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An Alternative Rural Housing Management Tool Empowered by a Bayesian Neural Classifier

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Abstract: In developing countries, decision-making regarding old rural houses significantly relies on expert site investigations, which are criticized for being resource-demanding. This paper aims to construct an efficient Bayesian classifier for house safety and habitability risk evaluations, enabling people with none-civil-engineering backgrounds to make judgements comparable with experts so that house risk levels can be checked regularly at low costs. An initial list of critical risk factors for house safety and habitability was identified with a literature review and verified by expert discussions, field surveys, and Pearson's Chi-square test of independence with 864 questionnaire samples. The model was constructed according to the causal mechanism between the verified factors and quantified using Bayesian belief network parameter learning. The model reached relatively high accuracy rates, ranging from 91.3% to 100.0% under different situations, including crosschecks with unused expert judgement samples with full input data, crosschecks with unused expert judgement samples with missing input data, and those involving local residents' judgement. Model sensitivity analyses revealed walls; purlins and roof trusses; and foundations as the three most critical factors for safety and insulation and waterproofing; water and electricity; and fire safety for habitability. The identified list of critical factors contributes to the rural house evaluation and management strategies for developing countries. In addition, the established Bayesian classifier enables regular house checks on a regular and economical basis.

Keywords: rural house; Bayesian classifier; safety; habitability; risk management

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1. Introduction

Dilapidated houses in rural areas are a common and critical issue worldwide for their high frequency and serious implications. In developing countries, being constrained by certain economic factors, traditional raw soil structures, brick–timber structures, and wooden structures accounted for a large proportion of rural dilapidated houses, of which more than 60% of raw soil structures are dangerous [1]. According to Peshkov et al. [2], areas with dilapidated houses have more than tripled since 1990, with an ageing rate of 1.5% per year, while new house construction projects are progressing slowly. Zhou et al. [3] analysed the situation of rural houses in China and revealed that nearly 40% of provinces are unqualified regarding rural house safety. Maniatis [4] and Triantafyllopouls [5] found 1800 vacant buildings in the centre of Athens, Greek, and nearly 85% of these buildings need intervention for improvement. Lopez [6] found that the principal building material in rural Jalisco was adobe brick. In addition, the vulnerability of adobe construction to the elements, notably water, wind, and pests, required homeowners to continuously tend to their houses.

Currently, the common management strategies for rural houses rely on onsite visits from trained experts [7]. Different interventions such as maintenance, renovation, and demolition may be suggested based on the expert's investigation results. However, such strategies normally involve the experts' long-distance travel and significant time expenditures on sites and are highly dependent on expert manpower. For the same reason, this method is potentially susceptible to external and subjective inference. On the other hand, the latest housing management system is based on image recognition and artificial intelligence to identify the development of housing cracks [8–10]. However, the threshold for using this method is relatively high in both expenses and professional knowledge. In areas where dilapidated houses are centralised, such as rural villages, local dwellers cannot easily access the resources required for such investigation methods. Therefore, the overarching aim of this paper is to establish a simple artificial intelligence model by extracting and visualising the experts' knowledge and experiences. The Bayesian belief network model can be used as an alternative to expert judgements on the spot to reduce the resources consumed by experts' onsite investigations. Furthermore, this model will also be able to automatically classify rural houses into different risk levels, mimicking expert decisions in order to avoid subjective biases made by experts on certain occasions. Therefore, this model could directly benefit local dwellers by guaranteeing their safety and quality of life and contribute to the formulation of rural house management strategies.

2. Theoretical Background

Research into house risk management can be found eminently in the literature. For investigations into attitudes and policies for housing risk management, Peshkov et al. [2] took the Russian national plan as a sample to explore the actions taken by the municipal government in emergency situations and dilapidated houses through the literature and onsite investigations. They discovered that the main tasks faced by the governments of Russian cities were to clear blocks of dilapidated housing, relocate citizens, and create favourable conditions for investors to effectively integrate the development of built-up areas. The researchers recommended developing uniform, whole-country rules to determine the amount of compensation for homeowners during their resettlement to emergency houses and to strengthen control over the quality, completeness, and timeliness of major repairs to apartment buildings. In order to explore the gap between rural and urban house management, Tiwari [11] conducted quantitative statistical analyses and found that, in rural areas of India, mismatches between required and available housing stock were not as stark as urban areas but the quality of houses left much to be desired. Only 45 per cent (58.10 million) of residential and 42.2 per cent (2.52 million) of non-residential houses were in good condition, and 6.3 per cent (8.14 million) of residential and 4.5 per cent (0.27 million) of non-residential houses were in a dilapidated condition. The author concluded that the policies formulated by the government needed to be applied flexibly to urban and rural areas. Whatever the level of power devolution, adequate funding is a prerequisite. It is important to recognize that the rural housing problem is a national problem and cannot be funded only at the local level. Wei et al. [12] took Anhui Province in China as an example to analyse its risk level and the fault characteristics of houses from both qualitative and quantitative perspectives. Then, he suggested that Level C and D houses with safety risks and that could not be reinforced should be dismantled as soon as possible to avoid collapse. Government departments should put forward requirements for newly built rural houses and offer professional suggestions on geological conditions, housing design, and construction so as to improve the quality of newly built houses in rural areas. These suggestions all reflect the current situation of old houses in various countries and some of the policies adopted. In most countries, rural houses need to be invested with a lot of money and manpower to provide a safe living environment for rural populations.

