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Multidimensional Risk Assessment of Biochemical Systems in Wastewater Treatment Plants Based on the 4M1E Framework and Hierarchical Weight Analysis

Mo Shi[1*], Nan Feng[1], Xinyue Cu[1], Sanggoo Kang[2], Xiaoxian Huang[3]

[1]School of Economics and Management, Ankang University, Ankang, China
[2]School of Architecture, Kyungpook National University, Daegu, Korea
[3]HaXell Elevator Co., Ltd., Shanghai, China
Email: *shimo0204@outlook.jp

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Abstract

Although biochemical systems in wastewater treatment plants are sensitive to construction deviations and operational disturbances, existing risk assessments often lack a multidimensional and quantitative approach. In line with realism, this study proposes a quantitative risk evaluation model based on the 4M1E (Manpower, Machine, Material, Method, Environment) management framework. By integrating expert survey data, a dual-layer hierarchical weighting system is constructed to calculate local weights (LW), total weights (TW), and impact factors (IF). Also, the calculated results are subsequently combined with occurrence probabilities using a risk matrix ($R = LS$) for multidimensional visualization. The results indicate that the comprehensive risk levels across the five dimensions follow the order: Machine > Environment > Material > Manpower > Method. The findings in this study indicate that mechanical equipment (e.g., core sewage pumps) and external environmental factors (e.g., influent flow and temperature variations) pose the highest risk levels and the largest fluctuation ranges, identifying these items as the core priorities for risk control. Conversely, the operational method dimension exhibits the lowest risk due to the inherent stability of mature treatment processes under normal conditions. In conclusion, this study extends the 4M1E into wastewater treatment engineering, providing an objective, reproducible method for critical risk identification, differentiated hierarchical on-site management, and the optimization of lifecycle maintenance resources.

Keywords

Wastewater Treatment, Hierarchical Weight, Risk Matrix, On-Site Management, 4M1E

1. Introduction

With the continuous escalation of water environment governance requirements, municipal wastewater treatment plants (WWTPs) are transitioning toward structural integration and process complexity [1]-[5]. As Fang *et al.* [6] indicate, although ensuring the long-term stable operation of the facilities is a fundamental prerequisite for continuous compliance with wastewater discharge standards, the biochemical systems in WWTPs are dynamic, multi-factor coupled networks that exhibit high sensitivity to operational conditions. Many practices emphasize that construction deviations and system commissioning not only cause disturbances that rarely remain localized but also cascade through the treatment process, disrupting the equilibrium of activated sludge, causing effluent quality violations, and exacerbating equipment degradation [7]-[10]. These cascading effects significantly elevate the lifecycle operation and maintenance (O&M) costs of the facilities. Due to this, identifying diverse disturbance sources and quantifying the specific impacts on biochemical systems has emerged as an urgent practical challenge for the fine-tuned management of wastewater treatment engineering.

Referring to many previous studies [11]-[16], current research in the wastewater treatment domain predominantly focuses on technical aspects, such as biochemical process optimization, water quality simulation, and the development of novel treatment technologies, thereby emphasizing the internal reaction mechanisms of the processes. There remains a notable deficiency in systematic risk assessment studies targeting the engineering implementation and operational phases. According to Tang *et al.* [17], existing risk evaluation approaches rely on qualitative expert judgments and single-dimensional analytical indicators, which suffer from fragmented element classification and a lack of a unified comparative baseline, which make it difficult to quantify the coupled impacts of multiple factors or differentiate the risk hierarchies of diverse disturbance variables, including personnel, equipment, materials, process schemes, and the external environment. As a result, current methodologies are insufficient to support differentiated and proactive risk management in practical projects.

As **Figure 1** illustrates, the 4M1E (Manpower, Machine, Material, Method, and Environment) theory is a systematic analytical framework in engineering quality management, which is widely applied in manufacturing quality control and civil engineering construction to categorize the influencing factors of complex systems [18]-[25]. Nevertheless, its application within process-oriented wastewater treatment engineering requires further expansion, as a quantitative assessment system adapted to the operational characteristics of biochemical systems has yet to be established, making it difficult to quantify constraint variables and reveal the operational risks induced by cross-dimensional synergistic disturbances. By integrating hierarchical weight calculation methods, qualitative expert evaluations in wastewater treatment engineering can be transformed into robust quantitative indicators, which are expected to provide engineering managers with a scientific basis to optimize resource allocation, identify critical control nodes, and implement risk prevention strategies at the source.

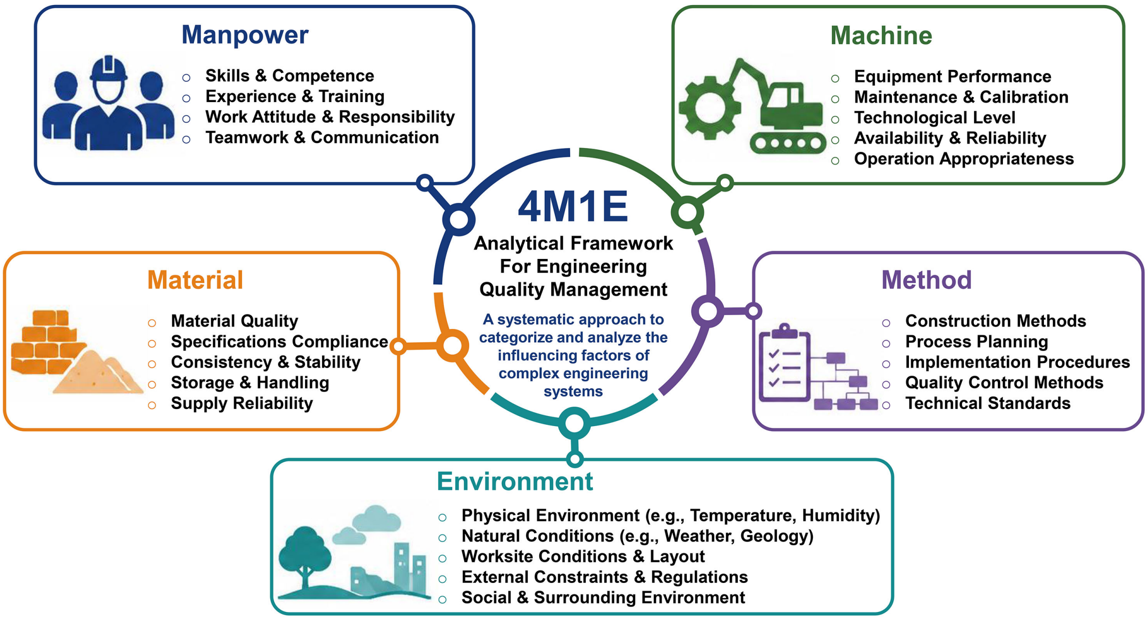

Figure 1. Conceptual framework of the 4M1E theory.

