BUILDING DECAY IN HONG KONG: ASSESSING AND MAPPING BUILDING CONDITION INDEX USING CHATGPT AND AIRBORNE POINT CLOUDS

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Abstract: Hong Kong faces critical challenges in the maintenance and redevelopment of aged buildings. Recently, advancements in multi-modal generative AI (GenAI) and high-definition urban geospatial data, such as point clouds, have offered new opportunities to the architectural, engineering, and construction industry. This paper defines, assesses, and maps a Building Condition Index (BCI) as the condition of aged building fabrics using GenAI and high-definition geospatial data. First, a BCI is defined as a numerical scale of multi-dimensional factors, including floor area, building age, management quality, and the presence of unauthorized building works. Then, multiple data sources, including building exterior photos, airborne point clouds, and government building datasets, are processed and trained for the BCI using multiple regression and image embedding with ChatGPT4. Finally, a comprehensive BCI map and focused BCI hot spots can be visualized for an urban area. Experiments with over 1,200 building data points in Kowloon City, Hong Kong, indicated the robustness of the BCI in explaining the exogenous factors causing decayed buildings while accurately reflecting the building condition of buildings.

Keywords: Building decay, Building condition index, Assessment and mapping, Airborne point clouds, Generative AI

1. INTRODUCTION

Hong Kong faces a critical impasse in addressing the challenges of aging buildings and their redevelopment, intensifying urban decay, a process characterized by the gradual decline of urban areas due to neglect and insufficient investment in the maintenance of old buildings. As of 2021, around 22% of Hong Kong's buildings, approximately 9,600 structures, are over 50 years old and increasingly unfit for habitation (BD, 2023a). Many of these are "three-nil" buildings, which lack owners' corporations, residents' organizations, or property management companies, leading to inadequate maintenance and rapid deterioration (Lee & Chan, 2008). Redevelopment efforts under Cap. 545 are further hampered by fragmented ownership structures that require developers to secure over 70% of undivided shares, a challenging and often prohibitive task in an uncertain economic environment (Wang et al., 2022). Even when shares are acquired, economic uncertainties often cause developers to delay redevelopment, leaving many buildings in disrepair.

Building maintenance is crucial for preserving the structural integrity, functionality, and aesthetic appeal of buildings, thereby ensuring safety and regulatory compliance (Seeley, 1987). This involves addressing various challenges such as wear and tear of building fabrics and building services issues like water seepage or structural issues. In Hong Kong's context of aging infrastructure, a range of maintenance strategies are employed to mitigate deterioration. Preventive maintenance includes regular inspections and timely repairs to prevent major failures, while ad-hoc maintenance responds reactively to defects as they arise (Chanter, 2008). Additionally, planned maintenance schedules activities based on thorough assessments of building conditions, ensuring a proactive approach to upkeep (Jasiulewicz-Kaczmarek, 2016). Policies such as Hong Kong's Mandatory Building Inspection Scheme (MBIS) underscore the importance of routine inspections in maintaining older structures, where buildings aged over 30 years old are required to be inspected every 10 years (BD, 2023b).

However, challenges persist in the maintenance of aged buildings in Hong Kong. First, fragmented ownership in these buildings complicates coordination among multiple stakeholders, making it difficult to implement consistent maintenance practices. Financial constraints are significant, as the high costs associated with repairing and upgrading older buildings often discourage property owners, particularly in Hong Kong, where property management companies assist in procurement processes. The complexities of managing multiple ownerships can lead to conflicts among owners, complicating decision-making for necessary repairs and renovations. This situation is exacerbated by instances of bid-rigging, where contractors collude to inflate prices or manipulate the bidding process. For example, in the Garden Vista case, a contractor was jailed for offering bribes to facilitate a bid-rigging scheme that resulted in a renovation contract worth HK$260 million (Leung et al., 2022). Worse still, the prevalence of "three-nil" buildings leads to inadequate maintenance and accelerated decay due to the absence of coordinated upkeep efforts (Ho et al., 2011; Hui et al., 2008). Moreover, the aging population residing in these buildings often lacks the resources or knowledge to advocate for proper maintenance, compounding the neglect issue (Hui et al., 2008). These multifaceted challenges create a complex environment that hinders the effective maintenance of Hong Kong's aging building stock, perpetuating urban decay and posing

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risks to public safety and the overall livability of the city.

AI technological advancements have significantly enhanced building maintenance strategies. For instance, the integration of 2D imaging embedding with deep machine learning into building inspection has gained traction in the industry for detecting building defects. Studies have shown that image embedding techniques can effectively identify issues such as cracks and spalling by analyzing visual data through deep learning algorithms (Jiang et al., 2021). This growing emphasis on structured maintenance is essential in addressing the challenges posed by aging buildings, thereby supporting efforts to combat urban decay and improve overall urban livability. With image embedding and other sensing and processing technologies, building surveyors are able to deliver more systematic and efficient approaches to building upkeep.