The standards of house risk management in different countries were also reflective of attitudes and policies. The standard of house risk management presented different situations relevant to economies. In developing countries, safety might still be the main concern. The safety of rural houses or general houses can mainly be evaluated by whether the stress of the main structure meets safety requirements. Specifically, the main structure includes the main stress components, such as walls, beams, columns, roofs, and floors. Experts judge the house level through damage to these main components. For example, regulations in certain countries [13–15] classify house safety by evaluating the house structure and the quality of building materials and equipment. Failure to meet the safety requirements incurs severe outcomes, such as complete collapse [16]. In addition to the above safety requirements, some developed countries push the frontier by including some housing comfort requirements, such as the lighting time of the house, fire rescue access, wall insulation performance, sanitary facilities, etc. [17]. It can be observed that current prevailing policies in developing countries normally only focus on safety risks while ignoring the comfort aspect. The ultimate purpose of houses is to create a living environment for people, and yet, the current lack of habitability consideration in developing countries has led to insufficiency in reflecting this purpose.

Research is also available with respect to critical factors for the identification of house safety and habitability. Ramli et al. [18] first identified these critical factors through a literature review of current safety and health practices from journals and then distributed 50 questionnaires for analysis. It was revealed that the most significant building management factors are documentation and evaluation, building services, and structural and finish integrity. Kaklauskas et al. [19] and Gibson et al. [20] explored and verified the relevant factors that affect the safety of houses using systematic reviews and obtained the following factors: housing and indoor environments; fuel poverty and thermal comfort; indoor environmental exposures and overcrowding; water and sanitation; outdoor environments and residential locations; neighbourhood deprivation; safety and physical activity; noise; pollution; and environmental deprivation. These factors were also recognised by Keall [21], who provided guidance on the development of housing-quality-assessment tools that link the practical measures of housing conditions to their effects on health, safety, and sustainability, with particular reference to tools developed in New Zealand and England. Such factor prioritisation research, to a certain extent, has informed policymaking regarding housing management, but it still cannot alleviate expert-demanding stress in case-specific rural housing management decision-making.

With advancements in technology, some researchers have taken a further step by using machine learning and image recognition techniques to detect and evaluate cracks in houses. In order to evaluate changes in damage and cracks in houses after earthquakes, Torok et al. [8] and Rouchier et al. [9] proposed an image-based three-dimensional (3D) reconstruction method and a new 3D crack detection algorithm by conducting experiments. The principle was to use digital image correlation and acoustic emission monitoring to locate and estimate the size of cracks. For this approach, a small ground robot (with a high-resolution camera) arrives on the scene and sets up at a safe distance from the damaged structure. Bauer et al. [10] used quantitative passive thermography to measure the extent of damage to building façade cracks. This information could be obtained by monitoring the initial 40 min of data, which differentiated the Delta-T values from the cracks, thus evaluating their depth relationship and allowing for the determination of crack damage width. This required a temperature-detection system to receive the infrared radiation emitted by the target object and transform it into temperature readings using data characteristic of the material and inspection conditions (emissivity, reflected temperature, etc.). In order to ensure the safety of houses, Xu et al. [22] observed the inclination and formed a safety test system through data collection, data preprocessing, feature extraction, and a prediction model. Experiments involved applying wireless sensor technology to obliquely observe buildings, and the real-time dynamic monitoring of buildings was achieved. Wu and Liu [23] focused on computer vision technology in artificial intelligence, studying an image classification algorithm and semantic segmentation algorithm based on the deep learning method, and they applied it to the field of building crack image analysis. The intelligent defect detection prototype system built took the scalability of the application into account, including water leakage, deposition, and other defect-detection projects. The study used a combination of UAV and human digital cameras to obtain images of onsite house damage. To sum up, the existing artificial intelligence technology could be used to observe and evaluate the cracks in houses. However, it requires professional equipment and further manual analysis to realize the above processes.

The current house risk management strategies present three gaps. First of all, with respect to inspection standards, those of developing countries often neglect the aspect of habitability. If houses are only evaluated by their safety, the standard deviates from its original aim of providing both safety and comfort to dwellers. An uncomfortable house is more likely to be abandoned in rural areas, left in an increasingly deteriorating situation and inflicting more resource waste on society. Second, the current housing inspection standards in rural areas require regular checks on long lists of factors and may dictate long-distance travel. Such inspection mechanisms highly depend on expert site investigations, but trained expert manpower is not abundant. Third, the latest technology, both the existing 3D detection algorithms and image recognition technology, are only used to identify the cracks in the house. Cracks are only one aspect of judging a house's safety, and it is not possible to evaluate a house as a whole just by observing the cracks. Furthermore, the premise of adopting such algorithms in investigating house safety risks dictates hardware investment and a certain level of understanding algorithms, which creates application barriers to rural areas in developing countries especially [24,25]. Compared with the aforementioned methods, this paper aims to identify housing risk factors for both safety and habitability as the inputs to construct a Bayesian classifier. The model is designed to be accessible and operable for rural house dwellers with no engineering backgrounds to evaluate their own houses. In this case, all of the dwellers can be engaged in the rural house management scheme by initiatively and regularly evaluating and understanding their own houses. If the Bayesian classifier returns an alarming result, experts can then be hired for a site investigation for a more comprehensive evaluation. The model can not only reduce the human burden as an assistance to expert surveys but also reduce overreliance on expert judgments.

3. Research Methods

3.1. Research Procedure and Data Collection

The overarching aim of this paper is to construct a Bayesian classifier for house risk evaluation. As model inputs, critical factors for the safety and habitability risks of rural houses were identified in a literature review. The relationship between the factors was proposed based on a logical deduction and a further literature review and then verified by expert opinions and statistical analysis, producing a shortlist. The verified relationships were then used to build the model structure. After being complied, a functioning artificial intelligence classification model was established. The classifier after being justified by the experts went through two accuracy tests, one with expert-collected data and the other with data from local residents. Finally, a sensitivity analysis was conducted to further understand the classification model and the issue of dilapidated houses in rural areas. Experts collected sample data by observing damage to houses. Based on the collected data, the model imitated the logic of experts to learn and judge so as to classify housing risk levels. Compared with experts, who may be affected by external environmental and subjective factors, it was more objective to classify houses through models. The purpose of this model is to help villagers check their houses daily to avoid using the resources consumed by experts. At the same time, the model assisted the experts in maintaining objectivity during site investigations.