To address the aforementioned gaps, this study proposes a hierarchical weight evaluation system based on the 4M1E framework, tailored for the entire implementation process of wastewater treatment engineering. By combining process mechanisms with engineering management requirements, a comprehensive evaluation index framework is established with the impact factor and occurrence probability as core metrics. In this study, empirical data are collected through field investigations and expert questionnaires to construct a dual-layer weighting model comprising local weights (LW) and total weights (TW). Furthermore, a risk matrix evaluation method is employed for quantitative calculations, accompanied by multidimensional visual analyses using error bar charts and radar charts. The findings in this study indicate that mechanical equipment and the external environment exhibit the highest comprehensive risk levels and the most significant fluctuation ranges, identifying them as the focal points for project risk prevention.

This study extends the 4M1E theory to wastewater treatment engineering practices, establishing an objective and reproducible multidimensional quantitative evaluation approach that compensates for the shortcomings of existing studies that heavily prioritize process mechanisms yet lack systematic, multi-factor risk-grading tools. The conclusions of this study offer vital data support for the implementation of a five-level differentiated on-site management system and the optimization of O&M resource allocation in wastewater treatment projects, which assist in mitigating system operational uncertainties, ensuring the stability of biochemical processes, and providing a valuable reference for the identification and management of disturbance factors in similar water environmental governance projects.

2. Descriptions

To acquire high-quality quantitative data, this study conducted on-site field investigations at four operating municipal wastewater treatment enterprises in Ankang City, Shaanxi Province, China. Following Msaki *et al.* [26], to address the low data fidelity common to unverified online questionnaires, all empirical data were collected via paper questionnaires administered alongside face-to-face interviews conducted at the treatment facilities.

Table 1. Information on wastewater treatment plants (WWTPs).

Wastewater Treatment Plant	Capacity (m^3/day)	Scale	Remarks
Jiangnan Reclaimed Water Plant	80,000	Medium	Distributed underground reclamation A^2/O biological treatment process
Guanmiao Reclaimed Water Plant	80,000	Medium	Semi-underground configuration Uses enhanced A^2/O process
Ankang Jiangbei Water Plant	35,000	Medium	Upgraded A^2/O process
Ankang Jianmin Water Plant	30,000	Medium	Undergoing further expansion A^2/O process

According to **Table 1**, the four surveyed plants in this study share comparable operational contexts, primarily utilizing Anaerobic-Anoxic-Oxic (A^2/O) treatment configurations. The design capacities of the surveyed plants range from 30,000 to 80,000 m^3/day, classifying them as mid-sized municipal facilities. The influent characteristics consist of typical domestic wastewater combined with a minor fraction of urban runoff. Moreover, the operational settings involve continuous automated SCADA (Supervisory Control and Data Acquisition) monitoring coupled with manual periodic inspections.

Also, to satisfy the mathematical requirements of the 4M1E hierarchical weight framework and risk matrix analysis, a three-stage screening process was applied to select valid expert datasets based on predefined criteria:

Inclusion Criteria: 1) Respondents must be active, full-time O&M engineers, process engineers, sludge treatment technicians, or construction/maintenance managers in the target facilities; 2) Respondents must possess verifiable technical expertise in biochemical wastewater treatment systems and have at least 1 year of direct on-site operational experience.

Exclusion Criteria: 1) Questionnaires containing uncompleted items, missing responses, or uniform scoring patterns; 2) Responses exhibiting logical inconsistency between the numerical ratings and the qualitative feedback provided during the face-to-face interview; 3) Questionnaires completed by temporary staff, administrative personnel, or interns who lacked system-wide operational familiarity.

Duplicate-Response and Identity Verification Criteria: Because all questionnaires were administered during on-site visits with mandatory face-to-face cross-checks, each paper response was verified against official facility employee logs and shift rosters. Referring to Adugna [27] and Kokubo Roche *et al.* [28], the physical verification eliminated automated multiple submissions, IP duplicates, or redundant scoring from the same duty shift.

Table 2. Description of the respondents.

Types	Details	Respondents
Individual Generation	1970-1979	1
	1980-1989	6
	1990-1999	13
Work Experience	0 - 9 (years)	9
	10 - 19 (years)	9
	20 - 29 (years)	2
Individual Position	Process Engineer	2
	Construction	1
	Sludge Treatment	2
	Producer	2
	Technician	2
	Operation Engineer	11

Through the systematic screening above, 20 high-quality, fully valid expert datasets were finalized and extracted (representing a 100% response integrity rate among the shortlisted qualified experts). As detailed in **Table 2**, including birth year, work experience, and professional position, the demographic profile of the respondents encompasses three specific dimensions. The sample is composed of young practitioners born between 1990 and 1999 (65%), followed by those born between 1980 and 1989 (30%), reflecting the current workforce dynamics within the wastewater treatment industry. Furthermore, the respondents exhibit a stratified distribution of professional experience, ranging from frontline technical personnel with 0 to 9 years of experience (45%) to seasoned management experts possessing over 20 years of practical expertise (10%). Position-wise, operation engineers constitute the core demographic (55%), supplemented by process engineers, sludge treatment personnel, and construction technicians. Spanning process design, daily operation, and equipment maintenance, the diverse compositional structure ensures that the collected data capture the entire lifecycle of wastewater treatment, thereby establishing credible foundational data for evaluating the subsequent risk factors [29]-[32].

Table 3. Evaluation index system.

