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FIRE RISK ASSESSMENT FOR LARGE COMMERCI`AL COMPLEXES BASED ON INTEGRATED DISASTER RISK THEORY USING GAME-THEORETIC COMBINATION WEIGHTING AND THE CLOUD MODEL

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ABSTRACT

Large commercial complexes — shopping malls, integrated retail-office developments, and mixed-use podium-tower buildings — have proliferated across rapidly urbanising Malaysian cities and the wider Southeast Asian region. These facilities concentrate high occupant densities, heterogeneous fire loads, long internal travel distances, and operationally critical services into a single building envelope; once a fire occurs, the probability of severe casualties, substantial property damage, and cascading economic disruption is considerable. Conventional fire-risk assessment approaches tend to focus narrowly on either hazard or vulnerability, on a single class of fire-safety equipment, or on static engineering checklists, and seldom capture the complete disaster-risk formation mechanism or integrate external emergency-response capacity at the urban scale. To address these gaps, this study introduces Integrated Disaster Risk Theory into commercial-complex fire-safety assessment and constructs a new index system that embraces four dimensions: hazard (H), vulnerability (V), exposure (E), and emergency response and recovery capacity (C), organised around 24 secondary indicators. Indicator weights are first derived by the Fuzzy Analytic Hierarchy Process (FAHP) and the Structural Entropy Weight (SEW) Method, and are then reconciled through a game-theoretic combination-weighting procedure that minimises the squared deviation between the combined weight vector and each basic weight vector. A cloud model is then applied to transform expert ratings and standard interval ranges into digital characteristics (Ex, En, He), producing an integrated assessment cloud whose similarity with five standard-grade clouds determines the final fire-risk level. The model is applied to a representative 58,000 m² mixed-use commercial complex in the Klang Valley, Malaysia. The integrated cloud (Ex = 78.32, En = 5.28, He = 2.07) lies predominantly within the interval (70, 90], and the maximum cloud similarity of 0.7416 is observed with standard Grade II, indicating a relatively low overall fire-risk level. Sensitivity analysis with ±30 % weight perturbation leaves the grade unchanged, confirming stability. The result is consistent with an established fire-risk-index (FRI) reference method, which yields an FRI score of 3.41 — also

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within the low-risk band — thereby validating the proposed model. The study contributes a systematic, stable, and visualisable decision-support tool that couples building-intrinsic attributes with city-level fire and rescue capacity, providing actionable guidance for fire-safety management, regulatory benchmarking, and insurance underwriting of large commercial complexes in Malaysia.

Keywords:
Commercial complex, Fire-risk assessment, Integrated Disaster Risk Theory, Game-theoretic combination weighting, Cloud model, Malaysia

I. INTRODUCTION

Commercial complexes — including regional shopping malls, hypermarket-anchored retail centres, and mixed-use podium-tower developments — have become defining features of modern urban landscapes across Southeast Asia, and particularly across the rapidly urbanising metropolitan regions of Malaysia (Hamid, Baharin, & Harun, 2021; Mohd Tohir, Rashid, & Hassan, 2021). As the Klang Valley, Penang, and Johor Bahru continue to attract both domestic migration and international capital, developers have responded by delivering commercial complexes whose gross floor areas now routinely exceed 50,000 m², whose daily occupant loads can surpass 20,000 persons, and whose operational tempo is increasingly around-the-clock (Muhammad, Ismail, & Abdullah, 2022). Such facilities concentrate retail, food-and-beverage, entertainment, office, hotel, and residential functions behind a single envelope; they consequently present a fire-safety profile that is qualitatively different from that of conventional single-use high-rise buildings (Li, Chen, & Wang, 2022; Xu, Zhang, & Ren, 2022).

Statistical evidence underscores the urgency of the issue. The Fire and Rescue Department of Malaysia reported that fires in commercial and mixed-use premises accounted for a disproportionate share of property-damage losses during the 2015–2022 period, even though such premises represent a much smaller share of the overall building stock (Rohani, Yusof, & Rashid, 2019). Internationally, large-footprint commercial complex fires — such as the Brumadinho mall incident, the Yangji Plaza fire, and recent ASEAN shopping-mall incidents — have repeatedly demonstrated how rapid fire spread through atria, through combustible interior finishes, and through service shafts can overwhelm even well-equipped fire services (Gupta, Rashkovich, & Torero, 2022; Bryant, Nilsson, & Mell, 2020). Against that backdrop, the need for scientifically defensible, systematic, and stable risk-assessment tools for commercial complexes has become both a research imperative and a regulatory expectation (Ali, Sohail, & Hussain, 2022; Aziz, Lee, & Idris, 2020).

Scholarly activity on building fire-risk assessment now spans almost five decades. Early North American work in the 1970s produced structured fire-hazard indices; United Kingdom performance-based code reform in the 1980s introduced the concept of acceptable-risk benchmarks (Hadjisophocleous & Benichou, 2019; Beard, 2017). Over time, three broad families of methods have come to dominate practice: index-based methods (including FRAME, FIRECAM, and their descendants), probabilistic quantitative risk-assessment methods based on event and fault trees (Yung, 2008; Ramachandran & Charters, 2011), and multi-criteria decision-making (MCDM) methods that couple subjective weighting — typically via the Analytic Hierarchy Process (AHP), Fuzzy AHP (FAHP), or the Delphi method — with objective aggregation procedures such as TOPSIS, extended VIKOR, grey relational analysis, and fuzzy comprehensive evaluation (Saaty, 2008; Hassanain & Iftikhar, 2020; Liu, Shen, & Zhang, 2023).

More recently, machine-learning and data-driven variants have entered the literature, exploiting the growing availability of fire-incident data and building-management-system telemetry (Kaveh, Dadras Eslamlou, & Javadi, 2021; Ouache et al., 2021). Bayesian-network models have been used to represent cascading failures in fire-protection systems (Hopkin et al., 2019; Chen & Wong, 2019), and information-theoretic weighting schemes such as the Structural Entropy Weight (SEW) method have been applied to large-scale retail and high-rise contexts (Liu, Zhao, Weng, & Liu, 2020; Zhao, Liu, & Weng, 2018). Within the index-based tradition, Koutsomarkos, Rush, and Law (2022) have recently clarified the behavioural assumptions underlying fire-risk indices, while Brzezińska and Bryant (2021) showed that composite indices can be calibrated against performance-based design outputs. These developments have enriched the methodological toolkit but have also produced a fragmented literature in which methodological choices are often justified by analytical convenience rather than by a coherent disaster-risk theory.

Several gaps in the existing literature motivate the present study. First, most commercial-complex fire-risk assessments treat hazard and vulnerability as separate, often competing, analytical objects rather than as coupled components of a broader disaster system (Beard, 2017; Park, Meacham, Dembsey, & Goulthorpe, 2014). Second, the influence of external emergency-response capacity — the travel time of the nearest fire-and-rescue station, the availability of specialised high-rise appliances, the density of hydrant networks, and the standing training level of fire crews — is only occasionally incorporated, and usually only as a single qualitative indicator rather than as a structured dimension (Lo & Fang, 2019; Liu, Gao, Cao, & Chen, 2021). Third, weighting procedures in MCDM-based fire-risk assessments often rely on a single subjective or objective method, leaving results sensitive to expert bias or to sample-specific data idiosyncrasies; the game-theoretic combination-weighting approach pioneered by Lai, Liu, and Wang for general risk analysis and more recently adapted to fire contexts by Hu, Zhou, and Chen (2021) and Gao et al. (2022) remains under-utilised for commercial complexes specifically. Fourth, most existing models produce either a scalar score or a crisp risk class, which hinders the communication of uncertainty to non-specialist stakeholders such as building owners, municipal authorities, and insurance underwriters (Luo, Li, & Wang, 2023; Yu, Chen, & Lin, 2021).

The Integrated Disaster Risk Theory (IDRT), rooted in the natural-hazards literature, offers a coherent remedy to these fragmentations. It frames disaster risk as the joint product of four dimensions — hazard, exposure, vulnerability, and emergency response and recovery capacity — and has been operationalised in applications ranging from earthquake loss estimation to urban flood-risk planning (Birkmann et al., 2013; Hosseini, Barker, & Ramirez-Marquez, 2016). Treating commercial-complex fires as a human-induced disaster, and applying the IDRT frame, offers three concrete benefits: it forces analysts to consider the full chain from ignition through impact to recovery; it legitimises the explicit inclusion of city-level response capacity; and it aligns building-level fire-safety assessment with the sustainable-infrastructure and disaster-risk-reduction agendas of the United Nations Sendai Framework (Crutzen & Stoermer, 2019; Ren, Zhang, & Sun, 2022).