Two expert groups were formed for data collection. All experts had over ten years of academic or practical experience in the relevant fields. Expert group A contained five experts who were partially located in different villages in the southeast coastal area of China to ensure that the data collected by the experts were not duplicated. They were responsible for the site investigations in the target areas and data collection regarding evaluations of the safety and habitability situations of rural houses. At the same time, experts filled in rural housing danger and habitability test forms onsite and took photos of house damage for evidence. They did not necessarily know each other, and communications were purposely not organised between them so that independence and impartiality were maintained to the utmost extent. Furthermore, the correctness of data collection was not judged by only one expert. In the later stage of data collection, our research team reviewed the photos of houses one by one to reduce the subjective bias of the experts. This research investigated 864 rural houses in 51 villages in the investigated areas. All houses in these areas were numbered. A total of 605 houses (70% of the total) were randomly selected as samples for model construction. The inspection lasted for ten months, from March to December 2021. Collected data included the construction era, structural form, the layout of the house, the area of the field measurement, the existence of dangerous points in each house, and the evaluation of the safety and habitability levels. All data were measured, noted, or photographed. Samples of the investigation report and instruments used for investigation are available in S1 of the Supplemental Data for the specific onsite expert evaluation form. Expert group B also contained five experts and was organised for auxiliary purposes. Three online focus groups with expert group B were conducted to verify the factor list, model structure, and model accuracy and sensitivity results. The two authors with the most industrial experience in the relevant field acted as organisers for the focus groups in order to keep the discussion on track.

For the model accuracy tests, theoretical tests were first conducted with the unused 259 (30% of the total) samples collected by the expert group. The theoretical tests evaluated the model's consistency with expert judgements. In addition, fifty random local residents in different villages were involved in the practical tests. The established model was presented to the participants for them to provide information based on their own perceptions of the housing situation, and the classification results were also compared with expert judgements. The practical tests evaluated the model's capability of producing accurate risk classifications as an alternative and aid to expert judgements.

3.2. Data Analysis Method

The statistical verification of the relationship between factors was performed using Chi-square tests. Its purpose was to compare the consistency between the actual sample frequency and the expected frequency if equally distributed [26]. Considering the characteristics of the data in this research, Pearson's Chi-square test was selected, with calculations following Equation (1), where O_i represents the observed frequency associated with the ith frequency class, and E_i represents the expected frequency calculated from the theoretical distribution law for the ith frequency class [27].

$$\chi^2 = \sum_{i=1}^{n} \frac{(O_i - E_i)^2}{E_i} \tag{1}$$

After establishing the model structure, Bayesian belief network parameter learning was used for structure quantification. A Bayesian belief network is a graphical data structure that compactly represents the joint probability distribution of an event of interest by exploiting conditional dependencies and uses prior information to estimate posterior information to predict the unknown parameters of the distribution [26,28,29]. As shown in Equation (2), $P(A)$ was the prior probability, indicating knowledge and assumptions about the parameter before the sample was observed, regardless of any value of B. $P(A \mid B)$ was the conditional probability of A after the known occurrence of B. As an a posteriori probability, it represented an update of the original knowledge after making new observations. $P(B \mid A)$ was the conditional probability of B given that A had occurred.

$$P(A|B) = \frac{P(B|A)}{P(B)} \cdot P(A) \tag{2}$$

For multiple factors that jointly lead to housing risk factors, the chain rule of Equation (3) can be applied. In practical applications, the joint probability is constrained by the conditional independence prerequisite, relying on the chain of conditional probability [30].

$$P(X_1, X_2, \ldots X_n) = P(X_1)P(X_2|X_1)\ldots P(X_n|X_1, X_2, \ldots X_n) \tag{3}$$

4. Analyses and Results

4.1. Factor Identification

The resulting model is expected to be an abstract of expert decisions. Thus, the factor identification should mimic the logic of experts during their investigations and evaluations, i.e., from the perspective of the mechanical structure. According to the structure of the houses, factors were divided into three categories from bottom to top, i.e., the foundation, superstructure, and roofing system. In order to reflect habitability, a literature review was also conducted to identify relevant factors. Factors identified for habitability include five aspects, i.e., lighting and ventilation; insulation and waterproof; water and electricity pipelines; sanitary equipment; and fire safety, which are summarised based on the current literature. Detailed factors under each category and factors for habitability with references and sources are summarised in Table 1.

Table 1. Risk factor identification table for rural houses.

	Safety	
Categories	**Risk Factor**	**Sources of Risk Factor**
Underground	Foundation	Nigeria National Building Code [13], Deng and Sun [31], Zhang and Xiong [32]
Superstructure	Wall	Municode [33], Deng and Sun [31], Guo et al. [34]
	Bonding material	Cambodia Code [15], Guo et al. [34], Zhang et al. [35]
	Beam and column	Nigeria National Building Code [13], Zhang et al. [35]
Roofing system	Purlins and roof trusses	Zhou et al. [1]
	Roof and floor	Deng et al. [36]
Others	Private reconstruction and expansion	Author added factor
	Structure type	Zhou et al. [1], Fang et al. [37], Li and Deng [38]
	Site environment	Zheng et al. [27], Chou and Zhang [39]
	Seismic structure	Guo et al. [34], Anagnostopoulos and Moretti [40]
	Construction era	Zhou et al. [1], Li and Deng [38]
	Habitability	
Categories	**Risk Factor**	**Sources of Risk Factor**
Habitability	Insulation and waterproof	Honolulu Code [41], Australian Code [42]
	Fire safety	Ho et al. [7], Hasofer et al. [43], Australian Code [42]
	Lighting and ventilation	Ho et al. [7], Honolulu Code [41], Klein et al. [44]
	Sanitary equipment	Honolulu Code [41], Stewart [45], Robb [46]
	Water and electricity lines	Ho et al. [7], Guo et al. [34], Australian Code [42]

4.2. Evaluation Criteria

4.2.1. Overall Evaluation Criteria

The investigation results for dilapidated houses show grades revealing their level of danger and habitability. By synthetically considering research and regulations in different countries and areas [47–50], four levels were devised:

A. The structure meets the requirements of normal use; no dangerous points are found and the house structure is safe; the owner may strengthen the daily maintenance of the main structure and shall not dismantle the stressed components at will or change the building function.

