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Emergence of AI—Impact on Building Condition Index (BCI)

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Abstract: The Building Condition Index (BCI) is a widely adopted quantitative metric for assessing various aspects of a building's condition, as it facilitates decision-making regarding maintenance, capital improvements and, most importantly, the identification of investment risk. In practice, longitudinal BCI scores are typically used to identify maintenance liabilities and trends and proactively provide indications when maintenance strategies need to be altered. This allows for a more efficient resource allocation and helps maximise the lifespan and functionality of buildings and their assets. Given the historical ambiguity concerns because of the reliance on visual inspections, this research investigates how AI and using ANN, DNN and CNN can improve the predictive accuracy of determining a recognisable Building Condition Index. It demonstrates how ANN and DNN perform over asset classes (apartment complexes, education and commercial buildings). The results suggest that DNN architecture is adept at dealing with diverse and complex datasets, thus enabling a more versatile BCI prediction model over various building categories. It is envisaged that with the expansion and maturity of ANN, DNN and CNN, the BCI calculation methodologies will become more sophisticated, automated and integrated with traditional assessment approaches.

Keywords: building condition index; asset deterioration; lifecycle assessment; ANN; DNN; building condition methodologies

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1. Introduction

The Building Condition Index (BCI) quantitatively measures a building's overall condition, a crucial facility management and maintenance metric derived from performing a Building Condition Audit or Assessment (BCA). While various methods can be adopted for calculating the BCI, the work presented here focuses on the methodologies developed or refined since 2015 to reflect the latest advancements and best practices in this domain. The presented findings will allow facility managers, property owners and policymakers to select the most optimal BCI for their specific needs, efficiently allocating available resources, prioritising maintenance activities and developing long-term asset sustainability plans [1]. However, practical BCI calculation is hindered by the difficulty in obtaining relevant and reliable data. Moreover, as noted by Lai et al. (2018) [2], the BCI reliability can be compromised due to the highly subjective and inconsistent building inspection methods that rely on visual assessments. Significant variations in BCI calculations also arise due to the variations in the scope and depth of data collection required for implementing various assessment methodologies [3]. For example, some approaches give precedence to the structural elements. In contrast, others may incorporate a broader range of factors (e.g., indoor air quality, energy efficiency and accessibility), reducing the potential for BCI standardisation and precluding comparisons across building types or sites that have been assessed using different metrics. The Building Condition Index (BCI) is essential in effective building management; however, most techniques could be more precise. The proposed method introduces ANN and DNN to improve BCI, making it an appropriate and crucial tool in diverse building maintenance planning and resource allocation.

1.1. Research Problem

The Building Condition Index, BCI, is a principal metric in evaluating the health and performance of structures for maintenance decisions, resource allocations and long-term planning. However, BCI scores are challenging to precisely predict because of factors that could influence building conditions, such as structural integrity, accessibility, occupancy and energy efficiency. Traditionally, assessment approaches tend to rely on human inspection or scoring tools that are rudimentary and simplistic. These approaches will be variable and biased, making BCI results unreliable, ambiguous and contestable. Optimising and aligning maintenance strategies with current building demands and installed equipment age, combined with increased maintenance planning, will be a step closer to reducing expensive structural damage and equipment failure and will result in better prediction accuracy for BCI.

Traditional BCI methods do not approach building data with sophistication and in a multi-dimensional aspect. A human-based inspection, coupled with component-based approaches, is informative but not as accurate in a dynamic setting. Advancements in AI, particularly those of neural networks, can potentially revolutionise BCI [4]. ANN and DNN can model complex relationships between variables in a building, thus allowing the generation of more accurate and reliable BCI forecasts. This makes the comparison of the effectiveness of ANN versus that of DNN in BCI applications a hitherto understudied aspect and forms the basis of this research assignment.

1.2. Research Objective

- To compare the prediction accuracy of current BCI methods with that of Artificial Neural Networks (ANNs) and Deep Neural Networks (DNNs) for BCI.
- To evaluate the performance of ANN and DNN in handling varying building types and conditions.
- To identify strengths and limitations of ANN and DNN models in BCI prediction for practical implementation in building management.

This research project aims to outline AI models that suitably contribute to the accuracy and efficiency of predicting BCIs for better building management.

2. Methods and Materials

The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) diagram in Figure 1 has been used to undertake a systematic review and visualise the literature screening process deployed in this research assignment. The flowchart illustrates how researchers narrowed the initial search results to the final journals and publications in multiple screening stages. The process begins with identification, where databases are searched, and records are collected. This is followed by screening, where duplicate records are removed and titles/abstracts are reviewed. During the eligibility assessment phase, full-text articles are evaluated against inclusion criteria. Finally, the included studies are determined and documented. Each stage is quantified, showing the number of studies retained or excluded. This standardised approach enhances reproducibility and allows readers to assess potential selection bias in the review process. The diagram's structured format ensures consistent reporting across different systematic reviews and meta-analyses, making it easier for researchers to compare methodologies and evaluate the thoroughness of literature searches.

This systematic review identified records, journals and publications from 135 databases and sources, including Google Scholar, Scopus, Academia, ResearchGate and Semantic Scholar, and involved publications from Frontiers, Buildings, Emerald, Elsevier, IEEE, Springer, Sage and ScienceDirect. Title searches included Building Condition Audit, Building Condition Assessment, Building Condition Index, Facility Condition Index, AI and Building Assessments, ANN and DNN Analysis and Different Analysis Methods for Building Assessments. The first screening level removed 19 publications due to duplications, resulting in a balance of 116 records. The second screening phase involved removing

documents and publications that did not address the research theme or scope of building maintenance strategies. This resulted in 23 records being removed and a balance of 93 remaining journals and publications. Finally, 21 records were removed as they were not considered academically appropriate or sufficiently peer-reviewed journals. The balance of reference documents, journals and publications used in this research assignment was 72 publications.

