, with less attention given to post-industrial neighborhoods. Our findings provide a deeper understanding of how various attributes of post-industrial neighborhoods impact residents' satisfaction. Harbin's old neighborhoods feature three dissatisfiers, two satisfiers, and three hybrids among eight factors, while Shenyang's post-industrial neighborhoods present three dissatisfiers, four satisfiers, two delighters, and three hybrids among twelve key attributes. Certain neighborhood attributes in both cities display differing associations with residents' satisfaction, underscoring the influence of local cultural contexts and practices. Despite common industrial roots and demographic profiles, the nuances in attribute impacts suggest that planners must adjust their strategies to resonate with the unique fabric and social dynamics of each city. Such tailored approaches can enable urban planners to effectively transform post-industrial communities.

5. Conclusions

Drawing on data from Shenyang, China, this study employed machine learning-augmented asymmetric impact-performance analysis (AIPA) to identify and prioritize the key attributes of post-industrial neighborhoods that significantly contribute to enhancing residents' satisfaction. Specifically, this research seeks to explore the role of historical urban conservation in improving satisfaction within these neighborhoods, assessing how efforts in heritage preservation impact residents' well-being.

Addressing the common issue of multicollinearity found in previous regression analyses, our integrated approach combines the predictive strengths of gradient boosting decision trees (GBDTs) and AIPA. This method effectively pinpoints the relative importance of various neighborhood attributes, revealing their diverse and complex nonlinear relationships with residents' satisfaction. The AIPA matrix clearly delineates these attributes, providing a visual tool for informed prioritization in urban planning decisions.

Using both MDI-based feature importance and permutation importance metrics, this study identifies 16 significant independent variables, 12 of which are related to the historic-built environment. These findings underscore the critical influence of historical urban conservation on residents' satisfaction in post-industrial neighborhoods. Notably, three-quarters of the top attributes identified, including key factors such as heritage maintenance and heritage publicity, asymmetrically influenced residents' satisfaction, with half of all pivotal attributes classified as satisfiers or delighters.

The AIPA matrix not only highlights the attributes requiring immediate improvement, such as heritage maintenance and property management, but also suggests nuanced renovation strategies for enhancing residents' satisfaction. For instance, attributes like greenery and public space are noted as 'low-hanging fruit' for improvements, offering significant satisfaction gains with relatively small efforts.

This research provides essential insights for urban planners and policymakers in revitalizing post-industrial neighborhoods, guiding targeted efforts to substantively improve residents' quality of life. These findings bear important implications for the transformation and betterment of post-industrial landscapes. However, the generalizability of our conclusions to other cities should be carefully assessed, considering the cultural, economic, and social uniqueness of each locale. By adapting both our strategic approaches and analysis methods to fit specific local conditions, the insights and methodologies from our study can be effectively applied to facilitate the revitalization of diverse post-industrial environments.

Supplementary Materials: A comprehensive explanation of the core principles and the detailed algorithm of GBDTs is available online. For an in-depth understanding, please refer to Video S1: https://www.youtube.com/watch?v=3CC4N4z3GJc (accessed on 11 April 2024); Video S2: https://www.youtube.com/watch?v=2xudPOBz-vs (accessed on 11 April 2024); and Document S1: https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.GradientBoostingRegressor.html (accessed on 11 April 2024).

Author Contributions: Conceptualization, X.J.; methodology, X.J.; software, X.J.; validation, C.L., F.S., Q.K., R.W., and C.D.; formal analysis, X.J.; investigation, C.L., F.S., Q.K., R.W., and C.D.; resources, X.J.; data curation, C.L.; writing—original draft preparation, F.S.; writing—review and editing, X.J.; visualization, C.L. and F.S.; supervision, X.J.; project administration, X.J.; funding acquisition, X.J. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Natural Science Foundation of China (No. 52208046).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available from the authors upon reasonable request.

Acknowledgments: The authors would like to thank Jason Cao of the University of Minnesota for his enlightenment on the original ideas of the research. The authors appreciate the anonymous reviewers for their valuable comments and suggestions.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A. The Algorithm of Gradient Boosting Decision Trees

The gradient boosting decision trees (GBDTs) model constructs a series of decision trees for classification. This model uses decision trees to split data at various points, predicting outcomes based on the average response within each leaf. Figure A1 shows a single decision tree targeting a continuous variable Y, utilizing two predictors, x_1 and x_2. The prediction space is initially split into two regions to estimate the response by averaging Y within each segment. The choice of predictor and split point is carefully optimized for the best fit. Further splits may subdivide these initial regions, continuing until a specific stopping criterion is reached. In our example, the space is divided into four regions—R1, R2, R3, and R4—identified through three split points: c_1, c_2, and c_3. The model then assigns a predicted value c_m to each region R_m, which is formalized in Equation (A1).