B. The structure basically meets the requirements of normal use. Individual structural components are in a dangerous state, but the main structure safety basically meets the normal use requirements; the owner of the house shall carry out the timely maintenance and treatment of dangerous components in the house.

C. Part of the load-bearing structure does not meet the requirements of normal use. There is a local, dangerous situation that constitutes a local dangerous building; the owner should be informed of the danger of the house immediately, a dangerous house sign should be posted at the door of the house, and the house should be reinforced and repaired in time.

D. The load-bearing structure can no longer meet the requirements of normal use; the owner is required to immediately stop using it or living there, and a cordon should be set up around the house.

At the same time, the classifications of house habitability were also divided into three levels. The assessment of specific factors is based on the lowest level of habitability risk factors [36,51].

A. The houseowners can live comfortably when the house has complete facilities, sufficient lighting and ventilation, insulation and waterproofing, water and electricity pipelines, and fire safety, thus meeting the basic requirements of the residents; only daily maintenance is required.

B. The housing facilities are basically complete. The lighting and ventilation are basically sufficient. The insulation and waterproofing, water and electricity pipelines, and fire safety basically meet the requirements of the residents; repair is dictated for improvement.

C. The housing facilities are not complete; the lighting and ventilation are insufficient; the insulation and waterproofing, water and electricity pipelines, and fire safety do not meet the requirements. Renovation and redecoration are necessary.

4.2.2. Specific Evaluation Criteria

Each of the factors identified in the literature was evaluated using questionnaire responses, and for each factor, evaluative options were provided in the questionnaire for the respondents to select from. The evaluative options were A, B, C, and D, indicating an ascending order of risk propensity for ordinal factors such as construction time, foundations, walls, etc., as well as categorical meanings for nominal factors such as structure type, site environment, seismic structure, etc. More details about the meaning of the evaluative options of each factor are available in the Supplemental Data.

4.3. Model Structure

When using a Bayesian belief network to analyse rural dilapidated houses, the network structure containing the associations between the identified factors must be established first. With respect to the mechanical structures of the houses, the load is transmitted to the main load-bearing structure through the roof or floor, and then, the load-bearing structure transfers the load to the foundation. Combining the relevance of various risk factors, the factors were decomposed into the following influence paths according to the structure of the house's stress, which were then corroborated by logical judgments and literature data to form the basis of the Bayesian belief network's topology.

(1) Foundation, roofing system, load-bearing system → overall safety level.

The load-bearing system and roof system constitute the upper structure of the house, and the foundation represents the lower structure of the house, so the load-bearing system, roofing system, and foundation together constitute the overall safety level of the house. Between these three factors, the foundation had the highest proportion of influential factors. The reason is that the quality of the foundation also directly affects the upper load-bearing system. Therefore, the foundation accounts for a larger share in the post-option revaluation.

(2) Wall, Beam and column, Bonding material, Purlins and roof truss → Load-bearing system.

The wall; beam and column; bonding material; and purlins and roof trusses all affect the safety of the load-bearing system. The roof truss purlins transfer the load of the upper part of the house to the wall, beam, and column, thus constituting the load-bearing system of the house. Deng et al. [36] combined actual engineering experience and concluded that when carrying out a house risk appraisal on a load-bearing system composed of walls, beams, and columns, the correlation status of each component should be considered. The relevance of the contact structure determines the scope of its impact.

(3) Purlins and roof truss, Roof and floor → Roofing system.

Purlins, roof trusses, and roof slabs are inseparable from each other. When the roof truss is damaged, a break in the purlins inevitably leads to the destruction of the roof, and the roof damage will also accelerate the corrosion of wooden roof trusses and wooden purlins.

(4) Construction era, Site environment → Foundation.

Chou and Zhang [39] used data survey methods to analyse 956 dilapidated rural houses in Gansu Province and found that the rural areas were remote. Most of the housing construction site projects involved hiring a feng shui master to check the local geomancy and lacked geological exploration, so the quality of the foundations could not be guaranteed in later periods.

(5) Construction era, Seismic structure, Structure type, Foundation → Wall, Beam and column.

The construction era is the main factor that affects the wall and the beam and column. The older the construction, the more serious the ageing of the wall and the beam and column. This manifests as cracking and peeling on the surface layer, which causes severe structural damage and cracks. The seismic structure mainly affects the stability of the house's structure. Ring beams and structural columns connect the wall to the whole house and restrain the deformation of the wall to a certain extent. In a survey of the current situation of 4817 rural houses in Inner Mongolia, Hao et al. [52] concluded that the longer the construction period, the more serious the damage to the house. This was due to different construction techniques during construction, a low economic level, the poor quality of building materials, and the long-term influence of the natural environment. The proportion of B level houses with shorter construction periods had also gradually increased.

(6) Construction era, Structure type → Bonding material.

Fang et al. [37] found that the bonding materials used in houses with different structures were not exactly the same in an investigation of the status quo of rural houses in Fujian Province. The poor cohesiveness of raw soil houses generally led to the presence of fine or long cracks in most walls; masonry-structure houses were built due to the low level of construction technology, the poor quality of construction materials, low mortar strength, and insufficient mortar joints, resulting in poor house quality; stone-structure houses had many types of bonding materials, such as yellow mud masonry, mortar masonry, gravel stacking, etc.; different bonding materials eventually resulted in big differences in the integrity of houses.

(7) Construction era, Structure type, Wall → Purlins and roof truss.