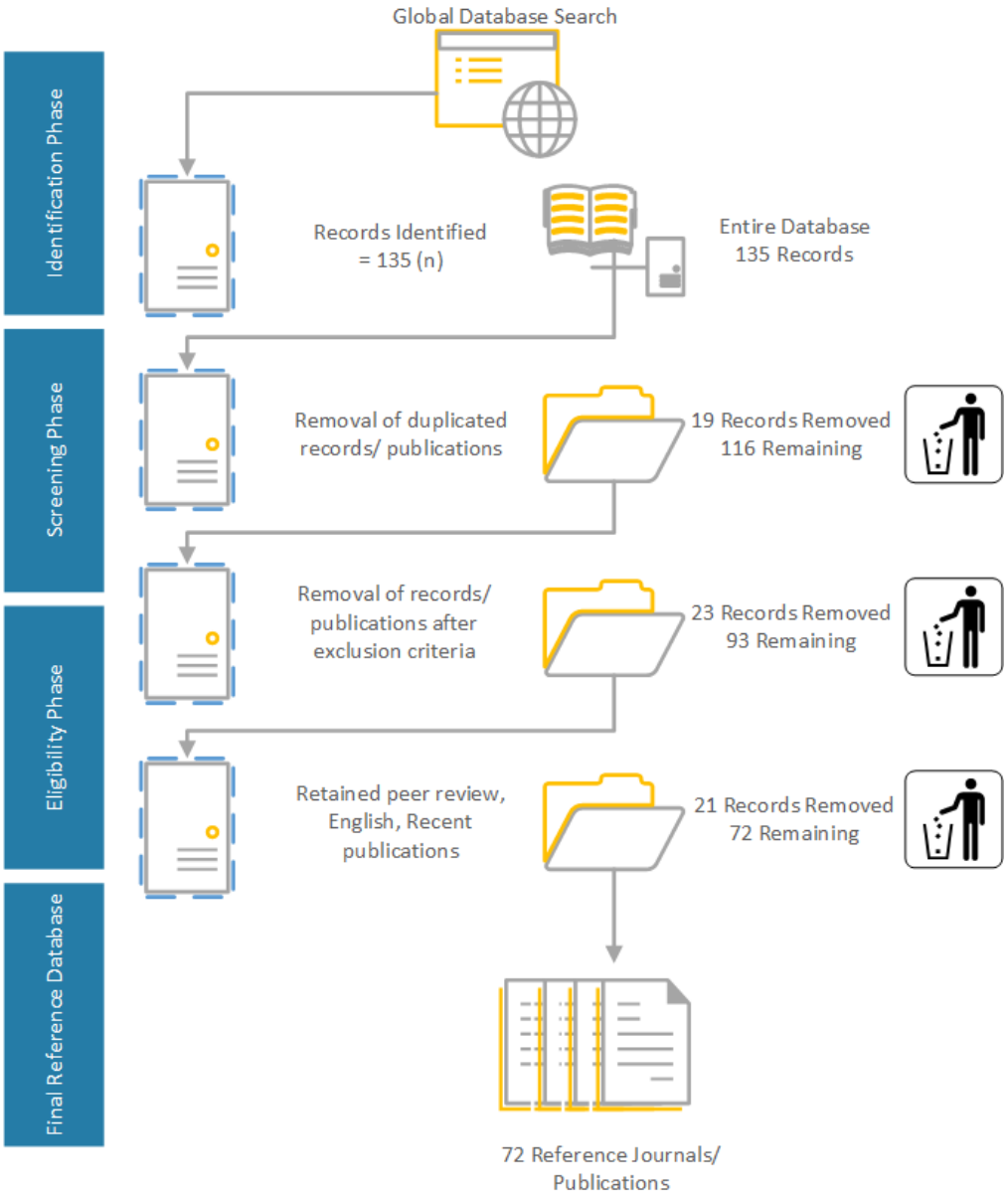


Figure 1. Prisma Model for Research Assignment.

Table 1 provides examples of documents scrutinised during the literature review, highlighting the different methodologies and processes the industry has adopted and used to address the assessment of a building's condition.

A qualitative research component was included to introduce relevance and currency to this research assignment. This involved surveying and interviewing fifty (50) facility managers, property and asset managers and asset management consultants /engineers who practice or are exposed to building condition auditing. The purpose of these surveys and interviews was to seek different perspectives and professional experiences from stakeholders who regularly use or are exposed to building condition assessments and have a

varying but reasonable working understanding of different methodologies available in calculating the Building Condition Index.

Table 1. Major reference journals and articles.

Author	Article Title	Publication Year
Ye et al. [5]	Influence of an integrated value-based asset condition assessment in built asset management	2023
Cecconi et al. [6]	Artificial Neural Network for non-destructive testing in building condition assessment	2019
Fathi et al. [7]	Predicting financial distress using the worst-practice-frontier data envelopment analysis model and Artificial Neural Network.	2023
Masoumi et al. [8]	Identifying building conditions using Artificial Neural Network (ANN) technique	2020
Chen et al. [9]	Data-driven monitoring and predictive maintenance for engineering structures	2023

3. Traditional Condition Assessment Methods

Traditional methods for calculating the BCI typically rely on visual inspections, during which component-level evaluations are based on standardised scoring systems. These inspections often serve as the starting point for more advanced techniques, such as those incorporating digital documentation and predefined condition states to enhance consistency and reliability [5].

3.1. Component-Based Assessment

In these assessments, scores assigned to individual building systems or components are weighted based on their relative importance and interdependencies, with their sum representing the overall BCI [10]. This granular approach allows for more targeted maintenance and renovation strategies and thus more optimal resource allocation. Furthermore, as the evaluation is based on clearly defined criteria for all individual components, it can be modified if any changes occur while reducing the potential for inconsistencies between ratings provided by different assessors. However, as a detailed evaluation of each building component is time-consuming and requires significant expertise, it is often unfeasible in practice [6]. In addition, its effectiveness is contingent on a comprehensive understanding of system-level interactions and interdependencies and their impact on the building's overall condition and functionality [11]. While basing BCI calculations on inaccurate or incomplete information would inevitably limit the utility of this index [12], it is also prone to errors due to the failure to update the assessment criteria and weightings to reflect technological advances in building materials and construction methods [13].

3.2. Standardised Rating Systems

As their name suggests, standardised rating systems are based on predefined criteria and scoring matrices, allowing comparisons across buildings and over time [13,14]. They are also helpful in making complex maintenance and upgrade decisions, as the obtained BCI scores can be stored in comprehensive building condition databases accessible to all relevant stakeholders [15]. However, they must be continually updated to align with modern infrastructure management approaches. For example, the assessment criteria and weightings can be modified to render them more context specific [16]. BCI ratings based on standardised approaches are increasingly incorporated into BIM and other digital asset management tools, thus streamlining the decision-making process [17]. However, Dejaco et al. (2017) [13] noted that even standardised methodologies are prone to subjective interpretation without clear guidelines. These guidelines must also stipulate actions to be taken in case of technological advances, changes in environmental factors or unforeseen events to ensure that these rating systems remain relevant [14].