Recently, advancements in multi-modal generative AI (GenAI), exemplified by the latest iterations of ChatGPT, offer new opportunities across various sectors by enhancing content creation, automating routine tasks, and facilitating more natural human-computer interactions (García-Peñalvo & Vázquez-Ingelmo, 2023). These GenAI systems can analyze and generate text, images, and sometimes audio. Hence, it seems that this provides a new opportunity for building maintenance, not only to conduct defect diagnosis but also to automatically provide feedback on their presence, provide herewith scheduled maintenance activities, predict potential failures, and provide real-time updates to residents, thus increasing efficiency and responsiveness. However, despite their potential, GenAI models exhibit notable limitations. They often produce hallucinations, generating information that appears plausible but is factually incorrect or nonsensical, which can lead to misinformation in maintenance reports (Salvagno et al., 2023). Additionally, GenAI struggles with understanding complex contexts and nuances, resulting in responses that may not align with user intentions or the specific requirements of building maintenance tasks (Chiu, 2023).

Another opportunity comes from the emergence of high-definition geospatial data, which presents significant opportunities for enhancing building maintenance and management practices. One of the most promising advancements in this field is the use of point cloud technology, which captures detailed three-dimensional data of buildings through methods such as laser scanning and photogrammetry. This technology generates a dense collection of points that represent the physical features of a structure, allowing for precise modeling and analysis of building fabrics on a larger scale. By segmenting point clouds, in-depth building characteristics can be identified, which presents new opportunities for aiding building inspections, monitoring structural integrity, and identifying maintenance needs with greater accuracy and efficiency. Furthermore, geospatial data can facilitate planned maintenance by analyzing spatial patterns under City Information Modelling (CIM) (Xue et al. 2021). For instance, integrating point cloud data with geographic information systems (GIS) enables the visualization of building conditions in relation to environmental factors, helping to prioritize maintenance efforts effectively.

In response to the aforementioned opportunity to promote the effectiveness of building maintenance, this paper introduces, assesses, and maps a Building Condition Index (BCI) as the condition of aged building fabrics using GenAI and high-definition airborne point clouds.

2. RESEARCH METHODS

2.1 Definition of Building Condition Index

The BCI in this paper is a numerical scale employed to assess the overall condition of a building's fabrics, typically ranging from 20 (very poor) to 100 (excellent). Equation (1) defines BCI on the impact of property management on building quality:

$$
\begin{aligned}
\ln(\mathrm{BCI}) = C &+ \beta_1(\mathrm{BUILDING\_AGE}) + \beta_2(\mathrm{BUILDING\_AGE}^2) + \beta_3(\mathrm{GFA}) + \beta_4(\mathrm{GFA}^2) \\
&+ \beta_5(\mathrm{FLOOR}) + \beta_6(\mathrm{FLOOR}^2) \\
&+ \beta_7(\mathrm{MANAGEMENT\_COMPANY}) + \beta_8(\mathrm{MANAGEMENT\_COMPANY} \times \mathrm{BUILDING\_AGE}) \\
&+ \beta_9(\mathrm{THREE\_NIL}) + \beta_{10}(\mathrm{THREE\_NIL} \times \mathrm{BUILDING\_AGE}) \\
&+ \beta_{11}(\mathrm{UBW}) + \epsilon \qquad (1)
\end{aligned}
$$

Where the BCI is the index, *C* is a constant, and the descriptions of the rest variables are listed in Table 1. The variables in Table 1 cover the multiple facets of building conditions, such as physical appearance in aesthetics, quality of management in maintenance organization, and the presence of unauthorized building works (UBW) in related legal issues. The BCI can thus provide a quantitative, overall measure of building health based on various factors, according to Ho (2013).

Table 1. Descriptions of Variables

Variables	Descriptions
BUILDING_AGE	The age of the building (linear term)
BUILDING_AGE²	The squared age of the building, capturing nonlinear effects
GFA	Gross Floor Area (linear term)

GFA²	The squared Gross Floor Area
FLOOR	The number of floors (linear term)
FLOOR²	Squared number of floors
MANAGEMENT_COMPANY	Dummy variable for the presence of a management company
MANAGEMENT_COMPANY × BUILDING_AGE	The interaction term between the dummy of the management company and the building age
THREE_NIL	Dummy variable for the “three-nil” status (buildings without proper management)
THREE_NIL × BUILDING_AGE	The interaction term between three-nil status and building age
UBW	Dummy variable of the presence of Unauthorized Building Works (UBW)
ε	Error term capturing unexplained variance in BCI

2.2 Case area and data source

As shown in Figure 1, the case area is selected as a part of the Kowloon City District in Hong Kong in this paper. The area was selected for encompassing typical aged and newly built buildings in the sub-districts of Kowloon City, Ma Tau Wai, and To Kwa Wan. A total of 1,211 buildings were selected and analyzed. As indicated by the colors in Figure 1, the majority of the buildings in the area were over 40 years old, while certain clustered blocks of buildings were over 60 years old (indicated as dark red).