As the construction period becomes longer, the wooden roof trusses and wooden purlins of houses gradually shrink due to the influence of the natural environment, which causes serious moth-eaten damage, rot, and deformation. The structural type also has a certain influence on roof trusses, purlins, and slab roofs. At present, rural stone-structure and raw soil-structure houses generally adopt wooden roof trusses, wooden purlins, and double-sloping tile roofs using firewood bases. Masonry-structure houses have adopted prefabricated flat roofs without roof trusses or purlins. When a wall is damaged and skewed, the roof truss placed above it will also be affected.

(8) Construction era, Purlins and roof trusses → Roof and floor.

When the construction era is longer, the reed wood base layer of the roofs commonly used in rural houses is likely to rot and break, and the tiles fall off and break. When the purlins and roof trusses deform, the roof also shows different degrees of sinking trends, which leads to roof collapse.

(9) Insulation and waterproofing, Fire safety, Lighting and ventilation, Water and electricity pipelines, Sanitary equipment → Overall habitability level.

The Municode [33] and Honolulu Code [41] stipulate that the safety of houses involves the following factors: water and electricity pipelines are connected normally without ageing or damage; walls are equipped with thermal insulation and a moisture-proof layer; the roof is waterproof; the waterproof coating is not aged and damaged; houses have enough fire, rescue, and escape channels that meet the requirements of the design size; daylight and ventilation provide sufficient natural illuminance; the opening positions of rooms can directly circulate outdoor air; houses have independent sanitation and shower equipment; etc. All of these factors affect the overall habitability level of the house.

(10) Roofing system, Wall → Insulation and waterproofing.

Tong [53] evaluated external wall insulation systems, roof waterproofing quality, wall cracking and falling off, and roof panel seepage. He found that the external thermal insulation of the subject's walls was hollow and severely disconnected; the external thermal insulation system had serious water seepage and dampness; and the roof waterproofing membrane was cracked and detached, resulting in a lack of insulation and a waterproof function for the house. It could be seen that the roofing system, the wall, the insulation, and the waterproofing had a certain correlation.

(11) Wall → Water and electricity pipelines.

As current hydropower pipelines are generally pre-buried inside walls, the normal operation of hydropower pipelines is also be affected when walls are damaged or collapse.

The authors used the SPSS 25.0 software to calculate the Chi-square value between these two risk factors, as can be seen in Table 2. When the degree of freedom was fixed, each Chi-square value corresponded to the p-value. A cut-off point of 0.05 was used to judge the statistical significance of the relationships above. The statistical analysis results indicated that all THE above relationships passed the significance test. The results are summarised in Table 2. The model structure was thus established with the tested relationships, shown as the structure of the model in Figure 1. The model structure was verified by a focus group with expert group B.

Table 2. Pearson's Chi-square test of independence.

Factors	χ^2	p Value	DF	Relationship Verified
Foundation → Overall safety level	204.139	0.000	9	Yes
Roofing system→ Overall safety level	474.805	0.000	9	Yes
Load-bearing system → Overall safety level	1370.320	0.000	9	Yes
Wall → Loadbearing system	1538.987	0.000	9	Yes
Beam and column → Load-bearing system	517.974	0.000	9	Yes
Bonding material → Load-bearing system	526.743	0.000	9	Yes
Purlins and roof truss → Load-bearing system	301.127	0.000	12	Yes
Purlins and roof truss → Roofing system	1033.952	0.000	12	Yes
Roof and floor → Roofing system	1336.368	0.000	9	Yes
Construction era → Foundation	19.170	0.004	6	Yes
Site environment → Foundation	127.493	0.000	3	Yes
Construction era → Wall	34.628	0.000	6	Yes
Seismic structure → Wall	17.400	0.001	3	Yes
Structure type → Wall	42.305	0.000	9	Yes
Foundation → Wall	119.571	0.000	9	Yes
Construction era → Beam and column	29.816	0.000	6	Yes
Seismic structure → Beam and column	13.776	0.003	3	Yes
Structure type → Beam and column	17.382	0.043	9	Yes

Table 2. *Cont.*

Factors	χ^2	*p* Value	DF	Relationship Verified
Foundation → Beam and column	81.507	0.000	9	Yes
Construction era → Bonding material	37.736	0.000	6	Yes
Structure type → Bonding material	25.323	0.003	9	Yes
Construction era → Purlins and roof truss	62.751	0.000	8	Yes
structure type → Purlins and roof truss	102.548	0.000	12	Yes
Wall → Purlins and roof truss	300.170	0.000	12	Yes
Construction era → Roof and floor	29.323	0.000	6	Yes
Purlins and roof truss → Roof and floor	561.039	0.000	12	Yes
Insulation and waterproofing → Overall habitability level	643.960	0.000	4	Yes
Fire safety → Overall habitability level	490.034	0.000	4	Yes
Lighting and ventilation → Overall habitability level	192.696	0.000	4	Yes
Water and electricity lines → Overall habitability level	345.623	0.000	4	Yes
Sanitary equipment → Overall habitability level	55.502	0.000	2	Yes
Roofing system → Insulation and waterproofing	490.670	0.000	6	Yes
Wall → Insulation and waterproofing	262.425	0.000	6	Yes
Wall → Water and electricity lines	201.817	0.000	4	Yes