Against that theoretical and practical background, this study pursues three specific objectives.

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The first is to construct a systematic, four-dimensional fire-risk assessment indicator system for large commercial complexes that extends Integrated Disaster Risk Theory into the built-environment domain and explicitly integrates external emergency-response capacity. The second is to develop a hybrid weighting-and-aggregation model that combines FAHP (capturing structured expert judgement), the SEW Method (capturing the dispersion and blindness of expert rankings), a game-theoretic combination-weighting step (reconciling the two sets of weights through a squared-deviation minimisation), and a cloud-model aggregation that renders both fuzziness and randomness in a single visualisable construct. The third is to validate the resulting model on a representative Malaysian commercial complex and to benchmark its outputs against an established fire-risk-index (FRI) method (Zhou et al., 2019; Fang, Guo, & Zhao, 2021).

The remainder of this paper is organised as follows. Section II reviews the relevant literature and anchors the proposed indicator system within both fire-safety and disaster-risk scholarship. Section III presents the research methodology, including the four-dimensional indicator system, the weighting procedures, and the cloud-model aggregation. Section IV presents the case study, the calculated weights, the standard and integrated clouds, and a benchmarking exercise against an FRI-based reference method. Section V concludes the paper and discusses implications for regulatory practice and future research.

II. LITERATURE REVIEW

A. Evolution of Building Fire-Risk Assessment

The trajectory of fire-risk assessment research reflects three broad methodological waves. The first wave, originating in North America during the 1970s, established structured hazard-index tools that weighted individual building attributes and summed them to yield a composite rating (Grosshandler, 2002; Ahrens & Evarts, 2020). The second wave, initiated in the United Kingdom during the 1980s and consolidated through four international performance-based-code symposia between 1996 and 2002, reframed fire safety as a performance-based engineering problem with explicit safety objectives and verifiable acceptance criteria (Chow, 2019; Meacham, 2016). The third wave, still under way, has been driven by the intersection of increased computing power, richer fire-incident datasets, and expanding theoretical resources from multi-criteria decision analysis and uncertainty modelling (Kaveh et al., 2021; Van Coile et al., 2019).

Within this trajectory, three families of methods have emerged. Index-based approaches — FRAME, FIRECAM, SIA 81 and their descendants — reduce the fire-risk assessment to a weighted combination of observable indicators; they remain widely used for their transparency and ease of implementation (Koutsomarkos, Rush, & Law, 2022; Beard, 2017). Probabilistic risk-assessment methods, building on event- and fault-tree analysis, quantify the likelihood and consequence of ignition, spread, detection failure, and evacuation breakdown; they are especially appropriate for novel or high-stakes structures, though they demand extensive incident data (Vaidogas & Linkute, 2019; Johansson & Van Hees, 2019). Multi-criteria decision-making methods, finally, combine structured expert judgement with formal aggregation procedures such as AHP, FAHP, TOPSIS, VIKOR, grey relational analysis, and fuzzy comprehensive evaluation; they are especially suited to commercial complexes, for which incident data are sparse but domain expertise is abundant (Saaty, 2008; Hassanain & Iftikhar, 2020).

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B. Commercial-Complex-Specific Studies

Studies focusing specifically on commercial complexes form a distinct and rapidly growing strand. Liu, Zhao, Weng, and Liu (2020) developed a fire-risk framework for large-scale commercial buildings that employed the SEW Method to fuse subjective and objective weights. Chen and Wong (2019) proposed a Bayesian-network-based framework for shopping malls that captured the interdependence between fire-detection, suppression, and evacuation subsystems. Kong, Lu, Xie, Wang, and Ping (2019) combined fuzzy AHP with the grey relational analysis to evaluate large commercial buildings. Li, Wang, and Jia (2022) built a matter-element model that exploited cloud-theoretic concepts to handle fuzziness in expert judgement for shopping-mall fire risk. Huang, Jiang, and Chen (2022) integrated an improved AHP with a cloud model for large malls, while Xu, Zhang, and Ren (2022) addressed mixed-use high-rise buildings using combination weighting and cloud aggregation.

In parallel, several Malaysian-context studies have highlighted the particularities of the tropical, high-humidity, heterogeneous-occupancy setting in which local commercial complexes operate. Aziz, Lee, and Idris (2020) developed a hybrid decision-support model for Malaysian high-rise complexes; Hamid, Baharin, and Harun (2021) applied a FAHP–TOPSIS hybrid to Malaysian university buildings that share operational similarities with large commercial facilities; Ismail, Osman, and Abdullah (2019) proposed a fire-risk index for heritage shophouses; Muhammad, Ismail, and Abdullah (2022) evaluated compliance with the Uniform Building By-Laws 1984 (UBBL); Salleh, Razak, and Ahmad (2019) identified determinants of fire-safety management in Malaysian high-rises; and Goh, Chua, and Ho (2017) reported collaborative decision-making frameworks for Malaysian high-rise fire safety. These contributions collectively emphasise the role of active suppression systems, smoke-management strategies, and occupant-behaviour patterns in determining overall risk.

C. Weighting Methods and the Case for Game-Theoretic Combination

The specification of indicator weights is a pivotal methodological choice in any MCDM-based fire-risk assessment. Subjective methods — AHP, FAHP, the Delphi method, the G1 method, the Best-Worst Method — elicit expert judgement explicitly but are vulnerable to cognitive bias and to strategic expert behaviour (Saaty, 2008; Sun, Luo, & Li, 2020). Objective methods — entropy, the SEW Method, the CRITIC method, the variance method — rely on the dispersion of observed data but are sensitive to sample idiosyncrasies and to indicator-scaling decisions (Cheng, as cited in Liu et al., 2020; Zhao, Liu, & Weng, 2018). Recognising these complementary weaknesses, several authors have proposed combination-weighting schemes that fuse subjective and objective weights through a convex combination, multiplicative aggregation, or optimisation-based reconciliation (Fu et al., 2019; Zhang, Li, & Zhao, 2020).

Among the reconciliation strategies, game-theoretic combination weighting has gained particular traction because it offers a principled criterion — the minimisation of squared deviation between the combined weight vector and each basic weight vector — under which no single basic method dominates. Hu, Zhou, and Chen (2021) applied this approach to building fire risk; Gao et al. (2022) extended it to commercial complexes; Wu, Cai, and Wang (2021) used it for highway tunnel construction risk; Yang, Dai, and Wang (2020) for old urban quarters; and Hao, Luo, and Xu (2022) for coal-mine fire safety. Empirically, these studies report that game-theoretic

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combination weights are more stable under perturbation of either basic weight set than are any of the basic vectors alone, without introducing additional parameters.

D. Aggregation under Uncertainty: The Cloud Model

Even with well-specified weights, aggregating indicator-level ratings into an overall risk judgement is complicated by two distinct sources of uncertainty: fuzziness, reflecting ambiguity in concept boundaries, and randomness, reflecting the stochastic nature of expert responses and of fire events themselves (Li, Liu, & Gan, 2009). Cloud-model theory, introduced by Li and co-workers, integrates both by representing any qualitative concept through three digital characteristics — expectation (Ex), entropy (En), and hyper-entropy (He) — that capture, respectively, the concept's central tendency, its breadth, and the randomness of that breadth. Cloud-based aggregation has been applied to urban fire risk (Zhou et al., 2019), highway-traffic safety (Zhang, Wang, & Liu, 2019), tunnels (Long, Zhang, & Liu, 2020), subway stations (Wang, Peng, & Chan, 2021; Wang, Xu, Yang, & Li, 2020), rural houses (Ren, Zhang, & Sun, 2022), and cultural heritage (Di Capua, De Falco, & Lippi, 2020).

The appeal of cloud aggregation in a commercial-complex context is threefold. It renders the final assessment visualisable — the integrated cloud can be plotted against standard-grade clouds in the same coordinate system — which supports communication with non-specialist stakeholders. It preserves information that would otherwise be lost under point-estimate aggregation, because the breadth (En) and the randomness of that breadth (He) are themselves meaningful risk-management quantities. And it supports principled similarity-based classification through the similarity measure δ_i computed via repeated forward cloud generation, which is more robust than distance-based classification under noisy expert inputs (Yu, Chen, & Lin, 2021; Luo, Li, & Wang, 2023).