	Target Aspect	Keywords
Manpower	Operator	Workforce Stability; Operator Availability; Operational Reliability
	Analyst	Laboratory Accuracy; Water Quality Monitoring; Data Reliability
	Maintainer	Maintenance Response; Equipment Reliability; Fault Recovery
	Responsor	Sludge Dewatering; Operational Competency; Process Stability
	Technician	Decision-Making; Technical Management; Process Optimization
Material	Water Filter	Filter Media; Filtration Efficiency; Material Quality
	Sorbent	Activated Carbon; Adsorption Capacity; Pollutant Removal
	Packing Material	Biofilm Formation; Carrier Performance; Biological Treatment
	Flocculant	Coagulant Quality; Chemical Stability; Flocculation Efficiency
	Membrane Material	Membrane Fouling; Membrane Integrity; Filtration Performance
Machine	Grit Remover	Grit Removal; Equipment Performance; Pretreatment Efficiency
	Sewage Pump	Pump Reliability; Hydraulic Capacity; Flow Stability
	RAS Pump	Sludge Transport; Pump Blockage; Mechanical Reliability
	Aerator	Aeration Efficiency; Dissolved Oxygen; Oxygen Transfer
	DAF	Air Flotation; Separation Efficiency; Equipment Performance
Method	Pretreatment	Pretreatment Control; Process Parameters; Operational Efficiency
	Primary	Primary Sedimentation; Retention Time; Settling Efficiency
	Biologic	Process Selection; Influent Characteristics; Treatment Compatibility
	Bio System	Sludge Retention; Biomass Control; Process Stability
	Sludge Disposal	Sludge Disposal; Resource Recovery; Environmental Sustainability
Environment	Influent Flow	Hydraulic Loading; Influent Fluctuation; System Adaptability
	Odor	Odor Control; Emission Management; Environmental Protection
	Chlorine Gas	Disinfection Safety; Chlorine Leakage; Chemical Risk
	Noise	Noise Control; Vibration Mitigation; Occupational Health
	Temperature	Temperature Variation; Microbial Activity; Biological Performance

To quantify the diverse factors influencing wastewater treatment projects, a multidimensional evaluation index system is constructed utilizing the 4M1E management framework. As presented in **Table 3**, this framework is divided into five fundamental dimensions, with each dimension comprising five specific evaluation indicators, culminating in a total of 25 targeted assessment criteria. The Manpower dimension evaluates operational impacts induced by human factors, such as operator unavailability, laboratory data distortion, and technical decision-making errors. The Material dimension assesses the performance stability of treatment media, encompassing filter media gradation defects, flocculant quality fluctuations, and membrane fouling. For the Machine dimension, the operational reliability of critical mechanical equipment is evaluated, highlighting severe risks like sewage pump failures, sludge transport blockages, and dissolved air flotation (DAF) system instabilities. The Method dimension focuses exclusively on process control vulnerabilities, analyzing the consequences of mismatched biological process selections, inappropriate pretreatment parameters, and fluctuating sludge retention times. The Environment dimension accounts for external operational disturbances, assessing the impacts of influent flow fluctuations, extreme temperature variations, and potential chemical hazards such as chlorine gas leakage.

Including the impact factor score and the occurrence probability, the quantitative assessment of the identified factors is executed across two distinct evaluation metrics, while each factor on the stable operation of the biochemical system was measured using an equidistant five-point scale. Within the scale for impact factor evaluation, a score of 1 indicates a negligible impact, while scores of 2 and 3 represent mild and moderate impacts that require only localized adjustments. Also, a score of 4 denotes severe impacts resulting in operational delays or financial overruns, and a score of 5 signifies a critical failure rendering the treatment process completely unachievable. On the other hand, the occurrence probability is quantified using a non-linear power function, assigning unequally spaced numerical values of 0.03, 0.1, 0.2, 0.5, and 1, which captures the frequency distribution of potential risk events, ranging from extremely low to extremely high occurrence probability, thereby facilitating a rigorous and highly reproducible multidimensional risk evaluation.

3. Discussion

3.1. Impact Factors & Occurrence Probability

3.1.1. Impact Factor

Based on the valid dataset derived from 20 expert questionnaires, the total impact factor scores reveal the relative severity of various disturbances on the stable operation of wastewater treatment projects. As depicted in **Figure 2**, the Manpower dimension maintains a high aggregate score, underscoring the critical and pervasive role of human intervention in plant operations. On the other hand, the Material dimension exhibits moderate yet stable scores, indicating that while material quality is fundamental, its disruptive impact can be effectively mitigated through periodic inspections. The Machine dimension showcases significant fluctuations in scoring, underscoring the need for continuous monitoring of critical mechanical assets, particularly sewage and return sludge pumps. Furthermore, the Method dimension scores exhibit distinct differences between primary and advanced treatment stages, whereas the Environment dimension shows pronounced variation due to the inherently site-specific nature of external disturbances.

The intra-group average score analysis illustrated in **Figure 3** further elucidates the distinct scoring characteristics within the 4M1E dimensions. The Manpower evaluation results are characterized by high stability and concentrated scores, particularly concerning technical managers with the minimal standard deviation, reaffirming an industry consensus on the indispensable nature of human factors. Similarly, the average scores within the Material dimension are concentrated within the middle range, with minimal fluctuation observed among indicators such as water filters, absorbents, and chemical agents, while the packing material indicator exhibits significant expert divergence with a larger standard deviation of 1.24.

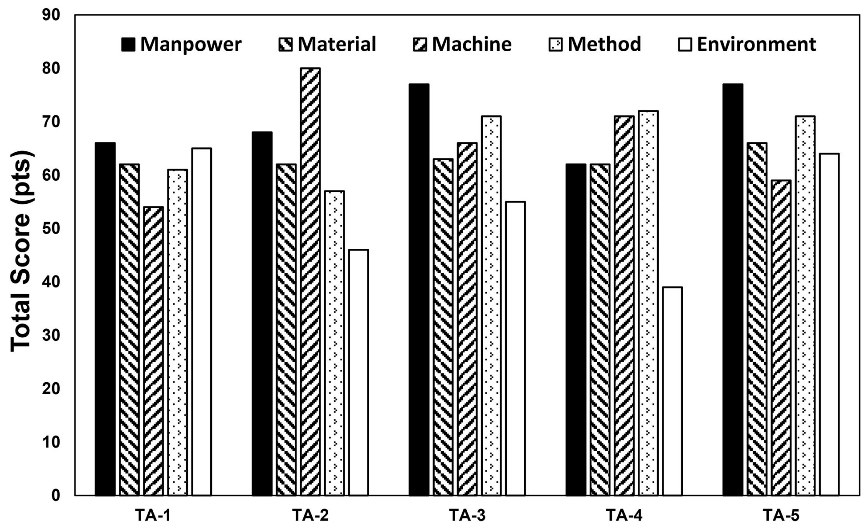

Figure 2. Total scores of the impact factor.