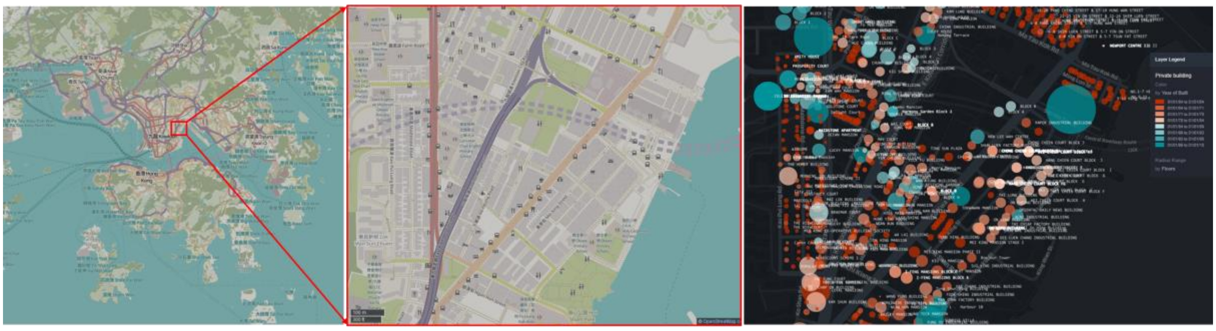

Figure 1. A case area of 1,211 buildings in Kowloon City District, Hong Kong (warmer color indicates older buildings, map sources: OpenStreetMap, MapBox)

Figure 2 stipulates the data sources and overall workflow to construct the BCI. Most of the independent variables marked in light green are available publicly online or via a site survey. For example, the source of building age, gross floor area, and number of floors is the Buildings Department’s building information and age records. Information regarding the presence of the management company and the three-nil status for each building is confirmed by searching the Land Registry records and verifying the registration of the Deed of Mutual Covenants for the building. Site visits to old buildings where the management company is absent were conducted to further confirm the absence of the owners’ corporation and owners’ committee, substantiating the three-nil status of these buildings.

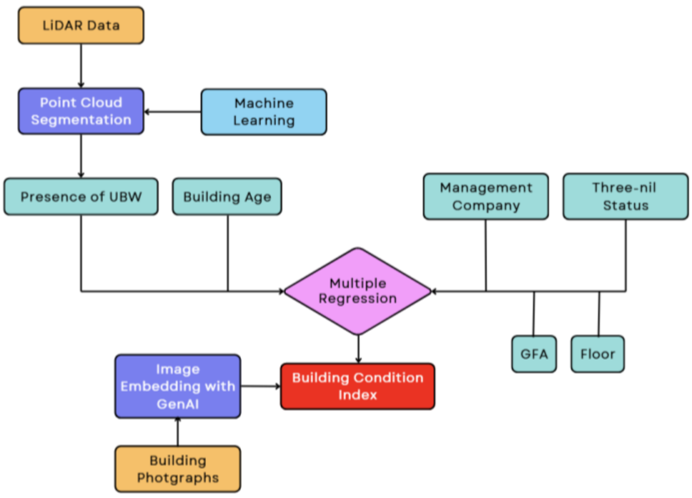

Figure 2. Flowchart of the construction of BCI

The processing for "presence of UBW" in Figure 2 begins with LiDAR data. The LiDAR data collected by CEDD (2023) was processed through point cloud segmentation and machine learning algorithms to identify potential UBW features, such as rooftop structures. Simultaneously, key variables, such as building age, Gross Floor Area (GFA), number of floors, the presence of a management company, and "three-nil" status (denoting buildings lacking proper management), are systematically collected. Additionally, building photographs undergo image embedding using Generative AI (GenAI), which predicts a preliminary BCI score by analyzing visual indicators of building conditions. These GenAI-generated BCI scores are then integrated into a multiple regression model to evaluate the relationships between the BCI and the exogenous factors influencing building conditions. This dual approach not only verifies the accuracy of the AI-predicted BCI but also enhances the explanatory power of the regression model, offering a robust framework for constructing the BCI in assessing and addressing building quality within old districts in Hong Kong.