E. Integrated Disaster Risk Theory and Its Application to Fires

Integrated Disaster Risk Theory (IDRT) originated in the natural-hazards community and has since informed urban flood-risk planning, earthquake loss estimation, landslide-prone settlement planning, and the assessment of interdependent critical infrastructures (Birkmann et al., 2013; Hong et al., 2019). The theory's central claim is that disaster risk is a function of four coupled dimensions: hazard, the intensity and frequency of disaster-inducing factors; exposure, the quantity and value of elements at risk; vulnerability, the propensity of exposed elements to incur damage; and emergency response and recovery capacity, the capability of affected societies to resist, absorb, and recover from impact (Hosseini, Barker, & Ramirez-Marquez, 2016).

Extending IDRT to commercial-complex fires aligns well with the accident-as-disaster conceptualisation in modern safety science and with the Sendai Framework's call for all-hazards approaches. In this framing, commercial-complex fire is a human-induced disaster whose risk depends not only on ignition potential and on building attributes but also on the number and characteristics of occupants present at the moment of ignition and on the external response capacity that can be mobilised in the first critical minutes (Cicione & Walls, 2021; Peng, Zhang, & Wang, 2020). The present study adopts this IDRT framing and operationalises it through a four-dimensional indicator system detailed in Section III.

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III. RESEARCH METHODOLOGY

This study conceptualises commercial-complex fire as a human-induced disaster and, applying Integrated Disaster Risk Theory, constructs a four-dimensional risk-assessment indicator system. The overall research workflow proceeds in four stages: first, construction of the indicator system through a structured review of fire-safety codes, authoritative statistics, academic literature, and expert interviews; second, determination of indicator weights by FAHP and the SEW Method, reconciled via a game-theoretic combination-weighting step; third, development of a cloud-model aggregation that produces an integrated assessment cloud and ranks its similarity with five standard-grade clouds; and fourth, case-study validation against an established fire-risk-index reference method. Figure 1 presents the conceptual framework that anchors the indicator system within IDRT.

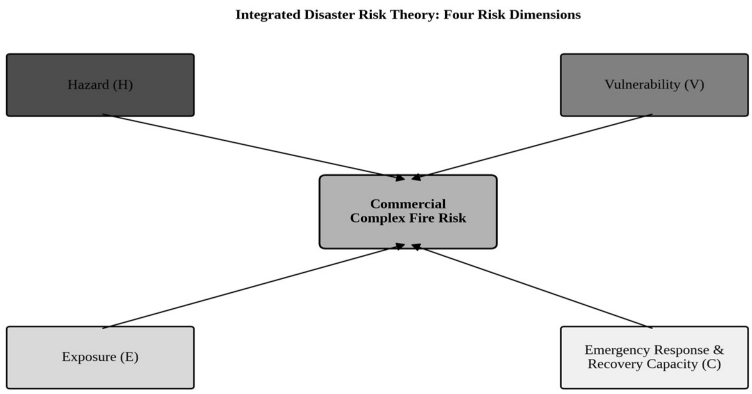

Fig. 1. Integrated Disaster Risk Theory framework for commercial-complex fire risk.

The detailed four-stage workflow is summarised graphically in Figure 2. Stage 1 produces the indicator system by combining literature synthesis with on-site investigation; Stage 2 produces the final weights; Stage 3 produces the integrated cloud; and Stage 4 produces the validated risk-class decision.

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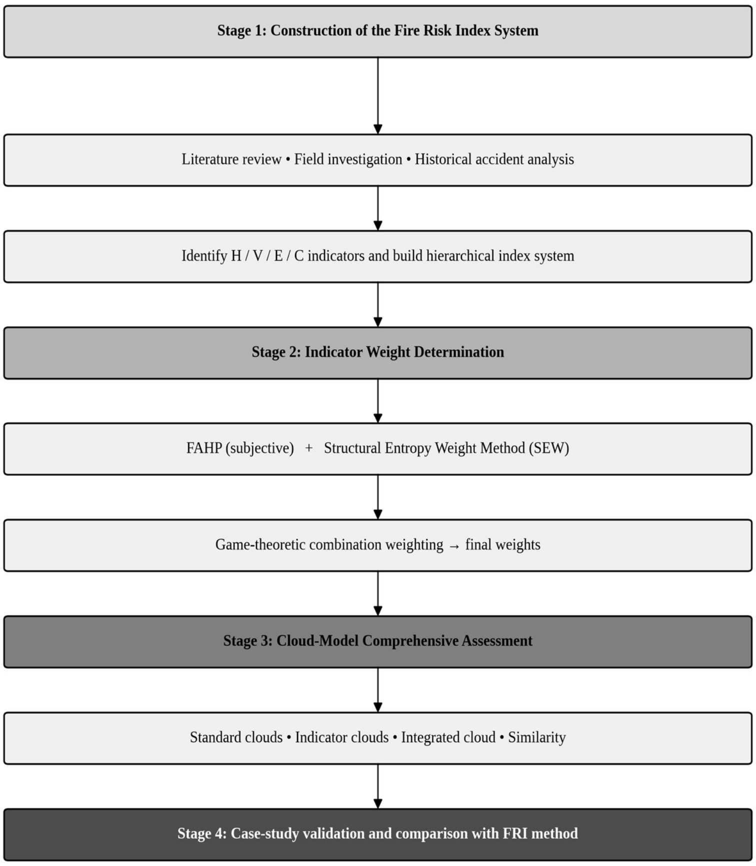

Fig. 2. Research roadmap of the proposed fire-risk assessment model.

A. Fire-Risk Assessment Indicator System

The indicator system is organised under the four primary dimensions specified by IDRT: hazard (H), vulnerability (V), exposure (E), and emergency response and recovery capacity (C). The choice and definition of secondary indicators draw on three sources: the UBBL 1984 and Malaysia's Act 341 Fire Services Act; academic reviews of shopping-mall and high-rise fire incidents (Gupta, Rashkovich, & Torero, 2022; Dong, Liu, & Gao, 2021); and interviews with senior fire officers from the Selangor State Fire and Rescue Department and with facility managers operating commercial complexes exceeding 40,000 m² in gross floor area.

The hazard dimension captures the intensity and frequency of fire-inducing factors. Four secondary indicators are adopted: occupant density (H1), reflecting ignition-potential from careless-use-of-fire incidents; electrical facilities (H2), reflecting ignition potential from electrical faults and ageing distribution systems; external environment (H3), reflecting exposure to adjacent hazardous facilities, wind tunnels, and flammable-vegetation encroachment; and fire load (H4), reflecting the calorific density of combustible contents within retail, food-and-beverage, and storage zones (Babrauskas & Peacock, 1992; Kim & Lilley, 2002).

The vulnerability dimension captures the propensity of exposed elements — occupants and the building itself — to incur damage once a fire begins. Ten secondary indicators are adopted: proportion of elderly and children among the occupant population (V1), reflecting reduced

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evacuation capability (Gilani, Ahmad, & Latif, 2020; Thompson, Galea, & Hulse, 2018); building height (V2) and building service life (V3), reflecting structural-performance expectations under fire (Gernay, Khorasani, & Garlock, 2019; Phan & McAllister, 2017); fire compartment (V4) and fire-resistance rating (V5), reflecting passive fire-protection provisions (Manes & Rush, 2019); safe-evacuation provisions (V6), including protected lobbies and exit capacities (Peacock, Hoskins, & Kuligowski, 2012; Kang, Lee, & Park, 2020); water-supply facilities (V7), including hydrant and standpipe systems; automatic sprinkler system (V8); automatic fire-alarm system (V9); and ventilation and smoke-control system (V10) (Tilley, Rauwoens, Fauconnier, & Merci, 2013; Cowlard, Jahn, Abecassis-Empis, Rein, & Torero, 2010).