3.3. Weighted Factor Method

While weighting is incorporated into most BCI calculation methods, this is the main feature of the weighted factor methods, making them particularly useful for application in settings subject to ongoing changes [16]. The weights are usually determined based on the components' criticality to building function, replacement cost and impact on occupant safety and comfort [12,13]. For instance, mechanical and electrical systems crucial for patient care would be given greater weight in a hospital setting. In contrast, precedence would be given to the envelope and structural components in an office building [11]. This strategic approach can lead to more efficient resource utilisation, especially when combined with BIM [17]. The main drawback of this approach stems from the subjective nature of weights, leading to inconsistent and less reliable BCI scores [6]. Accordingly, assessors need to periodically review their processes to ensure uniformity across their approaches and incorporate any new findings from research or practice [11,13]. They also view that the relative complexity of these methods may make their application challenging in practice. To mitigate this issue, strong collaboration among the teams conducting visual inspections and performance testing and all relevant parties is essential [12].

3.4. The Analytic Hierarchy Process (AHP)

The AHP was developed by Thomas L. Saaty in 1990 as a decision-making tool for complex systems and processes [18]. Since then, it has been applicable in various settings, including building assessment, as, when integrated into BCI, it allows the building condition evaluation to be conceived as a set of sub-problems at different levels of hierarchy. The process commences by determining the overall goal (assessing building condition) and the main quantitative and qualitative criteria (such as structural integrity, mechanical systems and aesthetics), along with viable alternatives (specific building components or systems) [19]. Its main strength derives from a framework for converting qualitative (potentially subjective) judgments such as aesthetic quality or user comfort into numerical values [20]. AHP also relies on pairwise comparisons, allowing evaluators to progress through the entire system sequentially, thus implicitly accounting for its complexity. By including a consistency check, the users can fully benefit from this highly flexible method without the risk of reducing its validity [19]. AHP can be easily adapted to different types of buildings and organisational priorities. For example, when used to assess heritage buildings, AHP can effectively balance the preservation aims with functional requirements [21]. Furthermore, AHP's mathematical rigour ensures that the quantitative output is clear and objective, making it easier to justify maintenance and renovation decisions to the stakeholders or secure funding for building improvements [18]. However, when AHP is used in BCI assessments, care must be taken to ensure that the required ranking among the identified alternatives is kept the same by adding new or modifying the existing elements [20]. This requires considerable expertise, challenging implementing this complex process [19]. Thus, the output quality depends heavily on the knowledge and judgment of the individuals involved in the assessment process [21].

3.5. Fuzzy Logic Systems

Fuzzy logic allows for meaningful representation of uncertainties, making it suitable for building condition evaluations, which often involve subjective judgments based on incomplete data. Thus, it is increasingly incorporated into BCI calculations. For example, Marzouk and Awad (2016) [22] developed a fuzzy logic-based model that incorporates linguistic variables describing component conditions, processed using fuzzy set theory to produce BCI as the output. This approach is beneficial when precise numerical data are unavailable while capturing valuable insights yielded by human reasoning [19]. This is accomplished by allowing for partial membership of the same variables in multiple sets, which is more intuitive when assessing building conditions [23]. As fuzzy logic systems can express outcomes in natural language, they are ideal when facility managers, building owners and maintenance personnel need to discuss the findings and have different levels of

technical expertise [24]. As expert knowledge is incorporated into the assessment process through fuzzy rules, and the relationships between input variables and building conditions can be non-linear, this allows for more sophisticated modelling [6], especially when fuzzy logic systems are integrated with other computational intelligence techniques, such as neural networks or genetic algorithms [25].

This computational complexity is also one of the drawbacks of this approach, as defining fuzzy sets and rules requires considerable expertise but may also lead to subjectivity and consistency [19]. As a result, adopting fuzzy logic systems is rarely practical for smaller organisations with limited resources [23]. However, even when these concerns are absent, processing many fuzzy rules and defuzzification for multiple complex buildings with many components may be prohibitively resource intensive [6]. The fuzzy logic system flexibility also reduces the potential for standardisation and precludes BCI score comparisons across different contexts and facilities [24]. Consequently, when exact numerical outputs are necessary, traditional assessment methods for obtaining BCI might be more appropriate [25].

3.6. The Multi-Criteria Decision-Making (MCDM)

The MCDM method is an ideal approach to BCI calculation, as it captures the multifaceted nature of building condition assessment. Several such approaches have already been used in practice. However, the hybrid MCDM model developed by Saleh et al. (2020) [26] is particularly noteworthy, as it combines the Analytical Network Process (ANP) with the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), allowing the interdependencies and performance of different building components to be evaluated relative to some predetermined ideal state. One of the primary advantages of incorporating MCDM into the BCI assessments is its framework comprising numerous, often conflicting requirements, such as structural integrity, energy efficiency and occupant comfort [18]. By clearly defining the assessment criteria (which can be both qualitative and quantitative), determining their relative weights and providing a transparent evaluation methodology, MCDM makes the building assessment process and its outcomes more accessible to diverse stakeholders [27,28]. MCDM methods can also be adapted to the specific requirements of customised assessments, making this approach particularly valuable for organisations managing complex building portfolios [29].

As with all other methods discussed thus far, MCDM's practical utility depends on the expertise and judgment of those responsible for designing the assessment framework [28]. The complexity of this methodology can also sometimes lead to scepticism or misinterpretation of results [27]. For this reason, MCDM techniques are often used for comparison rather than evaluation of a single building [28].

3.7. The Weighted Sum Model (WSM)

Like many others presented above, the WSM approach requires that the factors considered in the BCI assessment be assigned weights signifying their relative importance. However, it is unique in that the relationship between scores and overall building condition is assumed to be linear, and the criteria used in the assessment are considered independent. Different strategies can be used for this purpose, with the model developed by Aneesha (2024) [30] focusing on the criticality and replacement cost of individual building components. As the WSM design balances simplicity and accuracy, and the model incorporates multiple assessment criteria, it is more objective and comprehensive than the traditional methods. However, it is also more challenging for non-experts to use. Accordingly, research efforts in this domain focus on developing more user-friendly tools for practical application with a more transparent and intuitive means of weight determination [13].

As the WSM inputs can be easily adjusted, they are often used for sensitivity analysis, allowing the identification of components with the most significant impact on the building condition that would thus need to be prioritised [14]. This capability makes the WSM particularly valuable when managing diverse building portfolios [15], as it promotes trust

and facilitates communication [16]. However, the WSM outputs a single numerical index, so it cannot capture the unique characteristics and interdependencies between different building components [16]. In line with other methods discussed here, the WSM also necessitates a certain level of expertise when determining the importance of different criteria, which is inevitably subjective [13]. As the WSM does not provide mechanisms for incorporating uncertainty into the final index and cannot handle criteria measured on different scales, combining it with other building condition assessment methods can be challenging [12]. Lastly, the additive nature of the WSM may not accurately reflect how different components age or interact over time [16].