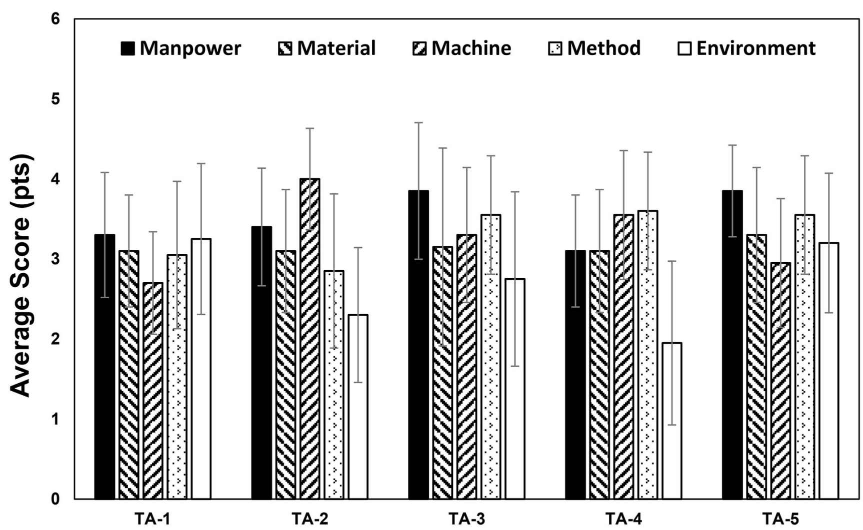

Figure 3. Average scores of the impact factor.

On the other hand, substantial evaluation in Figure 3 shows that discrepancies exist within the Machine and Method dimensions. Within the Machine category, sewage pumps achieved the maximum average score of 4.00, corroborating that hydraulic transportation constitutes the core mechanism of wastewater treatment and governs overall plant efficiency, while return activated sludge (RAS) pumps maintain only a moderate impact level with the average score of 3.30. Regarding the Method dimension, key elements such as biological treatment processes, biological systems, and sludge disposal scored higher compared to primary treatment units, reflecting that these foundational process designs directly determine effluent quality and overall project viability. The Environment dimension exhibits the most significant scoring variance across the surveyed experts. Indicators such as influent flow fluctuations, chlorine leaks, odor dispersion, and noise pollution are constrained by site-specific variables, including proximity to residential zones and external regulatory conditions.

Despite the intra-dimensional variations, the varying lengths of the error bars across the five dimensions suggest that while an empirical consensus exists for universal operational risks, site-specific environmental factors and localized management conditions continue to generate substantial evaluative divergence.

3.1.2. Occurrence Probability

Figure 4 illustrates the aggregated occurrence probability of risk factors as assessed by the expert panel. The Method dimension records the lowest overall probability of occurrence with an average score of 2.38, indicating that mature biochemical processes and standardized pretreatment protocols possess robust operational stability. In contrast, the Manpower dimension exhibits significant intra-dimensional divergence as operator errors display a relatively high occurrence probability, which is scoring 3.80, reflecting the frequency of frontline operational oversights, whereas analytical and technical misjudgments remain strictly infrequent, with the lower scores of 1.99 and 1.64, respectively.

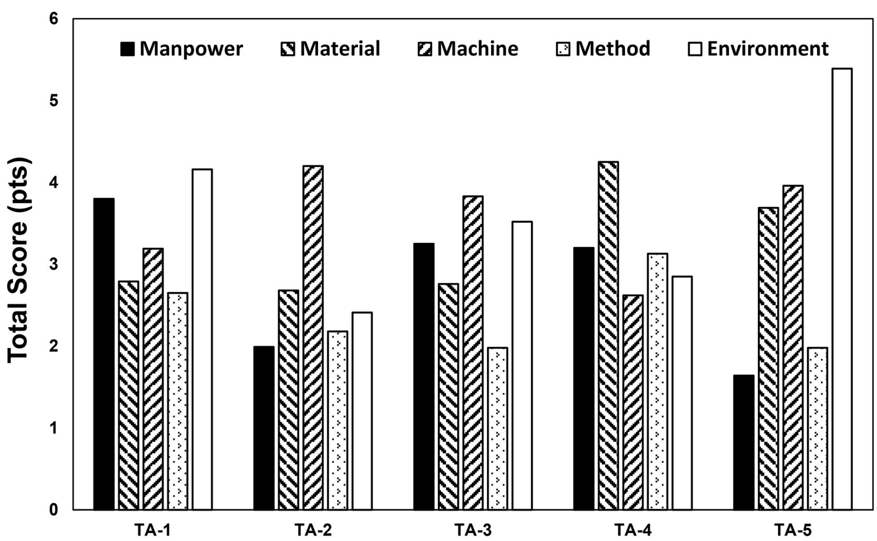

Figure 4. Total scores of the occurrence probability.

Furthermore, Figure 4 also indicates that the Material and Machine dimensions demonstrate moderate aggregate probabilities. Particularly concerning flocculants and membrane materials, Material degradation occurs with notable frequency, whereas mechanical wear in sewage pumps and dissolved air flotation (DAF) units represents a persistent, unavoidable operational disruption. Notably, the Environment dimension displays both a high aggregate probability with an average score of 3.67 and the greatest degree of dispersion with a larger standard deviation of 1.05. Risks associated with influent flow surges and temperature fluctuations are exceptionally prominent, with the larger scores of 4.16 and 5.39, respectively, underscoring the severe and unpredictable nature of external environmental shocks, which are governed by regional specificities and defy standardized mitigation.