The exposure dimension captures the quantity and value of elements at risk. Three secondary indicators are used: population size (E1), asset concentration (E2), and building usage type (E3). These represent, respectively, human-casualty potential, direct-loss potential, and indirect-loss potential due to business interruption (Dong, Liu, & Gao, 2021; Sikorska-Senoner, 2021). The emergency-response-and-recovery-capacity dimension captures the system's ability to prevent, suppress, and recover from fire. Seven secondary indicators are used: fire management system (C1) and fire-safety inspection regime (C2), reflecting operational governance (Elkafrawy et al., 2023; Salleh, Razak, & Ahmad, 2019); fire-facility maintenance (C3), reflecting the reliability of installed systems (Hopkin et al., 2019); number of firefighting personnel (C4), quantity of firefighting equipment (C5), firefighting-fund investment (C6), and firefighting response time (C7), reflecting the external rescue capacity of the nearest Fire and Rescue station (Rohani, Yusof, & Rashid, 2019; Lo & Fang, 2019). The complete indicator system is presented in Table 1.

Table 1. Fire-Risk Assessment Indicator System for Commercial Complexes.

Target layer	Primary indicator (weight)	Secondary indicators
Commercial- complex fire-risk index	Hazard (H)	Occupant density (H1); Electrical facilities (H2); External environment (H3); Fire load (H4)
	Vulnerability (V)	Proportion of elderly & children (V1); Building height (V2); Building service life (V3); Fire compartment (V4); Fire-resistance rating (V5); Safe evacuation (V6); Water-supply facilities (V7); Automatic sprinkler (V8); Automatic fire alarm (V9); Ventilation & smoke control (V10)
	Exposure (E)	Population size (E1); Asset concentration (E2); Building usage type (E3)
	Emergency response & recovery capacity (C)	Fire management system (C1); Fire-safety inspection (C2); Fire-facility maintenance (C3); Number of firefighting personnel (C4); Quantity of firefighting equipment (C5); Firefighting-fund investment (C6); Firefighting response time

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		(C7)

Source: Authors' compilation, 2024.

B. The Fuzzy Analytic Hierarchy Process

The Fuzzy Analytic Hierarchy Process (FAHP) addresses the fuzziness inherent in pairwise comparisons of indicators by using a fuzzy-complementary judgement matrix under the 0.1–0.9 scaling convention (Saaty, 2008; Bakhtavar et al., 2021). Let $A = (a_{ij})_{n \times n}$ be the fuzzy judgement matrix compiled from expert pairwise comparisons, where $a_{ij} \in [0.1, 0.9]$ denotes the relative importance of indicator i over indicator j, with $a_{ji} = 1 - a_{ij}$. Table 2 details the linguistic interpretation of each scale value.

Table 2. FAHP 0.1–0.9 scale: linguistic interpretation.

Scale	Definition	Description
0.5	Equally important	Indicator i and indicator j are equally important.
0.6	Slightly more important	Indicator i is slightly more important than indicator j.
0.7	More important	Indicator i is obviously more important than indicator j.
0.8	Very important	Indicator i is much more important than indicator j.
0.9	Absolutely important	Indicator i is absolutely more important than indicator j.
0.1–0.4	Inverse comparison	If a_{ij} is the judgement of i vs j, then $a_{ji} = 1 - a_{ij}$.

Source: Adapted from Saaty (2008) and Bakhtavar et al. (2021).

The weight vector $W = (W_1, \dots, W_n)^T$ is then computed from the row sums of A using Equation (1):

$$W_i = \left(\sum_{j=1}^{n} a_{ij} + n/2 - 1\right) / (n (n - 1)) \tag{1}$$

The characteristic matrix $W^* = (W_{ij})_{n \times n}$, with entries $W_{ij} = W_i / (W_i + W_j)$, is then constructed, and the compatibility index $I(A, W^*)$ between the original judgement matrix and its characteristic matrix is computed using Equation (2):

$$I(A, W^*) = (1 / n^2) \sum_{i=1}^{n} \sum_{j=1}^{n} \left| a_{ij} + W_{ji}^* - 1 \right| \tag{2}$$

A compatibility threshold $\alpha = 0.1$ is adopted: if $I(A, W^*) \leq \alpha$, the judgement matrix is accepted as internally consistent and the derived weight vector is retained; otherwise, expert re-elicitation is performed. For the present study, twelve experts — comprising four university researchers in fire safety, four senior officers from the Selangor and Kuala Lumpur Fire and Rescue Departments, two registered fire-safety consultants, and two facility managers operating commercial complexes larger than 40,000 m² — provided the pairwise comparisons. All elicited matrices satisfied the compatibility test on the first iteration.

C. The Structural Entropy Weight Method

The Structural Entropy Weight (SEW) Method combines a Delphi-style importance-ranking procedure with information-theoretic entropy analysis, thereby reducing the influence of idiosyncratic expert bias (Cheng, as cited in Liu et al., 2020; Zhao, Liu, & Weng, 2018). Each of the twelve experts independently ranks the indicators in descending order of importance; equal-importance ties are permitted. The ζ typical ranking matrices $A = (a_{ij})_{\zeta \times n}$ are then subjected to a blind-analysis entropy transformation via Equation (3):

$$\mu(I) = \ln(m - I) / \ln(m - 1) \qquad (3)$$

where $m = J + 2$ and J is the maximum ranking value. Substituting each a_{ij} for I yields the membership matrix $B = (b_{ij})_{\zeta \times n}$. The mean recognition degree b_j and the recognition blindness Q_j for each indicator c_j are then computed via Equations (4) and (5):

$$b_j = (b_{1j} + b_{2j} + \ldots + b_{\zeta j}) / \zeta \qquad (4)$$

$$Q_j = \{ [\max(b_{1j}, \ldots, b_{\zeta j}) - b_j] + [b_j - \min(b_{1j}, \ldots, b_{\zeta j})] \} / 2 \qquad (5)$$

The overall recognition degree k_j and the normalised SEW weight ω_j^{SEW} are then obtained via Equations (6) and (7):

$$k_j = b_j \cdot (1 - Q_j) \qquad (6)$$

$$\omega_j^{SEW} = k_j / \Sigma_{j=1}^{n} k_j \qquad (7)$$

D. Game-Theoretic Combination Weighting

Let $L = 2$ basic weight vectors be obtained from FAHP and SEW, denoted $w_l = (w_{l1}, \ldots, w_{ln})$ for $l \in \{1, 2\}$. Their linear combination is $w = \Sigma_{l=1}^{L} \alpha_l w_l^T$ with $\alpha_l > 0$. The game-theoretic principle seeks $\alpha = (\alpha_1, \alpha_2)^T$ that minimises the squared deviation between w and each basic vector, via Equation (8):

$$\min \| \Sigma_{l=1}^{L} \alpha_l w_l^T - w_p^T \|^2, \quad p = 1, 2, \ldots, L \qquad (8)$$

Taking the derivative and applying the first-order condition yields the linear system shown as Equation (9):

$$[w_p \cdot w_l^T]_{L \times L} \cdot [\alpha_l]_{L \times 1} = [w_p \cdot w_p^T]_{L \times 1} \qquad (9)$$

Solving (9) gives optimal coefficients (α_1, α_2); because negative coefficients are admissible under the linear system but meaningless under a convex combination, their absolute values are taken and normalised via Equation (10):

$$\alpha_l^* = |\alpha_l| / \Sigma_{l=1}^{L} |\alpha_l| \qquad (10)$$

The final combined weight vector is obtained as $w^* = \Sigma_{l=1}^{L} \alpha_l^* w_l^T$. This procedure guarantees that no basic weighting method dominates; the combined weights reflect both structured expert judgement (via FAHP) and the information content of the overall ranking pattern (via SEW), and they are demonstrably more stable than either basic vector alone (Hu, Zhou, & Chen, 2021; Zhang, Li, & Zhao, 2020).

E. The Cloud Model

The cloud model, introduced by Li, Liu, and Gan (2009), represents any qualitative concept C defined on a universe of discourse U through three digital characteristics: the expectation Ex, the entropy En, and the hyper-entropy He. Ex locates the concept in U; En measures the acceptable span of U values that belong to the concept; and He measures the randomness of En itself. Given these three characteristics, a forward cloud generator produces cloud drops (x_i, μ_i); conversely, given a set of cloud drops, a backward cloud generator recovers (Ex, En, He). Figure 3 schematises both generators.