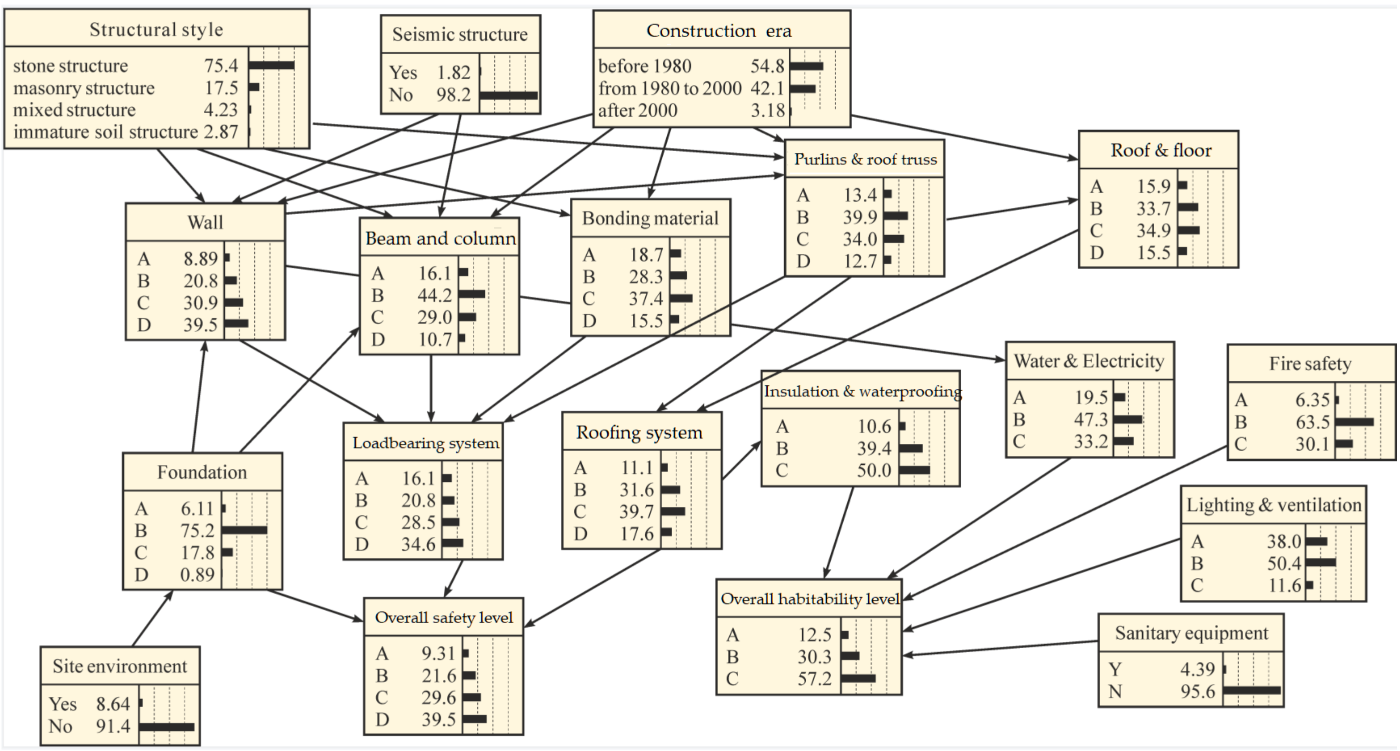

Figure 1. Bayesian model structure.

4.4. Structure Quantification

The training of the Bayesian belief network model was divided into structure training and parameter learning. The training of the model structure of the Bayesian belief network parameter learning was assisted by the Netica 32.0 software [54]. Structural training determined the independence and dependence of each factor and established the causal relationship between the factors, which were connected by arrows. Meanwhile, model parameter learning determined the conditional probability of each node given the link structures and the data [55]. Data from the 605 samples were organised according to their probabilistic distributions. After constructing the structure in Netica's interface with nodes and connections, each node was attached to a table containing probabilistic distributions of said node dependent on its parent nodes. The above identification factors were transformed into the parent node, intermediate node, and child node in the Bayesian belief network. With the help of the Netica 32.0 software, the model was drawn, and the parameters were learned using the Incorp case file in the software. Furthermore, the original statistical data were input into the prior probability and conditional probability tables. Finally, the Bayesian belief network structure diagram was formed, as shown in the structure of the model in Figure 1.

For application, a user needs to first evaluate the house performance pertaining to the nodes in the model. For more details on related evaluation criteria, please refer to the Supplemental data S2. When it is difficult to evaluate the purlins and roof truss, site environment, or other nodes, the user can leave the form blank. Therefore, the model can classify when some nodes are unknown. After assigning states to these nodes, the model will automatically classify the distribution of the safety state and the habitability state of the house. The user can take measures to resolve risks based on the model classification results.

4.5. Model Accuracy Test

4.5.1. Theoretical Test

The model accuracy was tested using two methods in parallel, i.e., the theoretical test and the practical test. During the theoretical test, the Bayesian neural classifier was tested under both conditions of complete data and incomplete data with the remaining 206 samples (30%) collected by the questionnaire survey. All nodes in the classifier were assigned with conditions according to the collected questionnaires for the complete data test, while different scenarios were designed to simulate possible situations of data unavailability. For incomplete data, the node with missing data was set as the initial probability. Then, the model brought the initial probability to sub-nodes for further calculation so as to obtain the probability of the final classification result. The incomplete data test mainly accounted for situations where certain factors were unobservable or observations of certain factors were vague. It was designed for dwellers with no civil engineering backgrounds as the users of the model and simulated the following three situations:

1. Scenario I: Difficulties in observing indoor roof ceilings, purlins, and roof trusses and uncertain judgement of fire safety;
2. Scenario II: Difficulties in obtaining construction eras; site environment unknown; and the beam and column damage is not clearly defined;
3. Scenario III: The foundation, bonding material, insulation, and waterproofing are unknown.

For risk level classification, the model achieved accuracy rates of 100% and 98% for complete and incomplete data, respectively; for habitability classification, the model achieved 96% and 91.3%. Detailed test results for each case are summarised in Tables S2 and S3 in the Supplemental Data. The accuracy of the model when dealing with incomplete data was slightly lower than when the data was complete, but it was still acceptable. The lowest accuracy rate for the habitability level was also above 80%, which could assess a house smoothly as well.