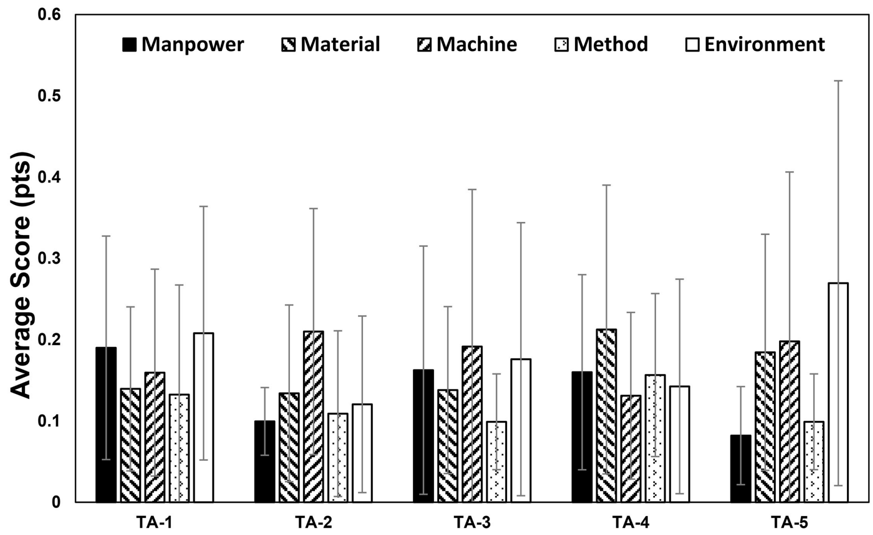

Figure 5. Average scores of the occurrence probability.

An analysis of the average occurrence probabilities and their standard deviations reveals varying degrees of expert consensus, as shown in **Figure 5**. Short error bars within the Manpower and Method dimensions signify a unified industry recognition regarding the frequency of the risks due to these two dimensions, which indicates that although human operational errors are acknowledged as common, systemic process failures are regarded as rare. Within the Material dimension, particularly for flocculants, analytical data dispersion in this study is more pronounced, which suggests that the likelihood of material-based disruptions is contingent upon specific process conditions and dosing strategies.

As shown in **Figure 5**, significant intra-group differences in occurrence probabilities are also evident within the Machine and Environment dimensions. Including sewage pumps, DAF units, and RAS pumps, core hydraulic and separation components exhibit higher probability values than auxiliary aeration equipment, identifying them as critical focal points for preventive maintenance. The Environment dimension presents the maximum overall dispersion, encompassing influent flow fluctuations, chlorine gas leaks, and temperature, which confirms that the frequency of environmental risks is tied to unique geographical constraints and facility-specific layouts, precluding an applicable risk frequency baseline.

3.1.3. Summarization

Table 4. Analytical results of the impact factor.

	Target Aspect	Total Score	Average Score	Standard Deviation
Manpower	Operator	66.00	3.30	0.78
	Analyst	68.00	3.40	0.73
	Maintainer	77.00	3.85	0.85
	Responsor	62.00	3.10	0.70
	Technician	77.00	3.85	0.57
Material	Water Filter	62.00	3.10	0.70
	Sorbent	62.00	3.10	0.77
	Packing Material	63.00	3.15	1.24
	Flocculant	62.00	3.10	0.77
	Membrane Material	66.00	3.30	0.84
Machine	Grit Remover	54.00	2.70	0.64
	Sewage Pump	80.00	4.00	0.63
	RAS Pump	66.00	3.30	0.84
	Aerator	71.00	3.55	0.80
	DAF	59.00	2.95	0.80
Method	Pretreatment	61.00	3.05	0.92
	Primary	57.00	2.85	0.96
	Biologic	71.00	3.55	0.74
	Bio System	72.00	3.60	0.73
	Sludge Disposal	71.00	3.55	0.74
Environment	Influent Flow	65.00	3.25	0.94
	Odor	46.00	2.30	0.84
	Chlorine Gas	55.00	2.75	1.09
	Noise	39.00	1.95	1.02
	Temperature	64.00	3.20	0.87

Table 4 synthesizes the statistical results for the impact factors, using total scores, average scores, and standard deviations to assess the magnitude of operational impacts and the dispersion of expert opinions. Because sewage pumps within the Machine dimension, maintenance and technical personnel within the Manpower dimension, and biological systems within the Method dimension rank at the forefront of the average scores, the analytical results indicate that high-priority critical factors are readily identifiable. In contrast, indicators such as odor, noise, and grit removers register lower scores, implying a limited systemic threat. Within the Material dimension, the scores are densely clustered, indicating that various consumables exert a uniformly moderate impact on the treatment system.

From the perspective of data dispersion in Table 4, the majority of the indicators yield standard deviations between 0.57 and 0.96, which underscores a consistency in risk perception among the expert panel, thereby validating the reliability of the empirical data. However, the standard deviations for packing materials, chlorine gas safety, and noise pollution exceed 1.0, revealing substantial evaluative divergence, which implies that the perceived severity of these specific factors is dependent upon external variables, such as site layout, operational management frameworks, and regional regulations, precluding a universally standardized assessment.

Table 5. Analytical results of the occurrence probability.

	Target Aspect	Total Score	Average Score	Standard Deviation
Manpower	Operator	3.80	0.19	0.14
	Analyst	1.99	0.10	0.04
	Maintainer	3.25	0.16	0.15
	Responsor	3.20	0.16	0.12
	Technician	1.64	0.08	0.06
Material	Water Filter	2.79	0.14	0.10
	Sorbent	2.68	0.13	0.11
	Packing Material	2.76	0.14	0.10
	Flocculant	4.25	0.21	0.18
	Membrane Material	3.69	0.18	0.15
Machine	Grit Remover	3.19	0.16	0.13
	Sewage Pump	4.20	0.21	0.15
	RAS Pump	3.83	0.19	0.19
	Aerator	2.62	0.13	0.10
	DAF	3.96	0.20	0.21
Method	Pretreatment	2.65	0.13	0.13
	Primary	2.18	0.11	0.10
	Biologic	1.98	0.10	0.06
	Bio System	3.13	0.16	0.10
	Sludge Disposal	1.98	0.10	0.06
Environment	Influent Flow	4.16	0.21	0.16
	Odor	2.41	0.12	0.11
	Chlorine Gas	3.52	0.18	0.17
	Noise	2.85	0.14	0.13
	Temperature	5.39	0.27	0.25

Table 5 delineates the average statistical characteristics of the occurrence probabilities, which predominantly fall within a controllable low-to-medium range of 0.08 to 0.27. Notably, environmental temperature (0.27), influent flow (0.21), flocculants (0.21), sewage pumps (0.21), and DAF units (0.20) exhibit occurrence probabilities reaching or exceeding 20%, which indicates that despite this overall manageability, specific indicators present elevated likelihoods. On the other hand, the likelihood of disruptions originating from technical staff, analytical personnel, biological processes, and sludge disposal operations remains at or below 0.1, highlighting the intrinsic reliability of mature operational protocols and rigorous backend management.