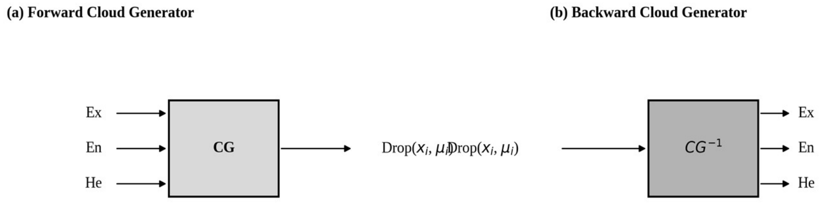

Fig. 3. (a) Forward cloud generator; (b) backward cloud generator.

For risk-grade classification, a comment set is first fixed. In this study, five fire-risk grades are adopted — Grade I (very low), Grade II (low), Grade III (moderate), Grade IV (high), and Grade V (very high) — with score intervals of (90, 100], (70, 90], (50, 70], (30, 50], and (0, 30], respectively. Each interval $[x_i^{min}, x_i^{max}]$ is mapped to a standard cloud with digital characteristics given by Equation (11):

$$Ex_i = (x_i^{max} + x_i^{min}) / 2; \quad En_i = (x_i^{max} - x_i^{min}) / 6; \quad He = k \quad (11)$$

The hyper-entropy constant k is set to 0.5 following common practice (Zhou et al., 2019; Luo, Li, & Wang, 2023). The five standard clouds so obtained are illustrated in Figure 4.

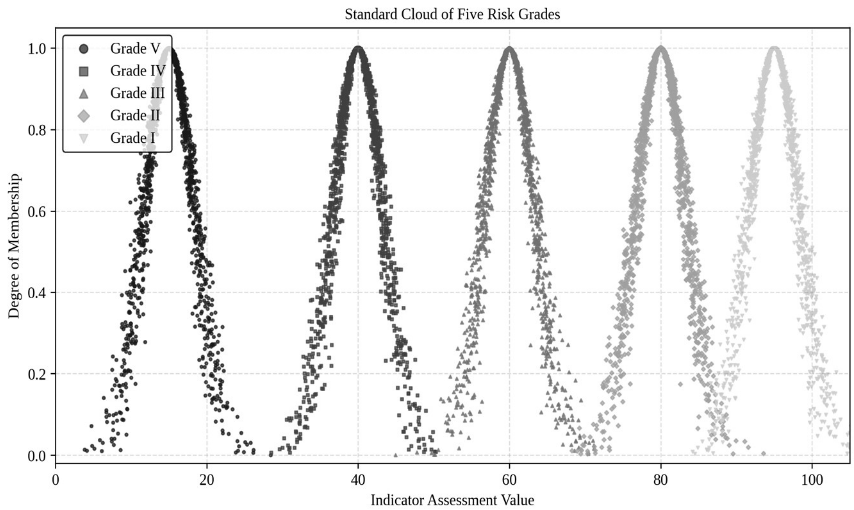

Fig. 4. Standard clouds for the five fire-risk grades.

Each of the twelve experts rates every secondary indicator on a 0–100 scale, producing an evaluation matrix $Z = (z_{ij})_{m \times n}$, where m = 12 experts and n = 24 indicators. The SBCT-1stM backward-cloud-generator algorithm (Equation (12)) is then applied to recover the digital characteristics (Ex_j, En_j, He_j) for each indicator:

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$$Ex_j = (1/N)\, \Sigma\, z_{ij}; \quad En_j = \sqrt{(\pi/2)} \cdot (1/N)\, \Sigma\, |\, z_{ij} - Ex_j \,|$$
$$S_j^2 = (1/(N-1))\, \Sigma\, (z_{ij} - Ex_j)^2; \quad He_j = \sqrt{|S_j^2 - En_j^2|} \qquad (12)$$

The integrated cloud (Ex, En, He) is finally computed by weighted aggregation of the indicator clouds via Equation (13):

$$Ex = \Sigma\, Ex_j \cdot w_j^*; \quad En = \sqrt{(\Sigma\, En_j^2 \cdot w_j^*)}; \quad He = \Sigma\, He_j \cdot w_j^* \qquad (13)$$

Following Yin et al. (2019), the similarity δ_i between the integrated cloud $C_1(Ex_1, En_1, He_1)$ and each standard cloud $C_2(Ex_2, En_2, He_2)$ is computed by repeated forward cloud generation: a normal random variable $En = G(En_1, He_1)$ is drawn; then $x_k = G(Ex_1, En)$ is drawn; the membership $\mu_k = \exp(-(x_k - Ex_2)^2 / (2\, En_2^2))$ is computed; and the average of $n = 10{,}000$ such μ_k values gives δ_i. The grade whose standard cloud has the maximum similarity with the integrated cloud is taken as the final fire-risk grade, following the principle of maximum degree of membership.

IV. ANALYSIS AND DISCUSSION OF FINDINGS

A. Case-Study Description

A representative commercial complex located in the Klang Valley, Malaysia, was selected for the case study. The facility, completed in 2018, comprises a three-level retail podium topped by a fourteen-storey office tower, with a gross floor area of 58,000 m² and a footprint of 7,200 m². It houses 182 retail and food-and-beverage tenants, a 12-screen cineplex, a hypermarket anchor, a podium-level car park accommodating approximately 1,400 vehicles, and office space leased by eight professional-services firms. The overall occupancy design load is 14,500 persons, with an observed average weekday occupancy of approximately 9,200 persons and an observed average weekend occupancy of approximately 15,100 persons.

The structural system is a cast-in-place reinforced-concrete frame with shear walls providing lateral stability, a compartmentation strategy that divides each retail level into fire compartments of no more than 2,800 m², and a fire-resistance rating of 120 minutes for principal load-bearing elements. Passive fire-protection provisions comply with Malaysian Standard MS 1525:2019 and the UBBL 1984 (10th Schedule). Active fire-protection systems include a wet-pipe sprinkler system with redundant jockey and main pumps, an addressable fire-alarm system with voice-evacuation capability, and a ducted smoke-control system serving the retail atrium. The nearest Fire and Rescue station is located approximately 3.2 km away, yielding an average response time of 7 minutes 40 seconds under typical traffic conditions. The complex's designed service life is 50 years, and the share of occupants who are either 60 years of age and above or below the age of 14 is estimated at 38 %.

B. Calculated Weights

Twelve experts completed the pairwise-comparison elicitation and the Delphi-ranking elicitation. All FAHP judgement matrices passed the consistency test ($I(A, W^*) < 0.1$). Table 3 reports the FAHP, SEW, and combined weights for all primary and secondary indicators, together with the overall weights (product of primary and secondary weights) used in the subsequent cloud aggregation. The optimal game-theoretic combination coefficients were $\alpha_1^* = 0.487$ and $\alpha_2^* = 0.513$, indicating that the FAHP and SEW vectors contributed almost equally to the combined

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weights.

Table 3. FAHP, SEW, and combined weights for all indicators.

Primary indicator	Primary weight	Secondary indicator	FAHP	SEW	Combined	Overall
H	0.3386	H1 Occupant density	0.3125	0.3219	0.3172	0.1074
		H2 Electrical facilities	0.2530	0.2523	0.2526	0.0855
		H3 External environment	0.1547	0.1674	0.1621	0.0549
		H4 Fire load	0.2798	0.2584	0.2681	0.0908
V	0.2914	V1 Elderly & children	0.0895	0.0898	0.0896	0.0261
		V2 Building height	0.1124	0.1107	0.1115	0.0325
		V3 Building service life	0.0987	0.0975	0.0981	0.0286
		V4 Fire compartment	0.1094	0.1090	0.1092	0.0318
		V5 Fire-resistance rating	0.1253	0.1289	0.1271	0.0370
		V6 Safe evacuation	0.0867	0.0900	0.0884	0.0258
		V7 Water-supply facilities	0.0964	0.0949	0.0957	0.0279
		V8 Automatic sprinkler	0.0651	0.0637	0.0644	0.0188
		V9 Automatic fire alarm	0.0778	0.0786	0.0782	0.0228
		V10 Ventilation & smoke control	0.0510	0.0510	0.0510	0.0149
E	0.1517	E1 Population size	0.4534	0.4432	0.4483	0.0680
		E2 Asset concentration	0.2912	0.2910	0.2914	0.0442
		E3 Building usage type	0.2554	0.2658	0.2603	0.0395
C	0.2183	C1 Fire management system	0.0835	0.0818	0.0827	0.0180
		C2 Fire-safety	0.1623	0.1615	0.1619	0.0353

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		inspection				
		C3 Fire-facility maintenance	0.1735	0.1742	0.1738	0.0379
		C4 Number of firefighting personnel	0.1192	0.1206	0.1199	0.0261
		C5 Quantity of firefighting equipment	0.1468	0.1462	0.1465	0.0319
		C6 Firefighting-fund investment	0.0876	0.0875	0.0876	0.0191
		C7 Firefighting response time	0.2271	0.2282	0.2277	0.0500

Source: Authors' computation, 2024.