3.8. Performance-Based Method

This method relies on measurable performance indicators rather than visual inspections or component-level assessments, making it more objective and well-suited for contexts where a building must meet specific performance criteria. Its application involves three steps—setting performance objectives, measuring actual performance and comparing it to the established benchmarks—resulting in a score that reflects the building's functionality [31,32]. These methods can be tailored to specific user requirements and diverse contexts [33]. Moreover, by focusing on specific performance metrics, such as energy efficiency, indoor air quality or structural response to loads, facility managers can identify and address any underlying problems and can initiate timely maintenance as well as schedule building performance monitoring [34,35].

As with other advanced methods presented above, performance-based methods are challenging to implement in practice, especially when assessing buildings with multiple functions or unique design features that would require bespoke performance indicators [32]. For example, occupancy patterns, weather conditions or equipment malfunctions can affect performance measurements, but determining their importance for the building's overall condition requires considerable expertise [33]. Performance-based methods rely solely on measurable performance metrics, so they may not adequately capture other relevant aspects, such as aesthetic deterioration or minor structural issues [32]. These methods also require significant technological infrastructure and data management capabilities, which may be costly to implement and maintain, especially for older buildings or smaller facilities [31]. Moreover, the lack of standardisation necessary to make this approach sufficiently flexible precludes direct comparisons of BCI scores across different buildings or sites [35].

3.9. Occupant Satisfaction and Comfort-Based Approach

As most BCI calculation methods overlook occupant feedback and comfort metrics (such as thermal comfort, acoustics and indoor air quality), Li et al. (2018) [36] proposed a framework that combines physical inspections with occupant satisfaction surveys, resulting in a user-centric BCI. Comfort metrics can also be captured using sensor-based measurements, making this approach more objective and standardised while focusing on user needs and preferences [37,38]. These approaches also offer valuable insights into the subjective aspects of building performance that are difficult to measure through objective means alone but can have significant ramifications for occupant productivity and well-being [39]. By identifying specific areas of dissatisfaction or discomfort, facility managers can prioritise improvements [37]. At the same time, regular occupant surveys and real-time comfort monitoring can provide ongoing insights into building performance, allowing for dynamic adjustments and proactive maintenance strategies [36].

However, these approaches are highly subjective, as they rely on self-reported user perceptions, making it difficult to establish consistent benchmarks for building conditions [38,39]. Occupant-centric approaches may also overlook critical technical aspects of building conditions that users need to directly perceive, such as structural integrity, energy efficiency or long-term degradation of building systems [36]. Suppose input data is solely obtained through occupant surveys. In that case, this strategy can be time-consuming and

impractical, while maintaining sensor networks for environmental monitoring may be relatively inexpensive without yielding generalisable data [37]. As respondent attrition and frequent changes in occupancy would preclude any long-term comparisons, these approaches may result in biased BCI assessments [38]. In addition, as occupants may prioritise immediate comfort over energy efficiency or sustainable practices, when their feedback drives decision-making, it can adversely impact the building's overall condition and long-term performance [38].

3.10. Risk-Based Performance Assessment (RBPA)

The RBPA approach allows the potential consequences of component failure or performance degradation to be incorporated into the BCI calculation. For example, the risk-informed model proposed by Bortolini and Forcada (2019) [40] integrates the probability of failure with its impact on building performance, resulting in a BCI that reflects the main risks to the overall building function. Thus, facility managers can use it to prioritise the most critical issues, leading to more effective resource allocation and improved building performance [1,41].

By quantifying risks associated with different building components and systems, RBPA supports evidence-based decision-making for capital investments, renovations and long-term facility planning [42]. This focus on safety also helps identify and eliminate potential hazards, enhancing occupant safety [43]. As risk-based approaches to building safety are increasingly adopted in regulatory frameworks, RBPA adoption improves compliance, which is essential in industries with stringent safety regulations [1]. However, these advantages also come at the cost of considerable complexity, mandating that model developers and assessors possess in-depth knowledge of risk analysis techniques and potential failure modes in various building systems [44]. A further drawback stems from the need to collect and maintain large datasets—including building components, historical performance and potential failure modes—which can be resource-intensive. At the same time, any inaccuracies in data capture or processing can reduce the RBPA effectiveness [41]. Moreover, estimating probabilities and consequences of various failure modes necessitates expert judgment, and this subjectivity hinders comparisons across different contexts [42]. While focusing on critical risks is essential, this approach neglects lower-risk components contributing significantly to building performance and longevity [43]. As a result, justifying the BCI assessment findings to stakeholders with different priorities may be difficult [1].

3.11. Resilience-Oriented Condition Assessment (ROCA)

Growing concerns about climate change and natural disasters have led to resilience-oriented approaches to BCI calculation. For example, Kammouh et al. (2019) [45] proposed a methodology that considers factors such as structural integrity, redundancy of critical systems and disaster recovery capacity, facilitating long-term building management planning and adaptation strategy development. By considering potential future challenges, this approach allows facility managers to identify critical vulnerabilities and adopt strategies for their timely mitigation [46]. This approach can lead to more sustainable design and maintenance practices, potentially reducing the building's environmental impact and operating costs [47].

The principal value of ROCA is its ability to identify sources of flexibility and adaptability within building systems and structures, rendering them more responsive to evolving needs or changes in tenancy dynamics [48]. Incorporating resilience considerations (redundancy, diversity, modularity and adaptability) into BCI assessments can also enhance stakeholder confidence in a building's long-term viability and reliability. This results in better occupancy rates, higher property values and easier access to improvement financing [46]. As governments and regulatory bodies increasingly emphasise resilience in building codes and urban planning, incorporating ROCA into BCI assessments can help avoid costly retrofits or penalties in the future [47]. However, evaluating a building's resilience requires consideration of multiple potential future scenarios, which can be time-consuming and

resource-intensive while requiring considerable expertise [48]. Moreover, projections of future environmental conditions and potential risks are inherently uncertain, making it difficult to justify investments in resilience measures when competing with more immediate needs [46]. Moreover, excessive investments in resilience measures that are never needed may limit the funding available for regular building maintenance and improvements [47].