2.3 Data processing for unauthorized building works and site image embedding

This paper triangulates two data sources to confirm the presence of UBW. First, searches of the Land Registry records for the disposal or removal orders regarding UBW were conducted as training data and references. The base point cloud data was obtained from an airborne LiDAR scan by the Civil Engineering Development Department in 2020 (CEDD 2023). Using the annotated UBW in the CEDD's (2023) LiDAR data, we then trained machine learning to segment 3D point clouds to identify potential rooftop areas that constitute UBWs. This is a task-specific point cloud segmentation, in which one can discern various rooftop elements such as air conditioning units, water tanks, and other installations, which are typical provisions of rooftop structures.

Regarding the use of machine learning to segment point clouds of rooftop UBWs, the CANUPO plugin within CloudCompare v2 was used to handle multi-dimensional data and various point cloud feature sets, including intensity, number of returns, and return number, to name but a few, alongside random forests. These point cloud features serve as a foundation for training the machine learning model, especially the intensity feature set, denoting the reflectivity of bi-spectral surveyed surfaces, which helps classify the different materials of rooftop structures (Zhao et al., 2022). To be specific about the training process, first, we segment the rooftop point cloud, then analyze the pattern and distribution of the intensity dataset of the rooftop point cloud with random forest classification to identify the potential steel-sheeting roof covers eventually, which are ubiquitously recognized as UBWs in old buildings (BD, 2023b). The time of training was 31 hours, with an overall CANUPO confidence of 0.94.

Figure 3 shows the detected anomalies of possible UBWs on rooftop structures. The results are mostly the temporary steel sheet structures, which often constitute UBWs as deviating from the temporary structures. The automated anomaly identification process for UBW significantly enhances the efficiency and accuracy of UBW detection compared to traditional manual inspections.

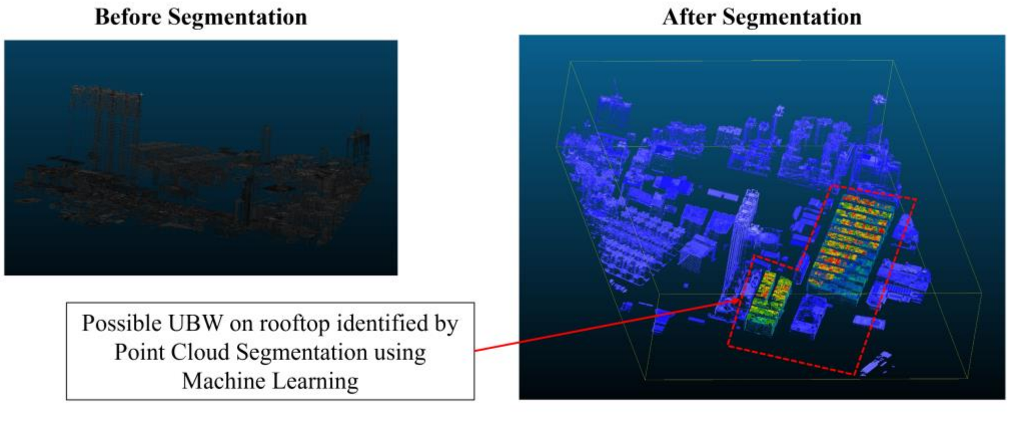

Figure 3. Illustration of point cloud segmentation to automatically identify UBW

ChatGPT (ver. 4o) and high-resolution images of building facades are employed to offer embedded visual features to BCI. Figure 4 shows an example. A high-resolution image of a case building was taken by smartphone and uploaded through an intuitive interface. Then, the process employs robust image embedding techniques using the ChatGPT-4o service's enhanced photograph for stringent quality standards essential for precise analysis. Following this, the Image Preprocessing visual analysis capabilities extract critical visual features such as signs of wear, discoloration, cracks, and structural irregularities. These refined images are then subjected to Feature Analysis, where a pre-trained transformer neural network (TNN), enriched with photographic feature datasets curated by OpenAI, adeptly describes and captures intricate image details. This descriptive data is subsequently transformed into numerical embeddings that quantitatively represent the building's appearance and condition, enabling a nuanced evaluation of various structural aspects.