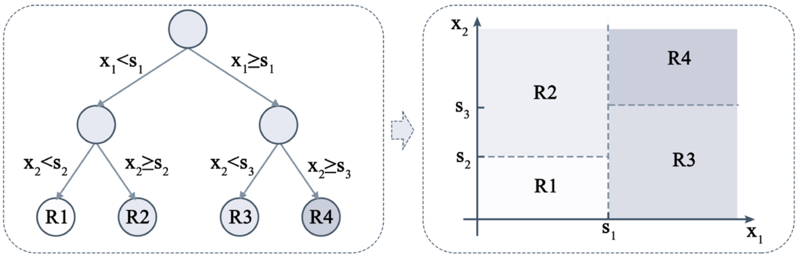


Figure A1. An example of the decision tree.

$$F_m(x) = \sum_{m=1}^{4} c_m \, I\{(x_1, x_2) \in R_m\}, \tag{A1}$$

The GBDT approach integrates decision trees with gradient boosting. The model is iteratively built, focusing on minimizing prediction errors through sequential model enhancements. Each tree is developed based on the residuals of the previous tree, thus progressively improving prediction accuracy (refer to Figure A2). The GBDT algorithm's process for regression tasks can be summarized as follows.

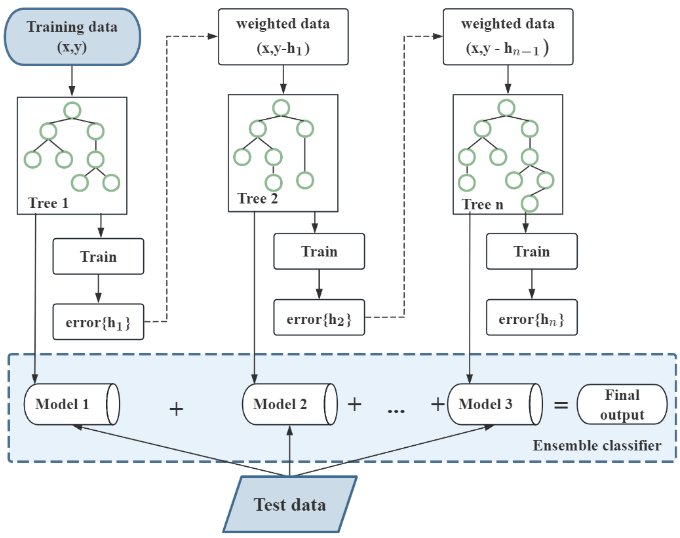


Figure A2. Illustration of the algorithm of GBDT.

Input: Data $\{(x_i, y_i)\}_{i=1}^{n}$, and a differentiable loss function $L(y_i, F(x))$.

Step 1: Initialize the model with a constant value:

$$F_0(x) = \underset{\gamma}{\text{argmin}} \sum_{i=1}^{n} L(y_i, \gamma), \tag{A2}$$

where y_i represents the observed values and γ represents the predicted values.

Step 2: Form m = 1 to M (m refers to the number of an individual tree):

(A) Compute:

$$r_{im} = -\left[\left(\frac{\partial L(y_i, F(x_i))}{\partial F(x_i)}\right)\right]_{F(x)=F_{m-1}(x)} \text{ for i = 1, 2, …, n}, \tag{A3}$$

where r_{im} represents the pseudo residual.

(B) Fit a regression tree to the r_{im} values and create terminal regions R_{jm}, for j = 1, 2, …, J_m.

(C) For j = 1, 2, …, J_m, compute:

$$\gamma_{jm} = \underset{\gamma}{\text{argmin}} \sum_{x_i \in R_{ij}} L(y_i, F_{m-1}(x_i) + \gamma), \tag{A4}$$

(D) Update:

$$F_m(x) = F_{m-1}(x) + \vartheta \sum_{j=1}^{J_m} \gamma_{jm} I(x \in R_{jm}), \tag{A5}$$

where ϑ refers to the learning rate.

Step 3: Output $F_M(x)$.

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