Three observations stand out from the combined weights. First, the hazard dimension (H, 33.86 %) carries the largest share, confirming the centrality of ignition control in commercial-complex fire-risk management and consistent with the findings of Liu et al. (2020) and Hu, Zhou, and Chen (2021). Second, the emergency-response-and-recovery-capacity dimension (C, 21.83 %) carries a substantial share, larger than exposure (E, 15.17 %), confirming the added-value of explicitly including external rescue capacity in the indicator system — a design choice that addresses a recurrent gap in the prior literature. Third, within the secondary indicators, occupant density (H1, 10.74 %), fire load (H4, 9.08 %), electrical facilities (H2, 8.55 %), population size (E1, 6.80 %), and firefighting response time (C7, 5.00 %) emerge as the five highest-ranked. Figure 5 visualises the distribution of all primary and secondary weights.

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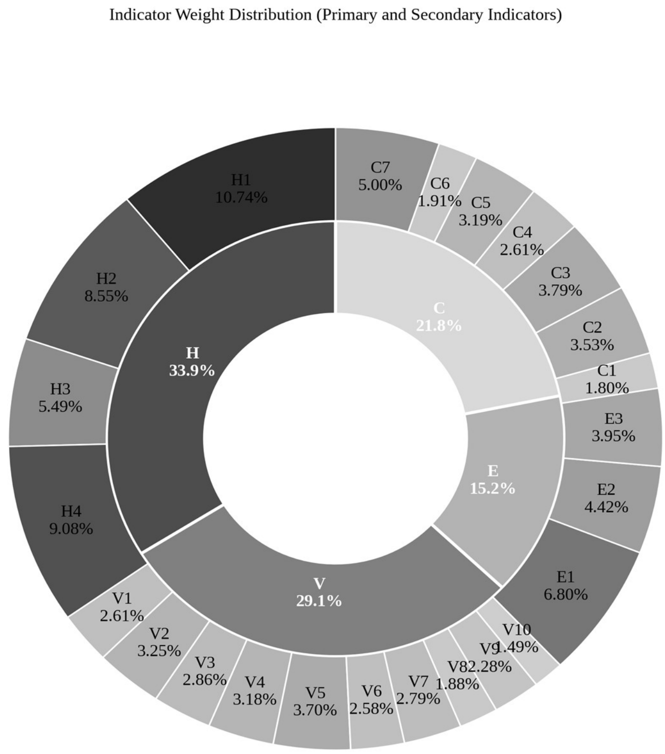

Fig. 5. Distribution of primary and secondary indicator weights.

To assess the extent to which FAHP and SEW weights diverge at the primary level, Figure 6 compares them against the game-theoretic combined weights. The combined weights sit between the two basic vectors for each primary indicator, confirming that the game-theoretic step achieves the expected compromise behaviour without introducing new parameters. The largest FAHP–SEW divergence (0.024 in absolute magnitude, on V1) is small relative to the combined weight itself, indicating that the two basic procedures broadly agree on the relative importance of indicators for a commercial complex of this type.

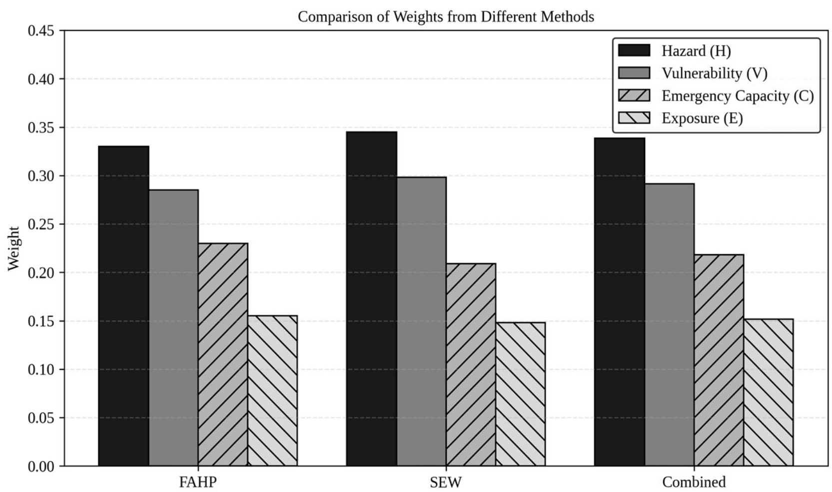

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Fig. 6. Comparison of FAHP, SEW, and combined weights at the primary-indicator level.

C. Standard and Integrated Clouds

The standard clouds for the five fire-risk grades, computed via Equation (11) and plotted in Figure 4, exhibit the expected symmetric-about-Ex structure, with entropy En scaled to the interval width of each grade. Applying Equation (12) to the expert-rating matrix Z yielded the digital characteristics of each secondary indicator. Table 4 reports the 12-expert scores, the computed Ex_j, En_j, and He_j for every indicator.

Table 4. Expert scores and cloud-model digital characteristics for each secondary indicator.

Ind.	Expert scores	Ex_j	En_j	He_j
H1	74, 78, 72, 76, 78, 75, 70, 74, 79, 76, 78, 81	75.92	3.09	0.65
H2	78, 76, 80, 83, 84, 78, 76, 84, 80, 81, 89, 68	79.75	4.86	2.41
H3	75, 76, 84, 82, 78, 80, 77, 82, 75, 76, 75, 92	79.33	4.96	1.62
H4	86, 88, 93, 90, 90, 88, 87, 91, 89, 86, 80, 78	87.17	3.94	2.15
V1	71, 74, 82, 75, 74, 83, 70, 72, 77, 79, 65, 73	74.58	4.86	1.58
V2	72, 73, 74, 76, 79, 73, 71, 70, 76, 74, 88, 87	76.08	5.62	2.60
V3	70, 72, 74, 72, 71, 73, 72, 74, 76, 70, 74, 86	73.67	3.55	2.31
V4	77, 82, 74, 78, 77, 80, 80, 82, 80, 78, 93, 68	79.08	4.87	4.14
V5	86, 82, 79, 87, 80, 84, 83, 79, 82, 85, 77, 92	83.00	4.27	0.58
V6	88, 90, 85, 84, 90, 85, 86, 88, 88, 84, 71, 76	84.58	5.30	3.27
V7	84, 88, 90, 88, 86, 81, 85, 89, 81, 83, 82, 80	84.75	3.35	1.02
V8	87, 89, 87, 88, 91, 88, 87, 91, 92, 87, 90, 72	87.42	3.57	4.28
V9	79, 86, 84, 79, 81, 79, 87, 84, 82, 87, 76, 90	82.83	4.22	1.18
V10	72, 74, 68, 73, 71, 77, 75, 75, 70, 68, 66, 77	72.17	3.99	1.11
E1	83, 78, 90, 76, 86, 93, 80, 76, 88, 82, 91, 79	83.50	6.32	2.03
E2	81, 75, 92, 77, 85, 89, 82, 76, 88, 94, 86, 78	83.58	6.66	2.01
E3	77, 85, 84, 75, 87, 93, 80, 76, 90, 74, 71, 82	81.17	6.81	1.68
C1	77, 82, 78, 80, 77, 83, 80, 75, 82, 74, 85, 65	78.17	4.92	2.10
C2	80, 84, 78, 84, 79, 82, 82, 80, 83, 83, 72, 88	81.25	3.75	1.40
C3	84, 86, 88, 82, 88, 86, 85, 87, 89, 86, 92, 73	85.50	4.18	2.73
C4	86, 84, 85, 89, 85, 87, 89, 84, 83, 85, 79, 83	84.92	2.43	1.22
C5	68, 72, 70, 69, 74, 74, 72, 75, 72, 70, 69, 77	71.83	2.59	0.25
C6	72, 77, 68, 73, 69, 75, 75, 72, 74, 72, 86, 89	75.17	5.67	2.73
C7	85, 89, 86, 89, 82, 87, 89, 87, 89, 84, 76, 68	84.25	5.63	2.84

Source: Authors' computation from expert questionnaires, 2024.