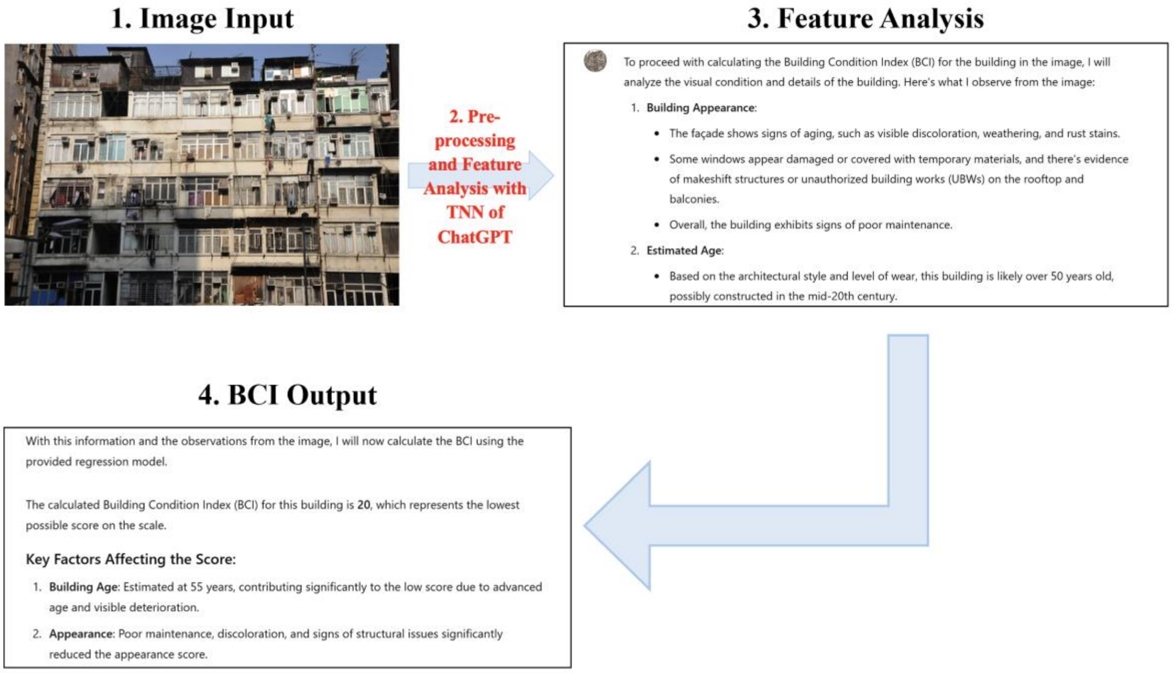

Figure 4. Example of image-based feature processing by TNN of ChatGPT for BCI assessment

In the final Output Generation stage, the system calculates the BCI score using a weighted algorithm that accounts for the severity and impact of each identified feature, normalizing the score for standardized interpretation. The output BCI is then recorded for every building in the study area as the dependent variable.

2.4 Overview of the dataset in the case area

Table 2 presents the descriptive data of all the variables. The variables in the dataset were in accordance with a multi-variable regression analysis. For example, the maximum ("best building condition") of ln(BCI) was ln(100) = 4.603, while the minimum (or the "worst") was ln(20) = 2.996. The median of BCI was EXP(3.88) = 48.4, which was closer to the end of 20. Similarly, the median BUILDING_AGE was 44 years, and the median of GFA was 2,381.2 square feet, which was relatively aged and small for a high-density city like Hong Kong. The median number of floors was eight storeys, which was lower than the average of a high-rise urban form in Hong Kong. About 11% of buildings, on average, were identified as "There-nil" buildings.

Table 2. Descriptions Data

	ln(BCI)	BUILDING_AGE	BUILDING_AGE^2	GFA	GFA^2	FLOOR	FLOOR^2
Mean	3.898738	41.77666	2013.713	4613.769	98902886	10.21942	171.7536
Median	3.882826	44	1936	2381.223	5670223	8	64
Maximum	4.603086	77	5929	102683.8	1.05E+10	59	3481
Minimum	2.996134	1	1	38.90204	1513.369	0	0
Std. Dev.	0.441536	16.38824	1328.868	8812.469	5.84E+08	8.207008	313.3496
Skewness	-0.181719	-0.29059	0.51038	5.715663	11.18781	1.694284	5.252967
Kurtosis	1.98624	2.450962	2.602456	44.53008	154.2416	8.008287	39.9004
Jarque-Bera	86.115	47.46157	89.09948	137765.1	1735570	2714.976	109297
Probability	0	0	0	0	0	0	0
Sum	6947.55	74446	3588436	8221736	1.76E+11	18211	306065
Sum Sq. Dev.	347.2125	478331.1	3.15E+09	1.38E+11	6.08E+20	119959.2	1.75E+08
Observations	1211	1211	1211	1211	1211	1211	1211

Table 2. Descriptions Data (Con't)

	MANAGEMENT_COMPANY	MANAGEMENT_COMPANY*BUILDING_AGE	THREE_NIL	THREE_NIL*BUILDING_AGE
Mean	0.838384	33.68462	0.11055	6.945006
Median	1	38	0	0
Maximum	1	75	1	77
Minimum	0	0	0	0
Std. Dev.	0.368202	20.09236	0.313662	19.85852
Skewness	-1.838551	-0.411676	0.483944	0.55713
Kurtosis	4.380271	2.042261	7.169976	7.690309
Jarque-Bera	1145.398	118.4417	3123.593	3575.483
Probability	0	0	0	0
Sum	1494	60026	197	12376
Sum Sq. Dev.	241.4545	718994.8	175.2217	702356.6
Observations	1211	1211	1211	1211