The lack of widely accepted resilience metrics and benchmarks compromises the ROCA's usefulness in BCI assessments and comparison findings in the broader industry context [48]. In addition, the data needed for assessments and decision-making are rarely available, making it challenging to validate resilience measures or assess their potential impact on building conditions and performance over time [47].

4. Introduction of ANN and DNN Digital Assessment Methods

Current methods used in computing a building condition index are predominantly manual scoring and component-based methods that depend on the visual inspection of predefined scoring systems [49]. Thus, they generally provide a general idea regarding the building conditions but can be limited by subjectivity and inconsistency in assessments, making their data unreliable. Component-based methods can be more detailed, but they are both time-consuming and require enormous expertise, making them impractical for large portfolios. Artificial Neural Networks (ANNs) have recently been developed to enhance BCI predictions by capturing complex relationships between variables such as structural integrity, occupancy and energy efficiency [50]. ANNs can process high-dimensional data, thus reducing the need for manual assessments. However, the performance of basic ANNs can sometimes be limited, especially when handling larger datasets or detecting intricate, non-linear patterns. ANNs can model complex, non-linear relationships between building characteristics and condition states and are thus increasingly utilised in BCI calculation [51]. For example, Fathi et al. (2019) [7] developed an ANN-based model that uses historical condition data and building characteristics to train the network, subsequently used to predict future building condition states and provide an overall BCI. Moreover, ANNs can be trained on various datasets, making them versatile tools for facility managers dealing with complex portfolios comprising diverse building types [8]. ANNs can also be continually improved by adding new data while performing well even when some data is missing or noisy or contains errors [52]. Furthermore, once trained, ANNs can provide rapid assessments of building conditions, facilitating quick decision-making and building condition monitoring over time [53].

On the other hand, Deep Neural Networks (DNNs) offer several key advantages over traditional Artificial Neural Networks (ANNs) when performing building condition audits. Unlike ANNs with limited layers, DNNs use multiple layers that progressively learn more complex features. Early layers might detect essential elements like edges and textures in building audits, while deeper layers identify complex patterns like crack networks or deterioration patterns. This hierarchical learning enables more sophisticated defect recognition than ANNs can achieve. Furthermore, DNNs offer superior imaging capabilities, particularly Convolutional Neural Networks (CNNs), specifically designed for image analysis. They maintain spatial relationships in visual data, crucial for understanding building defects in context. ANNs flatten image data, losing this spatial information and reducing accuracy in defect detection [54].

The deep architecture associated with DNNs allows them to recognise intricate patterns in building deterioration that simpler ANNs frequently tend to miss. This is particularly important for identifying complex failure modes or subtle signs of structural issues. Further supporting the advancements of DNNs, they can handle much larger datasets and learn more complex relationships between different types of audit data (visual, sensor, thermal) than ANNs. This greater capacity means that DNNs can better integrate multiple inspection parameters and provide more comprehensive condition assessments [52].

Like other advanced techniques that rely on complex mathematics, ANNs are difficult to understand for most users, rendering their output challenging to justify, which may

be an issue from the legal or regulatory compliance perspective [55]. ANNs also require substantial amounts of high-quality data for training, which may be challenging to obtain, especially for highly diverse portfolios comprising buildings that differ significantly from those in the training set [56]. As the ANNs can be highly sensitive to the choice of network architecture and hyperparameters, their use in BCI determination necessitates extensive experimentation and expertise, which can be resource-intensive and impractical for organisations without specialised data science capabilities [4]. While both ANNs and DNNs offer their benefits and advantages, with their more profound architecture, DNNs are better at generalising across different building types and conditions, reducing false positives and improving reliability compared to ANNs.

5. Results

The dataset for this study is fifty (50) different commercial properties, each described by the critical variables required to compute BCI. Variables considered for the data are the integrity, performance, and deterioration scores for the structural, internal fit-out, mechanical and electrical, fire and life safety and building compliance scores. Secondary data was also collated regarding the building's performance (energy and IAQ), occupancy rate/ density, tenant satisfaction, services and thermal comfort. By collating these different datasets, both traditional building assessments and emerging AI assessments in the form of ANNs and DNNs can be used to analyse building condition indexes using identical data.

5.1. AI Model Selection Preference

ANN and DNN were analysed because of their proven ability to process high-dimensional, structured data. ANN is more straightforward in its architecture and elegantly models variable relationships with precise predictions. DNN, on the other hand, with more layers, captures more complex, non-linear patterns, which is appropriate for larger datasets and varied building conditions.

5.2. Evaluation Metrics

Mean absolute error and R-squared were used to evaluate the models' performance. The former computes average absolute differences between predicted scores and actual BCI values, providing an idea about accuracy [57]. The latter, R^2, computes the degree to which models can explain the variance in data and reflects the overall prediction quality.

5.3. Analysis Process

Cleaning and normalising the data occurred during the first phase of analysing data. The models were also trained on the same data, and then actual scores in BCI were cross compared to their predicted scores. A quantitative method for comparison has been taken as MAE and R^2. Scatter plots with a visual approach are also part of this process. They presented how predictions from each model reflected scores seen to determine if one achieved more accuracy and more substantial results.

5.4. ANN and DNN Model Comparison

The comparative analysis between Artificial Neural Networks (ANNs) and Deep Neural Networks (DNNs) for predicting the Building Condition Index (BCI) shows in Figure 2 that DNN will provide slightly more accurate predictions. The mean absolute error for DNN is 13.72, whereas, for ANN, it is a high MAE of 16.77, showing that DNN predictions are closer to actual BCI scores.

However, both models show negative R-squared (R^2) values: -1.45 for ANN and -0.70 for DNN. Negative R^2 values signify that neither of the models fits the data well, as they fail to account for variability in actual BCI scores and perform worse than a mean baseline model. This implies that although DNN outperforms ANN slightly in accuracy, additional improvements are required in the model structure or data preparation before

applying it practically. Such improvements can be translated into more accurate and realistic BCI predictions for better construction and maintenance planning.

```
# Display the performance metrics
print("Mean Absolute Error (MAE):")
print(f"ANN: {mae_ann}, DNN: {mae_dnn}\n")
print("R-squared (R²):")
print(f"ANN: {r2_ann}, DNN: {r2_dnn}\n")
```

```
Mean Absolute Error (MAE):
ANN: 16.7742, DNN: 13.722599999999998

R-squared (R²):
ANN: -1.452511672876406, DNN: -0.6956899969961967
```

Figure 2. Performance results.