The dispersion of the occurrence probability data in Table 5 is constrained, with standard deviations ranging from 0.04 to 0.25, indicating excellent overall expert consensus. The Method dimension exhibits the highest degree of uniformity, whereas the Environment dimension shows the greatest variability. Standard deviations exceeding 0.15 for temperature, DAF units, RAS pumps, flocculants, and chlorine gas indicate that the perceived frequency of these events is sensitive to precise, real-world project conditions. Specifically, external environmental shocks, core power equipment, and critical process consumables, the findings in this study emphasize that future risk mitigation strategies must prioritize variables characterized by both high probability and high impact to guarantee systemic stability.

3.2. Hierarchical Weight Analysis

To quantify the relative significance of various risk factors within the 4M1E framework, a hierarchical weight calculation procedure is formulated in this study, which transforms raw subjective expert evaluations into objective, quantitative metrics through the derivation of local weight (LW), total weight (TW), impact factor (IF), and adjusted total score (AT). Within the procedural methodology, assuming $k = 1, 2, 3, 4, 5$ denotes the five criterion layers of the 4M1E system, and i represents the specific individual indicators under each respective criterion layer, the computational flow is expressed as Equations (1) - (4):

$$\mathrm{LW}_{ki} = \frac{C_{ki}}{C_k}, \quad C_k = \sum_i C_{ki} \tag{1}$$

$$\mathrm{TW}_{ki} = \frac{C_{ki}}{C}, \quad C = \sum_k C_{ki} \tag{2}$$

$$\mathrm{IF}_{ki} = \mathrm{TW}_{ki} \times M \tag{3}$$

$$\mathrm{AT}_{ki} = C \times \mathrm{TW}_{ki} \tag{4}$$

where, C_{ki} signifies the original evaluation score for the i-th indicator within the k-th criterion layer, C_k represents the aggregate score of all indicators within the k-th layer, and C denotes the cumulative total score across all criteria. The calculation of the local weight (LW_{ki}) standardizes the impact efficacy of indicators within the same criterion layer, serving to evaluate their relative intra-layer importance. By extending this localized assessment to a global scale, the total weight (TW_{ki}) is extrapolated to form a comprehensive evaluation metric that reflects the absolute weight of a single indicator within the entire biochemical treatment system.

As shown in Equation (3), to quantify the engineering severity of each disruptive factor, the impact factor (IF_{ki}) is calculated by multiplying the total weight (TW_{ki}) by the maximum scale value ($M = 5$) of the evaluation system. This conversion reflects the fractional total weight into a standard impact scale, bridging the gap between theoretical weighting and practical engineering consequences. Consequently, an indicator with a higher proportion of local weight will possess a larger total weight, thereby yielding a higher impact factor that denotes a more profound systemic disturbance.

Furthermore, Equation (4) illustrates that the adjusted total score (AT_{ki}) is derived by calculating the product of the cumulative total score across all criteria (C) and the respective total weight (TW_{ki}). Rather than relying on summation, the multiplicative recalibration redistributes the overall impact score based on the normalized weight of each specific indicator. By replacing the raw empirical scores (C_{ki}) with this weight-adjusted metric, the proposed 4M1E framework is expected to mitigate the subjective biases and localized evaluation deviations introduced by initial expert surveys. The value of the AT_{ki} accounts for both the severity of the risk event and the hierarchical importance of the indicator within wastewater treatment engineering, thereby providing a reliable and reproducible quantitative baseline for subsequent risk prioritization.

As illustrated in **Figure 6**, the three-dimensional radar charts reflect the local weight (LW), total weight (TW), and impact factor (IF) as distinct axes within the five dimensions of the 4M1E theory. As shown in **Figure 6**, indicators with higher LW values in the same layer correspondingly achieve elevated TW and IF values, indicating that components with higher local proportions inflict a more severe comprehensive impact, suggesting that the three parameters in each dimension of the 4M1E exhibit a highly stable, positive geometric correlation. Notably, **Figure 6(a)** and **Figure 6(b)** demonstrate that the score points for the Manpower and Material dimensions are symmetrically distributed with minimal dispersion, indicating that the relative importance of operational and technical personnel, as well as various process consumables like filter media and flocculants, is equitable, which can be attributed to the maturity of modern standardized management and material control systems.

On the other hand, as depicted in **Figure 5(c)** and **Figure 5(d)**, the radar charts for the Machine and Method dimensions exhibit significant dispersion and distinct polarization characteristics. Within the Machine dimension, the sewage pump dominates the LW, TW, and IF axes, substantially surpassing auxiliary equipment such as grit removers and aerators, demonstrating that continuous-operation power equipment is the paramount mechanical risk factor. Similarly, the internal differentiation within the Method dimension is pronounced, with the biochemical system and biological processes displaying considerably higher three-axis values than sludge disposal and physical pretreatment stages, reaffirming that biochemical treatment units determine the overall purification efficacy. Moreover, the most prominent polarization is observed in the Environment dimension, where the weights for temperature and influent flow overshadow odor and noise, as shown in Figure 5(e). Due to the inherent stochasticity of the Environment dimension, external hydrological and climatic conditions act as primary disruptive factors, which impact the stability of biochemical systems.