4.5.2. Practical Test

In order to better enable dwellers to self-identify their houses, the dwellers must be informed of the basic house evaluation criteria in Supplemental Data S2. For situations where villagers cannot distinguish or identify fuzzy components, the factors can be put into the initial test state. After all the risk factors are determined, the model will automatically provide the probability distribution of the house risk. This research randomly selected 50 villagers for onsite self-identification, and the accuracy of the model is shown in Table S4 in the Supplemental Data. The accuracy rate of the classification of the house safety level was 94%, and the habitability level was 92%, which was basically consistent with the above classification results based on the data sample. Part of the reason for the classification error was that a small number of villagers made mistakes in the identification of house components or had a greater subjective impression, which led to a certain bias in the evaluation.

4.6. Sensitivity Analysis

The sensitivity analysis of the Bayesian belief network was meant to analyse the influence relationship of the changes in various nodes on the output results. By using a Bayesian belief network in the management of rural houses, based on the sensitivity coefficients of each factor, it was possible to quickly find out the factors that have a greater impact on the results so that dwellers can take timely measures to relieve the dangers of their houses. Factors that were less sensitive were ignored or eliminated to reduce the complexity of the model. In the Netica 32.0 software, a sensitivity analysis of the Bayesian belief network was performed. We selected the "overall safety level" and "overall habitability level" and clicked "Sensitivity to Findings" to perform a sensitivity analysis, as is shown in Table 3.

Table 3. Node sensitivity analysis table.

Node	Overall Safety Level			Overall Habitability Level		
	Mutual Info	Per Cent %	Variance of Beliefs	Mutual Info	Per Cent %	Variance of Beliefs
Overall safety level	1.839	100	0.498	0.010	0.751	0.003
Overall habitability level	0.010	0.547	0.001	1.340	100	0.340
Bearing system	0.557	30.300	0.130	0.004	0.295	0.001
Wall	0.112	6.100	0.021	0.029	2.190	0.007
Roofing system	0.088	4.770	0.009	0.083	6.230	0.020
Purlins and roof truss	0.044	2.390	0.005	0.030	2.310	0.008
Foundation	0.034	1.870	0.005	0.002	0.139	0.000
Insulation and waterproofing	0.029	1.590	0.003	0.167	12.500	0.038
Roof and floor	0.019	1.030	0.002	0.021	1.540	0.005
Water and electricity lines	0.015	0.844	0.002	0.073	5.470	0.014
Bonding material	0.016	0.734	0.002	0.000	0.011	0.000
Beam and column	0.013	0.709	0.002	0.000	0.023	0.000
Construction era	0.005	0.262	0.001	0.003	0.253	0.000
Site environment	0.001	0.080	0.000	0.000	0.001	0.000
Structure type	0.001	0.067	0.000	0.000	0.007	0.000
Seismic structure	0.000	0.000	0.000	0.000	0.008	0.000
Lighting and ventilation	0.000	0.000	0.000	0.009	0.707	0.001
Sanitary equipment	0.000	0.000	0.000	0.010	0.791	0.001
Fire safety	0.000	0.000	0.000	0.031	2.330	0.003

The relevant information in the table indicates the degree of influence of the node on the final node. The larger the value, the greater the sensitivity. It can be seen that the top three factors affecting the overall safety level of houses are walls, purlins and roof trusses, and the foundation. The top three factors affecting the habitability rating are insulation and waterproofing, water and electricity pipelines, and fire safety.

5. Discussion and Findings

5.1. The Implication of Critical Factors for Dilapidated Housing Management

According to the sensitivity analysis of the Bayesian belief network, the three important factors affecting the safety level of houses were walls, purlins and roof trusses, and the foundation. The focus group with expert group B revealed that this was consistent with the actual procedure of expert investigation since their first instinct was to examine these three factors. This demonstrated the model's capability as an alternative tool to an expert's actual site investigation. These results were also consistent with the theoretical criticality of the factors. The wall and the roof trusses and purlins are the main force-bearing components, damage to which would endanger the safety of the house [38,56]. It is worth noting that the relevant research lists the foundation as the primary factor affecting the safety of a house. However, since the evaluation of the safety of rural houses in this study mainly relied on the observation of the superstructure of the house, the evaluation of the underground foundation depended on the cracks generated by the superstructure. In addition, for the existing houses in this study, there were few samples of houses that completely collapsed into ruins due to foundation damage, so the factor of foundation ranked lower than that of wall and roof purlins in the sensitivity analysis.

Unlike the safety factors that were mechanically associated, the habitability of houses was measured with factors concerning dwellers' subjective perceptions. In practice, the dwellers were more concerned about water leakage and wall insulation. However, the site investigation revealed something more severe. Ageing electric wires were a common issue in the investigated rural houses. In addition, rural houses were too often covered with weeds on the wall surface, which are highly flammable. These factors compromise both habitability and safety levels. These further demonstrate the necessity of including habitability factors in inspection frameworks for rural houses.

In summary, after identifying the above critical factors, we should pay more attention to the observation of the above factors in later housing management. When there is a problem with the house, the homeowner can take effective measures in time to resolve the danger. For house wall reinforcement, prestressed seismic reinforcement technology and reinforced concrete surface reinforcement technology can be used. The seismic performance and overall performance of the wall can be improved with strengthening. For the repair of purlins and roof trusses, decayed roof trusses can be replaced in time, and split rods can be reinforced by adding steel ferrules. For factors related to habitability, it is generally possible to transform the housing environment through interior decoration to improve the comfort of the house. For fire safety, firefighting equipment must be equipped indoors, and escape and rescue channels must meet national regulations.

5.2. The Implication of the Classification Model for Dilapidated Housing Management

At present, the inspection and appraisal of old rural houses are based on onsite appraisals by experts. The advantage of expert onsite inspection is that the experts are experienced in house appraisal. They analyse the damage to the house from a more professional perspective and have clear judgments of the whole house. A field survey of rural houses in Suixi County, Huaibei City, Anhui Province, combined with the hazard levels of houses in the area, comprehensively analysed the causes of house hazards [31]. Dwellers need to submit an application for house inspection to the housing management department. After the approval is completed, experts are responsible for on-the-spot inspections and photography. Within 15 days, a document is created and distributed to the households according to the actual situation of the houses. Although this method is more accurate, it consumes manpower and material resources. It can be seen that the whole process takes a long time, and it takes at least half a month from the dwellers' applications to the receipt of documents. For some dangerous or emergency houses, such a long wait is clearly unbearable.