5.5. Building Type Insights

A more detailed evaluation of the dataset revealed variations in the models' performance depending on the building type. For instance, in apartment complexes, the predictions of ANN and DNN were fairly accurate, and DNN was marginally better than ANN. However, DNN was always in line with the true BCI ratings for intricate commercial buildings where the situation was more unstable. Interestingly, educational buildings with distinct occupancy and structural properties also benefited from increased prediction accuracy using DNN. The results suggest that DNN architecture is particularly adept at dealing with diverse and complex datasets, thus enabling a more versatile BCI prediction model over various buildings [58]. Altogether, DNNs performed significantly better, with emphasis placed on complex and dense occupancy buildings; it would seem a suitable model for BCI applications in different building structures.

A correlation matrix was used to visualise the relationships among all numeric features, identifying significant correlations within the dataset, and a confusion matrix was developed using this data to create Figure 3.

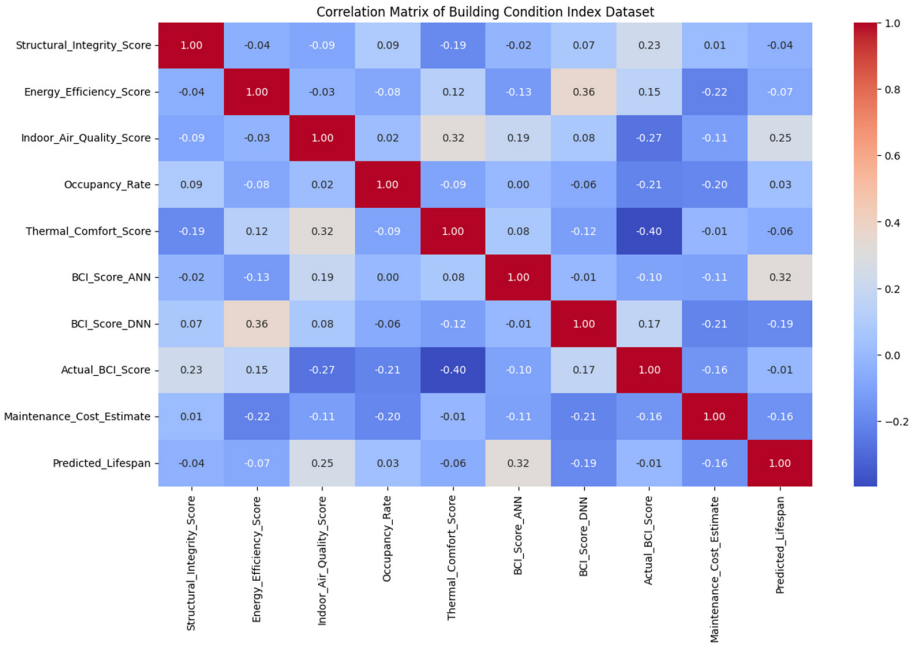


Figure 3. Confusion matrix.

5.6. Scatter Plot Analysis of the Dataset

A scatter plot is a powerful data visualisation tool that reveals relationships between variables (ANN and DNN) by displaying data points on a two-dimensional graph. Its primary benefits include instantly identifying patterns, trends, correlations and outliers within datasets. Users can quickly spot whether relationships are positive, negative or non-existent and determine if they are linear or nonlinear. Scatter plots also help in identifying clusters of data points and gaps in data distribution. The scatter plot in Figure 4 compares ANN and DNN predictions to actual BCI scores, with a line for perfect prediction to gauge model accuracy, while Table 2 provides the same data in table form.

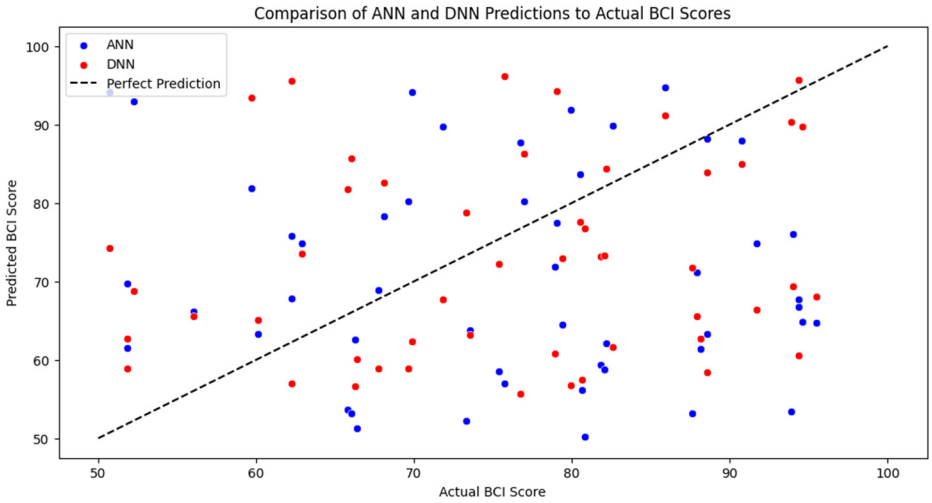


Figure 4. Comparison of ANN and DNN predictions to actual BCI scores.

Table 2. Comparison of ANN and DNN to actual BCI table.

Building	Actual BCI Score	ANN Predicted BCI Score	DNN Predicted BCI Score
1	85.88	94.75	91.14
2	87.92	71.15	65.51
3	66.28	62.58	56.63
4	71.84	89.76	67.74
5	80.54	83.65	77.56
6	52.26	92.89	68.72
7	94.61	64.88	89.77
8	91.67	74.87	66.40
9	62.26	75.75	95.54
10	50.72	94.11	74.21
11	93.87	53.39	90.36
12	73.55	63.76	63.16
13	75.35	58.59	72.28
14	82.15	62.08	84.38
15	78.95	71.84	60.81
16	94.36	66.77	60.58
17	94.38	67.76	95.72
18	90.76	87.99	85.01
19	79.91	91.85	56.72
20	87.64	53.17	71.75
21	81.83	59.40	73.21
22	76.95	80.20	86.25
23	56.04	66.14	65.54
24	88.13	61.44	62.74
25	88.57	63.29	58.40
26	79.42	64.51	72.99