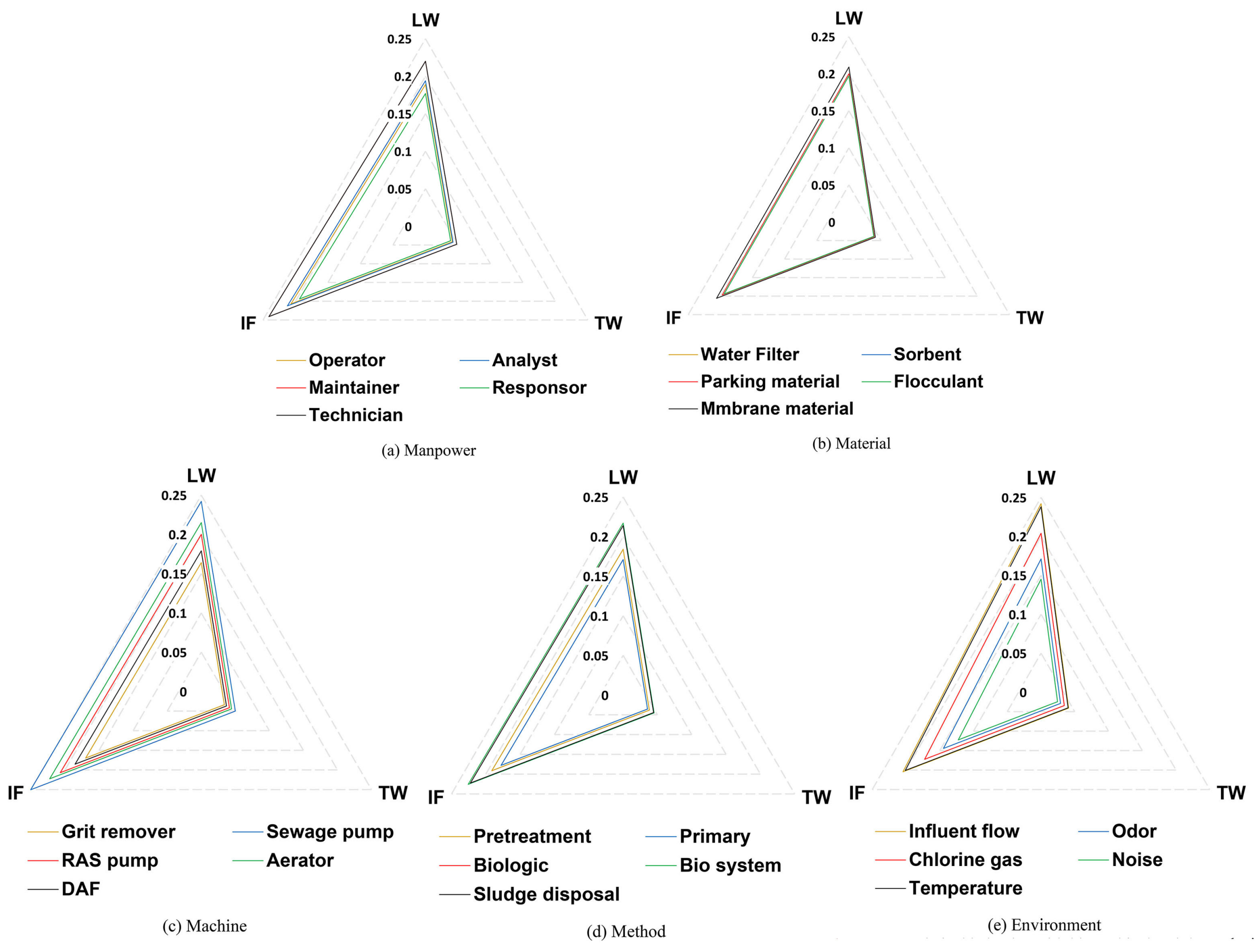

Figure 6. Statistical behavior with hierarchical weight analysis.

Table 6. Comparison analysis under hierarchical weight.

	Target Aspect	Local Weight (LW)	Total Weight (TW)	Impact Factor (IF)	Adjusted Total (AT)
	Operator	0.189	0.041	0.207	66.060
	Analyst	0.194	0.042	0.212	67.808
Manpower	Maintainer	0.220	0.048	0.241	76.895
	Responsor	0.177	0.039	0.194	61.866
	Technician	0.220	0.048	0.241	76.895

Continued

Material	Water Filter	0.197	0.039	0.194	61.939
	Sorbent	0.197	0.039	0.194	61.939
	Packing	0.200	0.039	0.197	62.882
	Flocculant	0.197	0.039	0.194	61.939
	Membrane	0.209	0.041	0.206	65.712
Machine	Grit Remover	0.164	0.034	0.170	54.181
	Sewage Pump	0.242	0.050	0.250	79.950
	RAS Pump	0.200	0.041	0.207	66.074
	Aerator	0.215	0.045	0.223	71.030
	DAF	0.179	0.037	0.185	59.137
Method	Pretreatment	0.184	0.038	0.191	61.082
	Primary	0.171	0.036	0.178	56.767
	Biologic	0.214	0.045	0.223	71.041
	Bio System	0.217	0.045	0.226	72.037
	Sludge Disposal	0.214	0.045	0.223	71.041
Environment	Influent Flow	0.242	0.041	0.204	65.273
	Odor	0.171	0.029	0.144	46.123
	Chlorine Gas	0.204	0.034	0.172	55.024
	Noise	0.145	0.025	0.123	39.110
	Temperature	0.238	0.040	0.201	64.194

Table 6 provides a detailed comparative analysis of the hierarchical weights, revealing a coupling relationship where the adjusted total (AT) exhibits a strong positive correlation with LW, TW, and IF. In cases where an indicator possesses a high local weight but the entire macro-category is assigned a lower overall weight, the total weight TW is constrained, prompting the AT metric to recalibrate the final comprehensive score based on the hierarchical structure. Within the Manpower dimension, maintenance personnel and technical engineers achieved the highest integrated scores (AT = 76.895), emphasizing their critical regulatory role during the equipment installation, debugging, and implementation phases. For the Material dimension, the AT scores are densely concentrated between 61.0 and 66.0, with membrane materials (AT = 65.712) scoring only marginally higher than other consumables. The concentrated distribution for the material dimension corroborates the balanced radar chart configuration, suggesting that no single material factor dictates system stability, thereby necessitating uniform standardized management.

According to Table 6, the quantitative risk hierarchy is evident in the Machine, Method, and Environment dimensions. The sewage pump commands the highest metric across the entire dataset (AT = 79.950, LW = 0.242), establishing itself as the foremost critical risk node whose failure would inflict maximum systemic shock. In the Method dimension, the biochemical system (AT = 72.037), biological processes (AT = 71.041), and sludge disposal (AT = 71.041) operations outweigh pretreatment mechanisms, underscoring the absolute priority in process regulation. Furthermore, environmental perturbations are dominated by influent flow (AT = 65.273) and temperature (AT = 64.194), while noise pollution registers the lowest value in the evaluation matrix (AT = 39.110). Based on the discussion above, the analysis in this study indicates that the comprehensive AT scores differentiate between critical intra-layer parameters and overall bottleneck risks, providing theoretical references for differentiated, priority-based site management.