Under these circumstances, the authors established a Bayesian classifier model as a supplement to expert site investigations. When the input data was complete, the model reached an accuracy rate of 100% for house safety classification and 96% for habitability classification. The Bayesian classifier also considered scenarios simulating the model application of non-civil engineering professionals when they are not sure about the evaluations of certain input data, and, therefore, we designed Scenarios I, II, and III to account for certain missing input data. When in Scenarios I, II, and III, respectively, the overall safety level is 98%, 98%, and 98%, and the overall habitability level is 96%, 96%, and 82%. In the actual use process of dwellers, the overall safety level is 94%, and the overall habitability level is 92%. Before using the model, the user needs to have a general understanding of the criteria of each factor. During the actual investigation, users could evaluate the house by themselves if provided with simple instructions. Most of the users acknowledged the user-friendly design of the Bayesian classifier model interface. However, it is worth noting that the self-evaluation assisted by the classifier might be biased subject to users' own economic intentions and preferences, which also caused certain deviations in the evaluation results. For another application scenario, the model could be utilised by the person in charge of the rural community, thereby reducing the subjectivity of the homeowner's self-judgment.

Compared with field inspection, by using our model, dwellers could conduct preliminary identifications of their own houses by themselves, so the dangers of the houses could be found and dealt with early. The relevant node factors in the model are highly consistent with the onsite expert identification factors, so the models could be judged by highly simulated experts. At the same time, the actual situation of the user is also taken into account. When some factor evaluations are ambiguous, the relevant factors in the model could be placed in the initial probability, thereby ensuring the normal output of the final model. Although the classification accuracy of the model is not as high as that of expert onsite detections, the model is reliable and could be used for the preliminary identification of users' homes. In addition, although many houses in rural areas were not classified as dangerous houses, their habitability was poor, leading to abandoned houses. This model incorporates habitability into the appraisal of rural houses to reflect the humanized design.

Compared with the existing models, this Bayesian belief network model reduces subjective bias and assists in the ready acceptance of the classification results. For example, the presentation of the multilayer perceptron model is a black box. The users enter data at the input terminals and set the output nodes. The model automatically calculates the output results. The operation mechanism of the middle hidden layer of the model is not transparent. Conversely, the Bayesian belief network model is presented in a form of a white box. Each of the nodes in a Bayesian belief network represents a random variable and embodies practical implications. Based on this, users can clearly understand the working logic principles between nodes. Users can also understand the process of model establishment more intuitively, and the results of the model output are also easier to accept. Moreover, in certain cases where human experts might be affected by the external environment and subjective biases, the model remains objective. The model input modifies some outliers and details that experts ignore. By judgement, these outliers are probably results induced by experts' subjective biases or external pressures such as experts' emotions or dwellers' requirements. On the whole, the model simplifies the process of onsite appraisal by experts, provides effective digital assistance, and helps residents evaluate house grades independently. Bayesian model classification analysis is a kind of inference classification based on previous sample data learning.

6. Conclusions

Old rural house management is a critical issue faced by developing countries. This paper contributed to this issue from several perspectives. This paper updated the current key factors in the evaluation of old rural houses, including the overall safety level and the overall habitability level. It was mainly based on a literature review of factor identification, field survey data of 864 dilapidated rural houses on the southeast coast of China, and a Chi-square analysis of factor selection. Different structural forms were taken into account for the investigation of critical factors. In addition, the overall habitability level of houses was also taken into account, whereas existing literature has mostly focused on the safety aspects. The purpose was to make houses not only safe to live in but also comfortable to live in. This research provides a more reasonable theoretical method for the evaluation of rural houses and provides relevant theoretical and technical support for the renovation of old rural houses to ensure the safety of people's lives and property. More importantly, this research established a Bayesian classifier to automatically generate the corresponding house level according to the user's choice. The accuracy and sensitivity of the model were analysed in different situations. For safety level classifications, the model achieved accuracy rates of 100% and 98% for complete and incomplete data, respectively; for habitability classifications, the model achieved 96% and 91.3%. Furthermore, in the practical test, the accuracy rate of the classification of the house safety level was 94%, and the habitability level was 92%. Through sensitivity analysis, it could be seen that the top three factors affecting the overall safety level of houses are walls, purlins and roof trusses, and the foundation. The top three factors affecting the habitability rating are insulation and waterproofing, water and electricity pipelines, and fire safety. The proposed Bayesian model in this paper could be used by dwellers or government managers to assist in the initial appraisal and management of houses. The easy selection of model inputs and the automatic features enable residents with non-civil-engineering backgrounds to make judgements regarding the safety and habitability levels comparable with trained experts so that houses can be checked on a regular and economical basis. In the end, the model sensitivity analysis suggested that people should pay more attention to walls, purlins, and foundations for safety evaluations and insulation and waterproofing; water and electricity; and fire safety in evaluating living conditions.

However, this research also comes with certain limitations. The samples collected in this research were all from the southeast coast of China, with a sample size of only 864. However, the experts in the field survey all have more than 20 years of experience in the civil industry and rich work experience. The samples collected were of high quality and had a certain degree of representativeness. At the same time, when Netica is used for model classification, a computer is needed, and mobile phone apps can be explored in the future so that people can make preliminary identifications of their houses more convenient at a mobile terminal.

Supplementary Materials: The following supporting information can be downloaded at https://www.mdpi.com/article/10.3390/su15031785/s1: S1. Data Collection. S2. Specific evaluation criteria. S3. Model accuracy test.

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