Table 2. *Cont.*

Building	Actual BCI Score	ANN Predicted BCI Score	DNN Predicted BCI Score
27	88.56	88.19	83.92
28	80.62	56.15	57.44
29	59.71	81.90	93.44
30	62.88	74.88	73.58
31	60.09	63.34	65.07
32	67.73	68.89	58.94
33	51.83	61.53	62.68
34	79.06	77.52	94.25
35	65.82	53.67	81.81
36	80.82	50.23	76.70
37	68.11	78.26	82.60
38	82.04	58.74	73.30
39	66.01	53.19	85.66
40	62.25	67.86	57.00
41	73.31	52.28	78.77
42	82.57	89.90	61.66
43	66.37	51.24	60.05
44	94.02	76.05	69.36
45	51.84	69.73	58.86
46	69.64	80.24	58.95
47	95.48	64.77	68.08
48	75.75	56.98	96.14
49	69.90	94.18	62.36
50	76.72	87.75	55.72

5.7. Use of Box Plot Analysis

Box plots (also known as box-and-whisker plots) are invaluable statistical visualisation tools that provide a comprehensive summary of data distribution in a compact, easy-to-interpret format. They efficiently display five critical statistical measures, the minimum, first quartile, median, third quartile and maximum values, allowing for quick assessment of data spread and central tendency. One of the critical advantages of box plots is their ability to identify outliers, making them excellent for data quality checks and anomaly detection. The box plots compare distributions, variability and central tendencies achieved when comparing the actual BCI score across multiple building categories, as demonstrated in Figure 5 (education, commercial and residential/apartment complex buildings).

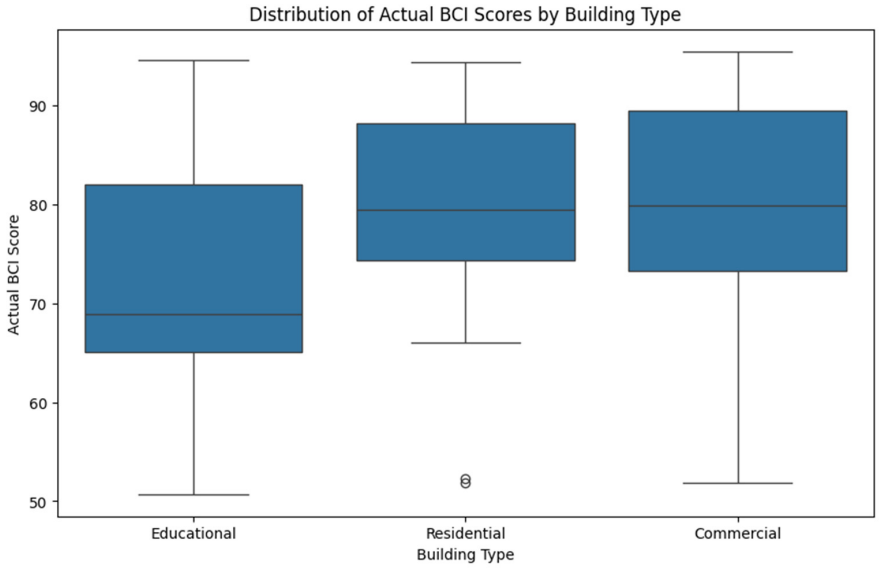


Figure 5. Distribution of building type.

5.8. Structural Integrity Plots

Structural integrity plots are visualisation tools for comparing predicted versus actual structural assessment scores, offering insights into the accuracy and reliability of prediction models. The plot in Figure 6 and Table 3 displays the predicted values of BCI when performed by ANN and DNN predicted methodologies compared to the actual BCI. The plots below are precious in building condition assessment, as they help identify systematic biases or errors in prediction models. When points consistently deviate from the ideal diagonal line, it indicates potential systematic over- or under-prediction issues that need addressing. The spread of points around the diagonal line provides immediate visual feedback about prediction precision and model reliability. Colour coding of ANN (blue), DNN (red) and actual BCI (purple) was used to highlight different prediction modelling scores. Where the dots are closer together or denser in positions indicates where the model performs best. When focused on one building asset, the structural integrity analysis report can assist in identifying if the model performance degrades for specific conditions or improves over time.

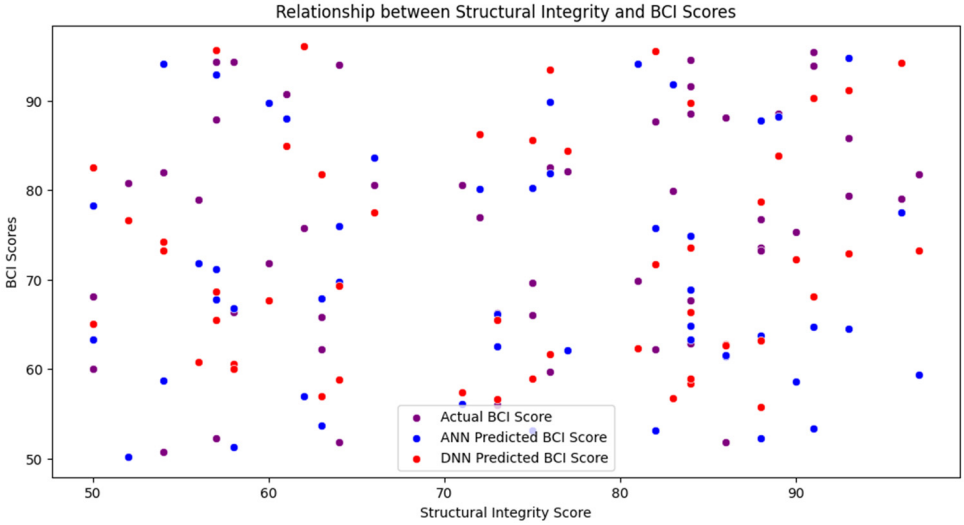


Figure 6. Relationship between structural integrity and BCI scores.

Table 3. Comparison of Structural Integrity, BCI, ANN and DNN table.