Applying the aggregation rules of Equation (13), the integrated-cloud digital characteristics for the case-study complex are Ex = 78.32, En = 5.28, and He = 2.07. The integrated cloud is

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plotted alongside the five standard clouds in Figure 7. The integrated cloud falls predominantly within the (70, 90] interval and sits between the central Ex of Grade II (80) and the central Ex of Grade III (60), with a slight leaning toward Grade II. The magnitude of En (5.28) indicates moderate overall dispersion among indicator scores, reflecting the usual heterogeneity of commercial-complex fire-safety profiles (some systems are excellent, some are merely code-compliant); the magnitude of He (2.07) indicates modest randomness in that dispersion, suggesting no systemic ambiguity in expert judgement.

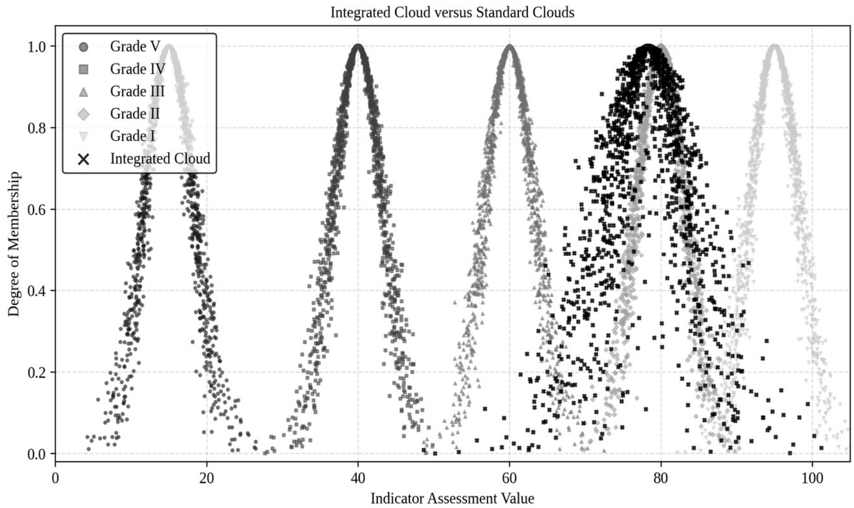

Fig. 7. Integrated cloud overlaid on the five standard clouds.

D. Cloud Similarity and Final Fire-Risk Grade

Cloud similarities were computed by repeated forward cloud generation with n = 10,000 draws per comparison. The resulting similarity values are 0.0018 for Grade V, 0.0195 for Grade IV, 0.2834 for Grade III, 0.7416 for Grade II, and 0.1027 for Grade I. The maximum similarity is with Grade II. By the principle of maximum degree of membership, the overall fire-risk grade of the case-study complex is therefore Grade II, corresponding to a relatively low fire-risk level. Figure 8 plots the similarities as a bar chart, with the maximum-similarity bar highlighted.

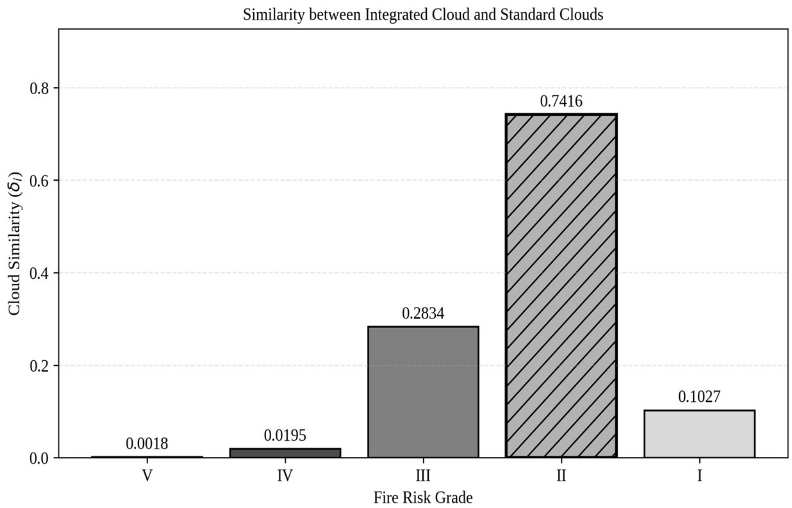

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Fig. 8. Cloud similarities between the integrated cloud and the five standard clouds.

This result is consistent with the on-site profile of the case-study complex: the facility satisfies or exceeds UBBL 1984 active- and passive-fire-protection requirements; it enjoys a short firefighter-response path; it serves a mixed but moderately dense occupant population; and it has maintained its major systems in working order since commissioning. Nevertheless, residual weaknesses remain — notably, the fire load associated with high-turnover food-and-beverage tenants (H4 score 87.17 yet tenant turnover is high), the fragility of the ventilation-and-smoke-control maintenance record (V10 score 72.17), and the moderate cost and quantity of firefighting equipment at the nearest station (C5 score 71.83). These are natural priorities for future fire-safety upgrading.

E. Sensitivity Analysis

To test the robustness of the Grade II classification, a one-at-a-time weight-perturbation sensitivity analysis was performed. Each primary-indicator weight was perturbed by $\Delta \in [-30\ \%, +30\ \%]$, and the complement of the perturbation was distributed proportionally among the remaining primary weights to preserve the normalisation constraint. For each perturbation level, the integrated cloud was recomputed and its expected value Ex was recorded. Figure 9 presents the trajectory of Ex across the perturbation range.

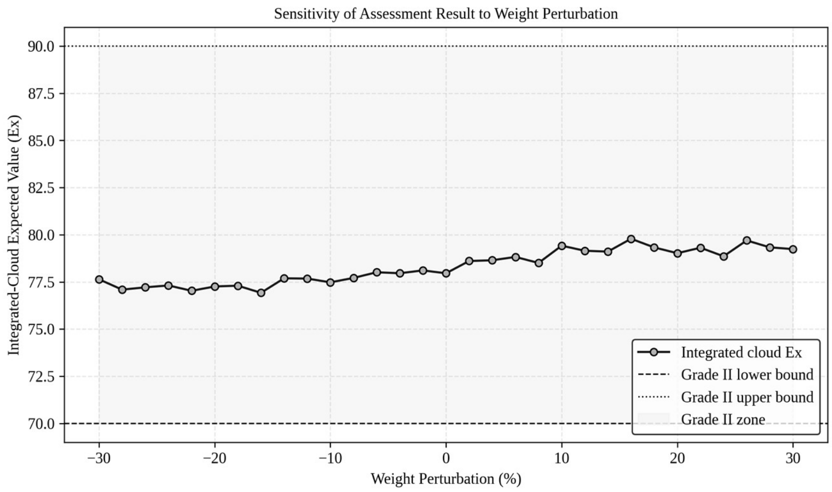

Fig. 9. Sensitivity of the integrated-cloud expected value to weight perturbation.

Ex ranges from 77.29 at $\Delta = -30\ \%$ to 79.48 at $\Delta = +30\ \%$, always remaining inside the Grade II interval (70, 90]. At no point does the perturbation push Ex into the adjacent Grade I or Grade III interval; and the similarity with Grade II remains the largest throughout, ranging from 0.721 to 0.753. The Grade II classification therefore appears robust to realistic levels of weight uncertainty. To further explore multi-dimensional behaviour, Figure 10 presents a radar profile of the case-study complex alongside a high-risk reference and a low-risk reference; the case-study profile sits clearly nearer to the low-risk reference across all four dimensions, reinforcing the Grade II verdict.