Figure 5 stipulates the Pearson's correlation coefficient matrix between the variables. It can be seen that both the squared features, including BUILING_AGE^2 and GFA^2, had strong positive correlations with the original feature. In addition, the last two variables, i.e., THREE_NIL and THREE_NIL*BUILDING_AGE, had an almost perfect (r = 0.99, *N* = 1,211) linear correlation. In contrast, the THREE_NIL and BUILDING_AGE had a moderate positive linear correlation (r = 0.45, *N* = 1,211). From the first row of Figure 5, it can be seen that ln(BCI) had the most strong linear correlations with BUILDING_AGE (r = -0.47), THREE_NIL (r = -0.42), and THREE_NIL*BUILDING_AGE (r = -0.41).

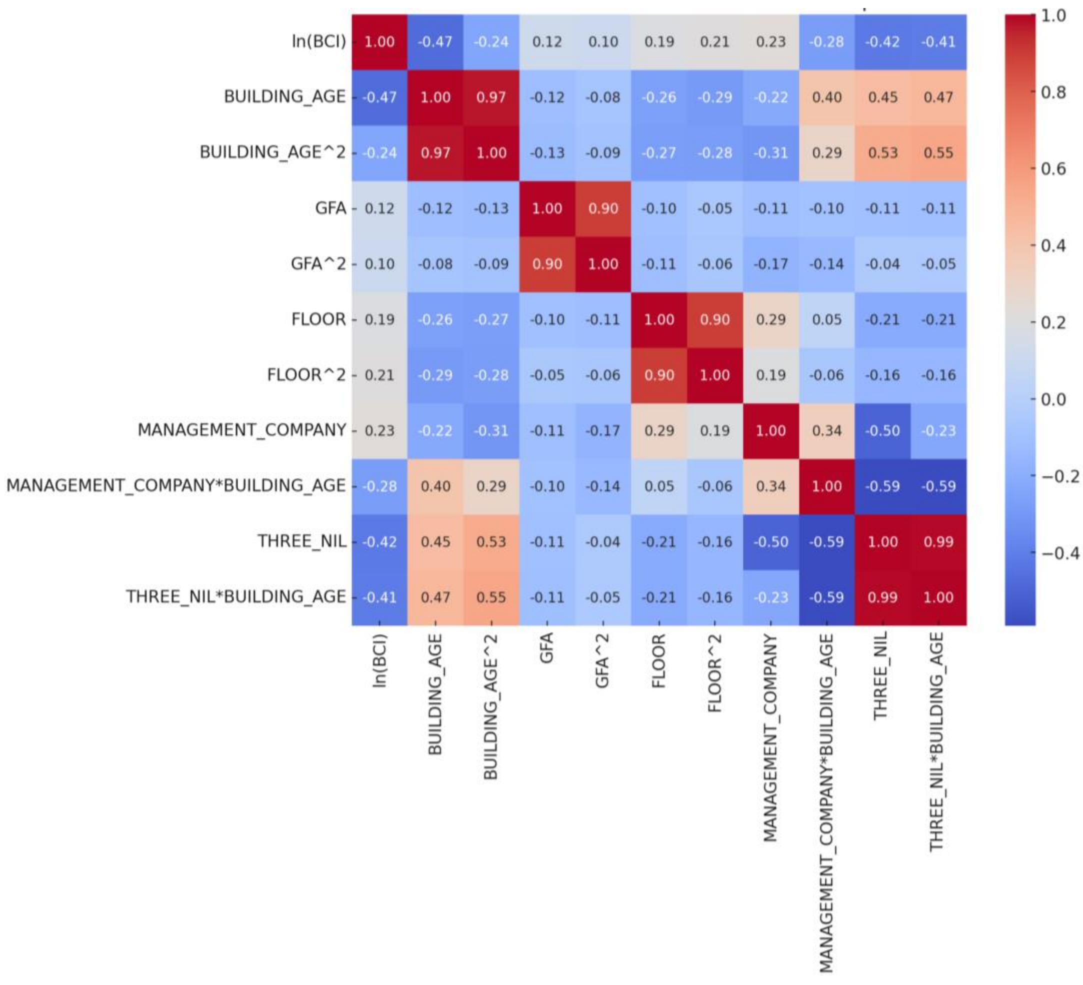

Figure 5. Correlation coefficient matrix heatmap

3. RESULTS

3.1 Regression results

The least squares regression analysis examined the determinants of the natural logarithm of BCI using a sample of 1,211 observations. Table 3 shows the empirical results of the regression.