Building	Structural Integrity Score	Actual BCI Score	ANN Predicted BCI Score	DNN Predicted BCI Score
1	93	85.88	94.75	91.14
2	57	87.92	71.15	65.51
3	73	66.28	62.58	56.63
4	60	71.84	89.76	67.74
5	66	80.54	83.65	77.56
6	57	52.26	92.89	68.72
7	84	94.61	64.88	89.77
8	84	91.67	74.87	66.40
9	82	62.26	75.75	95.54
10	54	50.72	94.11	74.21
11	91	93.87	53.39	90.36
12	88	73.55	63.76	63.16
13	90	75.35	58.59	72.28
14	77	82.15	62.08	84.38
15	56	78.95	71.84	60.81
16	58	94.36	66.77	60.58

Table 3. *Cont.*

Building	Structural Integrity Score	Actual BCI Score	ANN Predicted BCI Score	DNN Predicted BCI Score
17	57	94.38	67.76	95.72
18	61	90.76	87.99	85.01
19	83	79.91	91.85	56.72
20	82	87.64	53.17	71.75
21	97	81.83	59.40	73.21
22	72	76.95	80.20	86.25
23	73	56.04	66.14	65.54
24	86	88.13	61.44	62.74
25	84	88.57	63.29	58.40
26	93	79.42	64.51	72.99
27	89	88.56	88.19	83.92
28	71	80.62	56.15	57.44
29	76	59.71	81.90	93.44
30	84	62.88	74.88	73.58
31	50	60.09	63.34	65.07
32	84	67.73	68.89	58.94
33	86	51.83	61.53	62.68
34	96	79.06	77.52	94.25
35	63	65.82	53.67	81.81
36	52	80.82	50.23	76.70
37	50	68.11	78.26	82.60
38	54	82.04	58.74	73.30
39	75	66.01	53.19	85.66
40	63	62.25	67.86	57.00
41	88	73.31	52.28	78.77
42	76	82.57	89.90	61.66
43	58	66.37	51.24	60.05
44	64	94.02	76.05	69.36
45	64	51.84	69.73	58.86
46	75	69.64	80.24	58.95
47	91	95.48	64.77	68.08
48	62	75.75	56.98	96.14
49	81	69.90	94.18	62.36
50	88	76.72	87.75	55.72

6. Discussion

6.1. Interpretation

The MAE values for both DNN and ANN prediction indicated that the DNN output was closer to actual BCI scores than the output from the ANN model concerning lower MAE, even though both models have a negative R-squared value for explaining the variance of the actual BCI scores. An R^2 value less than zero means that it is worse than a horizontal mean line, meaning the model might be overfitting or underfitting [59]. Therefore, the results indicate that though the DNN outperformed ANN regarding MAE, more fine-tuning or feature engineering might be needed to improve the prediction quality further.

6.2. Implications for Building Management

The accurate forecasts of a BCI assist in identifying maintenance liabilities and rates of deterioration and allow facility managers to rank those buildings or parts of them that need to be repaired or actions taken to fix them [60]. Using valid forecasts for BCI can help asset inspectors and engineers quickly and accurately assess buildings to identify any risks associated with a building due to outstanding maintenance or poor building performance or identify trends associated with assets incurring accelerated deterioration and premature lifecycle expiry. Analysing buildings and determining an accurate BCI further contributes to a building's environmental and sustainability targets where resources such as energy or

structural material are wasted, and through identifying variations, engineers can pinpoint errors and faults to take the necessary actions and optimise operational expenditure.

Through this analysis, DNN was found to be more effective than ANN in predicting the BCI and offers better accuracy in evaluation, which is critical in asset management and strategic maintenance planning. The findings thus establish the appropriateness of DNN for complex data sets and encourage its usage in predictive maintenance and resource optimisation, possibly with further integration with visual data models such as CNN.

6.3. Internet of Things (IoT) and Sensor Networks

Internet of Things (IoT) devices and sensor networks can significantly improve BCI calculation by providing real-time, continuous monitoring of building conditions [61]. These sensors can track a wide range of parameters, including the following:

(a) *Structural Integrity*—Structural integrity is, therefore, one of the significant features of safety and longevity to measure in a building; it gives the structure the capability to withstand all kinds of loads and stress over time. So, high structural integrity scores correspond to stable, well-maintained buildings with fewer chances of major repairs and more periods of life [62]. Thus, low scores indicate several risks and chances of structural failure, which may impact the Building Condition Index (BCI).

(b) *Indoor Air Quality*—Indoor air quality plays a significant role in the health and comfort of the occupants. IAQ metrics encompass the levels of pollutants, ventilation effectiveness and humidity. Poor air quality may cause respiratory problems and decreased productivity [63]. It is among the most critical factors for BCI. Good IAQ is achieved by constant monitoring and filtration, which has an excellent effect on the building's condition since it ensures that internal environments are safe and healthy.

(c) *Energy Consumption*—Energy consumption measures a building's efficiency in terms of resource use. For instance, electricity and heating energy consumption are high. Low consumption levels usually mean low energy usage, which calls for sound insulation and modern HVAC systems—a characteristic that BCI will thrive upon. High energy usage portrays inefficiency, which exerts strain on resources and increases the cost of operating. Due to sustainability issues, energy efficiency is currently incorporated into BCI.

(d) *Occupancy Patterns*—Occupancy patterns reveal occupancy intensity, a direct indicator of wear and tear. For instance, a highly occupied commercial building would require frequent maintenance to avoid deterioration, which would affect BCI scores [64]. Patterns allow for proactive maintenance to preserve buildings' quality.

(e) *Thermal Comfort*—This is the ability of buildings to regulate temperature and moisture, which is considered pivotal for the satisfaction of inhabitants. Comfortable thermal conditions, therefore, enhance users' experiences and, indirectly, the BCI of optimising HVAC systems [60]. On the other hand, inefficient warming and cooling lead to increasing energy consumption and discomfort for the inhabitants, causing reduced BCI.

7. Conclusions

It is envisaged that with the expansion and maturity of ANNs, DNNs and CNNs, the BCI calculation methodologies will become more sophisticated, automated and integrated with traditional assessment approaches. With the introduction of AI and ML, these digital solutions are expected to significantly contribute to more accurate defect detection, strategic maintenance strategy decisions and the development of dynamic BCI calculations. However, realising the full potential of these innovative strategies will require the following to be established and promoted across the more comprehensive construction and facility management industries.

(a) *Standardisation and Interoperability*—As BCI generation technologies become more advanced, standardisation and interoperability between different systems and methodologies will become necessary [65].

(b) *Common Data Formats*—Standardised BCI generation also necessitates the development of standard data formats for building condition information [56].
(c) *Open Protocols*—Open protocols for data exchange between different building management systems, IoT devices and BCI calculation tools will be essential for advancing BCI generation and use. These protocols enable a more integrated approach to building condition assessment, allowing for seamless data flow between various systems and stakeholders.
(d) *Training and Development*—As new systems, computers and software applications are introduced into buildings, current and emerging facility managers, asset managers and asset inspectors are required to train and develop.

As was shown in this assignment, the evolution of BCI methodologies since 2015 reflects a broader trend towards more intelligent, more sustainable buildings and cities. By leveraging these advanced technologies and methodologies, facility managers, property owners and asset inspectors will be better equipped to identify and report on building maintenance standards and outstanding liabilities and improve on the accuracy of building conditions, thereby identifying investment risks and operational inefficiencies.

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