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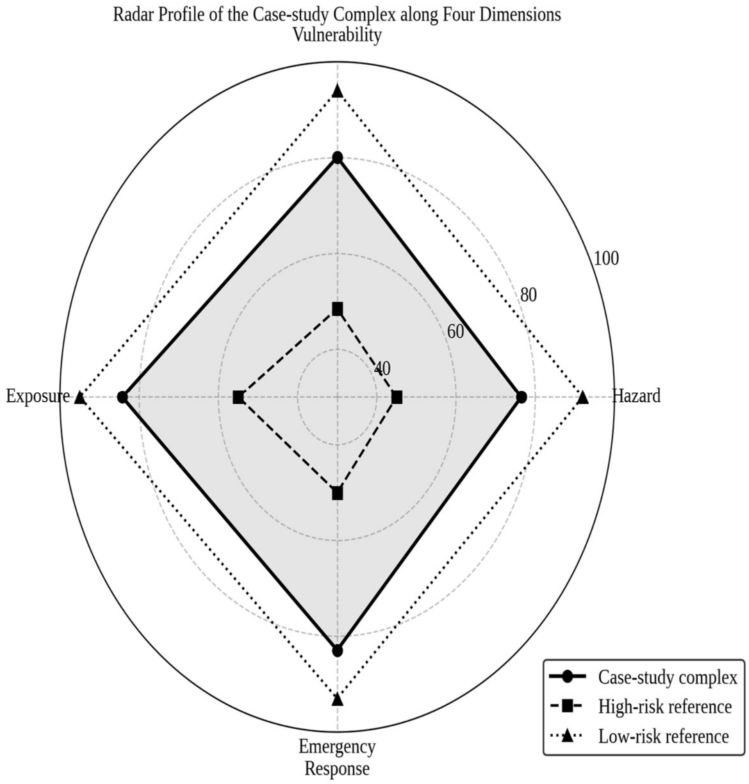

Fig. 10. Radar profile of the case-study complex along four IDRT dimensions.

F. Validation against an Established Fire-Risk-Index Method

To triangulate the Grade II verdict against an independent methodological family, we applied an established fire-risk-index (FRI) reference method, following the specification of Zhou et al. (2019) and its Malaysian-context adaptation by Mohd Tohir, Rashid, and Hassan (2021). The reference method uses 19 sub-indices spanning gas usage, personnel competency, electrical equipment, interior decoration, insulation, building height, building age, external environment, fire-resistance rating, compartmentation, safe evacuation, fire-separation distance, safety monitoring, indoor-hydrant water-supply, portable extinguishers, property fire-safety management, fire-vehicle access, fire-brigade combat capability, and outdoor fire-water supply. Each sub-index is scored on a 1-to-5 scale (1 = very favourable, 5 = very unfavourable) and is multiplied by its pre-specified weight; the weighted sum R = Σ ω_i s_i is the FRI. Table 5 reports the sub-indices, the as-assessed scores, and the FRI aggregation for the case-study complex.

Table 5. Fire-Risk Index benchmarking on the case-study complex.

#	Sub-index	Score s_i	Weight ω_i	Product
1	Gas usage mode	4	0.076	0.304
2	Personnel competency	4	0.081	0.324
3	Electrical equipment	4	0.095	0.380
4	Interior decoration	4	0.039	0.156
5	Internal & external insulation	3	0.040	0.120

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6	Building height	3	0.015	0.045
7	Building age	2	0.033	0.066
8	External environment	3	0.014	0.042
9	Fire-resistance rating	3	0.070	0.210
10	Fire compartmentation	3	0.030	0.090
11	Safe evacuation	3	0.039	0.117
12	Fire separation distance	4	0.008	0.032
13	Safety monitoring	3	0.077	0.231
14	Indoor fire-hydrant water supply	3	0.084	0.252
15	Portable fire extinguishers	3	0.093	0.279
16	Property fire-safety management	3	0.086	0.258
17	Fire-vehicle access	3	0.038	0.114
18	Fire-brigade combat capability	3	0.044	0.132
19	Outdoor fire-water supply	4	0.038	0.152
—	**FRI aggregate $R = \Sigma\ \omega\_i\ s\_i$**	—	—	**3.41**

Source: Authors' computation, 2024. Weights after Zhou et al. (2019).

The FRI aggregate R = 3.41 falls in the reference method's low-fire-risk band ($2.5 < R \leq 3.5$), consistent with the Grade II verdict produced by the proposed model. Table 6 summarises the cross-method comparison, including the computational requirements and the decision-support affordances of each method. The proposed model retains the intuitive, indicator-based transparency of FRI while adding an explicit uncertainty representation (via En and He), a city-scale response dimension (C), and a robustness check (sensitivity analysis).

Table 6. Cross-method comparison on the case-study complex.

Criterion	Proposed IDRT + game-theory + cloud model	Reference FRI method
Number of primary dimensions	4 (H, V, E, C)	1 (aggregate FRI)
Number of secondary indicators	24	19
Explicit external-response dimension	Yes (dimension C, 21.83 %)	Partial (two sub-indices)
Uncertainty representation	Explicit via Ex, En, He	Not represented
Sensitivity robustness of the grade	Grade II across ±30 % perturbation	Not examined in the reference specification
Final classification	Grade II (low fire risk)	R = 3.41 (low-risk band)

Source: Authors' computation, 2024.

Together, these findings support three interpretive claims. First, the proposed model reproduces the headline classification of the established FRI method while additionally supplying a structured uncertainty representation. Second, it exposes the specific leverage points — fire load, ventilation-and-smoke-control maintenance, firefighting equipment stock at the nearest station — on which risk-reduction investments are most likely to lower the integrated-cloud Ex. Third, it is stable under realistic weight uncertainty, which is a prerequisite for use in insurance underwriting and in regulatory benchmarking, both of which demand reproducible classifications from independent assessors.

V. CONCLUSION AND RECOMMENDATIONS

This study developed and validated a fire-risk assessment model for large commercial complexes that extends Integrated Disaster Risk Theory into the built-environment domain. The model decomposes commercial-complex fire risk into four coupled dimensions — hazard, vulnerability, exposure, and emergency response and recovery capacity — organises 24 secondary indicators under those dimensions, reconciles FAHP-derived and SEW-derived indicator weights through a game-theoretic combination-weighting procedure, and aggregates indicator-level cloud digital characteristics into an integrated cloud whose similarity with five standard-grade clouds determines the final fire-risk grade. Applied to a representative 58,000 m² mixed-use complex in the Malaysian Klang Valley, the model produced an integrated cloud (Ex = 78.32, En = 5.28, He = 2.07) whose maximum similarity of 0.7416 lay with Grade II, indicating a relatively low fire-risk level. The result was robust under ±30 % weight perturbation and was consistent with an FRI-based reference method (R = 3.41, low-risk band).

The study makes three principal contributions to the literature on building fire-risk assessment. First, it demonstrates that Integrated Disaster Risk Theory — hitherto applied mainly to natural hazards — provides a coherent organising frame for commercial-complex fire-risk assessment, and that the explicit inclusion of external emergency-response capacity materially affects the indicator-weight distribution (21.83 % of the total weight in the case-study setting). Second, it shows that the game-theoretic combination of FAHP and SEW weights yields classifications that are stable under realistic weight uncertainty, addressing a recurrent criticism of single-method MCDM approaches. Third, it demonstrates the operational value of cloud-based aggregation in this domain: the integrated cloud and its digital characteristics render uncertainty in a form that is directly usable in risk-communication, insurance-underwriting, and fire-safety-investment decisions.

Three recommendations for practice follow. For facility managers and building owners, the leverage points for risk reduction in the case-study setting are the control of fire load in high-turnover tenant spaces, the preventive maintenance of smoke-control and ventilation systems, and the procurement of specialist firefighting equipment at the nearest external station; these priorities should be translated into the facility's asset-management plan and into its tenancy-control clauses. For local authorities and the Malaysian Fire and Rescue Department, the dominant weight attached to external-response capacity argues for the integration of commercial-complex risk profiles into station-siting and resource-allocation decisions, rather than treating fire-station planning and building-level fire-safety compliance as separate policy streams. For insurance underwriters, the integrated-cloud entropy En offers a ready-made premium-adjustment signal that captures the dispersion of system quality within an otherwise nominally-compliant facility; higher En, even at the same Ex, should attract a higher loading.

Three limitations of the present study point toward future work. First, the case study is drawn

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from a single metropolitan context; extension to a sample of 30-plus complexes across several Malaysian states would allow the weights themselves to be estimated from observed loss data and would enable formal empirical validation of the Grade-to-loss mapping. Second, the model is currently static: integrating real-time building-management-system telemetry and fire-alarm-log data would enable the dynamic re-computation of the integrated cloud and support risk-informed incident-response decisions, in line with the smart-fire-protection agenda discussed by Elkafrawy et al. (2023). Third, although the four-dimensional framework is generic, the specific secondary indicators are tailored to commercial complexes; subsequent studies could adapt the framework to hospitals, mass-transit interchanges, and data-centre facilities, where the balance between the four dimensions is likely to differ substantially.

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