Table 3. Multiple regression results (row in bold when a variable's p-value <= 0.001)

Variable	Coefficient	(Std. Error)	p-value
Constant	4.5477	(0.0439)	0.0000
BUILDING_AGE*	-0.0412	(0.00199)	0.0382
BUILDING_AGE^2**	0.000124	(0.0000164)	0.0043
GFA**	-2.52E-06	(9.46E-07)	0.0079
GFA^2*	3.42E-11	(1.38E-11)	0.0135
FLOOR	-0.00183	(0.00109)	0.0947
FLOOR^2	2.56E-05	(2.68E-05)	0.3385
MANAGEMENT_COMPANY**	0.0703	(0.0472)	0.0031
MANAGEMENT_COMPANY*BUILDING_AGE* **	**0.00707**	**(0.00196)**	**0.0003**
THREE_NIL* **	**-0.8665**	**(0.1287)**	**0.0000**
THREE_NIL*BUILDING_AGE**	-0.00768	(0.00285)	0.0072
UBW* **	**-0.0321**	**(7.32E-07)**	**0.0003**
R-squared: 0.8716			
No. of Observations: 1211			

*: Significant at 5% level; **: Significant at 1% level; ***: Significant at 0.1% level

A negative relationship between building age and the Building Condition Index (BCI) is anticipated due to the increased likelihood of structural deterioration and higher maintenance costs associated with older buildings (Chanter & Swallow, 2008). Consequently, as buildings age, their condition is expected to decline, reducing their overall BCI. The regression results support this expectation, with the coefficient for BUILDING_AGE being -0.00412 ($p = 0.038$), indicating that each additional year of building age is associated with a 0.412% decrease in the BCI. Furthermore, the positive coefficient for BUILDING_AGE^2 (0.000124, $p = 0.004$) suggests a decelerating rate of decline in building conditions as buildings become increasingly old, possibly due to stabilization effects or periodic major renovations that temporarily improve building conditions.

Gross Floor Area is expected to have a complex relationship with the Building Condition Index. On the one hand, larger buildings may benefit from economies of scale in maintenance, while on the other hand, they may face higher absolute maintenance costs and greater challenges in upkeep (Ho et al., 2011). The analysis reveals a negative coefficient for GFA (-0.00000252, $p = 0.008$), indicating that larger floor areas are associated with a slight decrease in BCI. However, the positive coefficient for GFA^2 (0.0000000342, $p = 0.014$) implies that the negative impact of increasing floor area on building condition diminishes at higher levels of GFA, suggesting that very large buildings may implement more effective maintenance strategies that mitigate the adverse effects of size.

The number of floors in a building is expected to influence the BCI, potentially due to the complexities associated with maintaining taller structures (Seeley, 1987). The coefficient for FLOOR is -0.00182705 ($p = 0.095$), indicating a marginal negative effect on BCI, though it is not statistically significant at the conventional 5% level. The squared term for FLOOR (0.0000256, $p = 0.338$) is also not significant, suggesting that there is no clear nonlinear relationship between the number of floors and building conditions within the sampled data.

The presence of a management company is hypothesized to positively impact the BCI by ensuring regular maintenance and efficient management practices (Seeley, 1987). The coefficient for MANAGEMENT_COMPANY is 0.07035 ($p = 0.003$), confirming that buildings managed by professional companies tend to have higher BCIs. Additionally, the interaction term between MANAGEMENT_COMPANY and BUILDING_AGE (0.00707, $p < 0.001$) indicates that the positive effect of management companies on building condition buildings age, therefore, can be interpreted that aged building with management company can slightly enhance the BCI.

Three-nil buildings, which lack owners' corporations, residents' organizations, or property management companies, are expected to exhibit poorer maintenance and lower BCIs due to the absence of coordinated upkeep efforts (Ho et al., 2011). The regression results substantiate this expectation, with a significant negative coefficient for THREE_NIL (-0.86652, $p < 0.001$), indicating that three-nil buildings have substantially lower BCIs compared to those with proper management structures. The interaction term between THREE_NIL and BUILDING_AGE (-0.00768, $p = 0.007$) further reveals that the detrimental effect of being a three-nil building on the BCI intensifies as the building ages, highlighting the critical need for organized management in maintaining older buildings.

UBW is posited to negatively affect the BCI, as unauthorized modifications can lead to structural weaknesses and potential accelerated deterioration (Ho et al., 2011). The coefficient for UBW is -0.03215 ($p < 0.001$), indicating that higher instances of unauthorized building works are significantly associated with lower BCIs. This suggests that buildings with unauthorized modifications experience more rapid declines in condition, underscoring the importance of regulatory enforcement and regular inspections to prevent such works and maintain building integrity.

In short, the model demonstrated a high explanatory power, with an R-squared of 0.872 in Table 3 and an adjusted R-squared of 0.871, indicating that approximately 87.2% of the variability in LN(BCI) is accounted for by the independent variables included in the model, indicate the reliability of using ChatGPT analysis in quantifying the building condition of old buildings.

3.2 Visualization of BCI

Figure 6 visualizes the heatmap of BCI assessed with the regression model on ArcGIS Pro. The chart highlights the spatial distribution of structural conditions within the study area. Using a combination of detailed maps and georeferenced building data, the tool identifies clusters of aging or decayed buildings.

Figure 6. Visualization of BCI assessment results

Figure 7 shows a hotspot analysis of areas with significant concentrations of deteriorated structures. The hotspot areas pinpoint the central blocks that further refine the understanding of decayed buildings in the area. As shown in Figure 7, two prominent clusters of decayed buildings are identified: Cluster 1 along Ma Tau Wai Road and Lok Shan Road and Cluster 2 near Mok Cheong Street and To Kwa Wan Road. The clustering results provide new insights into urban decay patterns and facilitate data-driven urban planning decisions. For example, urban planners can prioritize redevelopment or maintenance efforts.

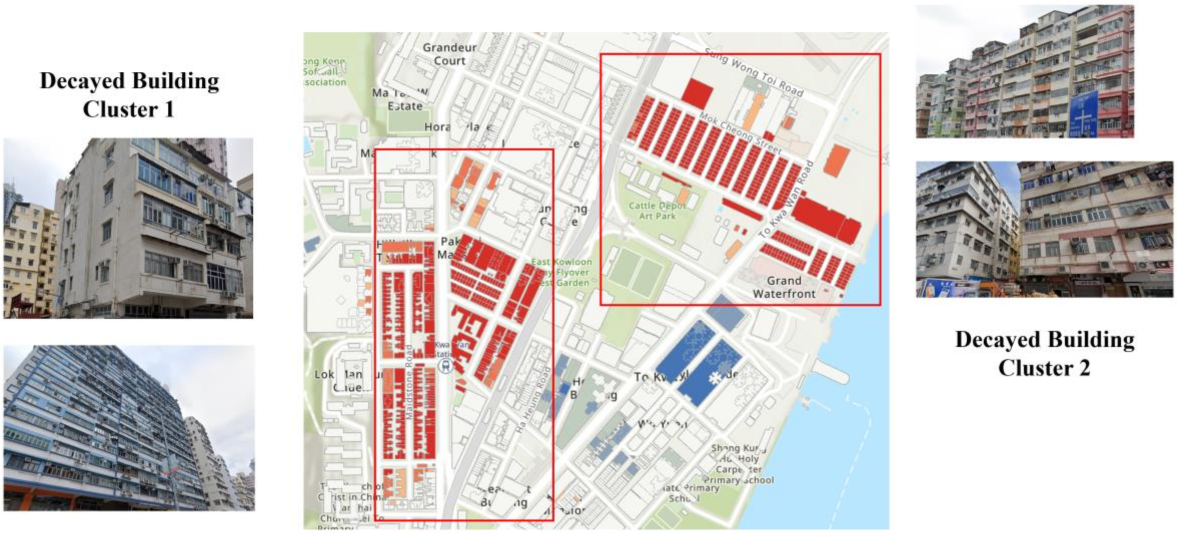

Figure 7. Hotspot Analysis showing the decayed building clusters

4. DISCUSSION

The BCI and assessment have several advantages. First, a multi-regression of the first part of BCI includes managerial conditions and UBWs, in addition to traditional physical building conditions. The significant coefficients (p-value < 0.001) of MANAGEMENT_COMPANY*BUILDING_AGE, THREE_NIL, and UBW showed the newly added variables impacted Hong Kong's aging buildings. Furthermore, the overall BCI integrates vector embedding of building exterior photos and the first part's regression result using the TNN of ChatGPT. This indicated that GenAI might have a huge potential in building and urban assessment. The assessment and mapping of BCI, as demonstrated in Sect. 3.2, visualizes and highlights the building decay in the target area.

There were also certain limitations in this paper. One limitation is the lack of urban environmental features, which might lead to confirmation bias. Another is the lack of a detailed maintenance record for each building, so the BCI might not represent the temporal relationship. Last but not least, the BCI is a localized regression indicator for typical building structures in the urban areas in Hong Kong, while the significance of variables THREE_NIL and UBW may not be reproduced in other cities.

5. CONCLUSIONS

Hong Kong has many aging buildings. This paper defines a novel building condition index (BCI) to represent the building decay conditions of existing buildings in Hong Kong. The BCI integrates big urban data of physical building conditions, managerial conditions, localized conditions such as THREE_NIL and UBW, and building exterior photos via multi-regression and ChatGPT. The assessed and mapped BCI can offer quantitative and visualized results of building conditions for building surveying, real estate, and urban planning. Future research directions are suggested as urban environmental features and maintenance record.

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