3.3. Risk Analysis and Assessment

To evaluate the comprehensive risk levels of various factors affecting WWTPs, the risk evaluation in this study is calculated utilizing the risk matrix approach. The quantitative calculation process is shown in Equation (5):

$$R = L \times S \tag{5}$$

where, L represents the mean occurrence probability of each respective indicator, while S denotes the mean impact severity, which represents the average score of the impact factor. With the product of L and S in Equation (5), R signifies the calculated risk value for a single assessment indicator within the 4M1E framework.

By multiplying the probability of occurrence by the consequence of the event, the established risk matrix translates subjective multidimensional evaluation criteria into objective, quantifiable risk values. The computational approach with Equation (5) enables a precise and structured prioritization of the diverse disturbance factors across the 4M1E framework, facilitating the formulation of targeted risk mitigation strategies for engineering applications.

Table 7. Results of risk assessment.

	Manpower	Material	Machine	Method	Environment
TA-1	0.627	0.432	0.431	0.404	0.676
TA-2	0.338	0.415	0.840	0.311	0.277
TA-3	0.626	0.435	0.632	0.351	0.484
TA-4	0.496	0.659	0.465	0.563	0.278
TA-5	0.316	0.609	0.584	0.351	0.862

As illustrated in Table 7, the risk distribution within the manpower dimension exhibits a distinctive bimodal pattern, with pronounced risk peaks observed at TA-1 (0.627) and TA-3 (0.626), indicating a medium-high risk interval. On the other hand, the risk values for TA-2 (0.338), TA-4 (0.496), and TA-5 (0.316) recede to lower levels, reflecting that while conventional operational errors are frequent, the probability of extreme, large-scale personnel-induced accidents remains low. In contrast, the material dimension demonstrates a pattern of stability within low-risk intervals followed by a significant elevation in medium-high risk situations. Specifically, the risk values for TA-1 through TA-3 maintain a stable equilibrium (0.415 - 0.435), whereas TA-4 reaches a dimensional peak (0.659) before experiencing a minor decline at TA-5 (0.609), which aligns with the inherent degradation cycles of consumables, such as chemical reagents and membrane materials, which manifest risks through gradual attrition rather than abrupt, catastrophic failures.

The mechanical equipment dimension concentrates within the medium-high risk category in Table 7, highlighting the critical vulnerability within the wastewater treatment process. Notably, TA-2 registers a substantial risk value of 0.840, constituting the second-highest peak across the entire evaluation matrix, surpassed only by the environmental extreme. Furthermore, TA-3 (0.632) and TA-5 (0.584) similarly reside in elevated risk tiers, which are driven by the severe systemic disruptions precipitated by the failure of core mechanical components, such as continuous operation pumps. Based on the discussion above, the amplified comprehensive risk necessitates that mechanical reliability be prioritized as the paramount focus for systemic risk management and preventive maintenance protocols.

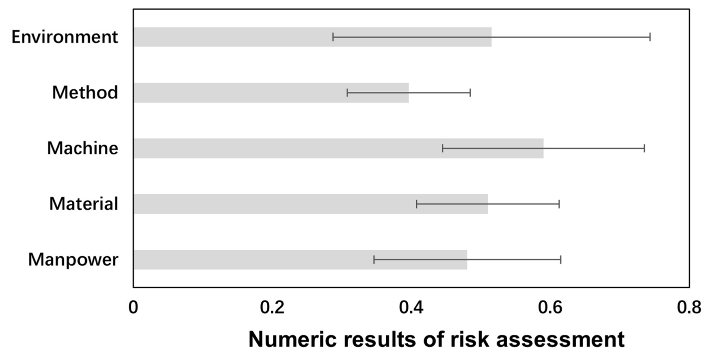

Figure 7. Risk analysis and assessment.

Comparatively, the process method dimension has the lowest overall risk profile among the five fundamental aspects in Table 7, with a maximum recorded value of 0.563 at TA-4, while the remaining tiers fluctuate within a narrow, low-risk range of 0.311 to 0.404. The findings above substantiate that the established biochemical treatment frameworks are mature and possess robust stability under standard operating conditions, only demonstrating heightened vulnerability when subjected to the superimposition of multiple operational constraints. On the other hand, the environmental dimension exhibits an extreme bipolar risk distribution, which encompasses both the absolute maximum risk value in the entire assessment (TA-5 at 0.862) and the lowest recorded values (TA-2 and TA-4 at 0.277 and 0.278), illustrating a staggering differential of 0.585 and 0.584. Due to the risk assessment escalating during severe fluctuations in influent water quality or temperature, yet diminishing during stable environmental periods, this divergence elucidates that environmental risks are site-specific and dependent on external conditions.

According to the comprehensive statistical analysis depicted by the bar chart in Figure 7, the average risk hierarchy of the five dimensions is explicitly ordered as follows: Machine > Environment > Material > Manpower > Method. The mechanical equipment dimension unequivocally ranks first with the highest average risk (R = 0.590), reiterating that failures in core dynamic machinery can directly obstruct the continuous operational flow of the treatment process, yielding profound negative consequences. The environmental (R = 0.515) and material (R = 0.510) dimensions occupy the second and third positions with proximal risk values, such as influent flow and temperature fluctuations, which emphasize the significant uncertainties introduced by external conditions coupled with the operational impact of consumable quality control. Manpower ranks fourth (R = 0.481), driven primarily by operational deviations and technical limitations, while the method dimension secures the lowest risk (R = 0.396), further validating the reliability of contemporary treatment protocols.

Except for the mean values, the error bars delineate the standard deviation, which captures the dispersion of expert evaluations and the potential fluctuation amplitude of each risk category. As shown in Figure 7, the environmental dimension exhibits the largest error bar of 0.228 among all cohorts, indicating the most severe divergence in expert consensus and the highest susceptibility to extreme upward and downward risk shifts induced by external geographical and climatic variances. Simultaneously, the mechanical dimension is characterized by a high mean risk of 0.590 coupled with a substantial error margin of 0.145, which signifies an expansive fluctuation range and a realistic probability of high-tier systemic failures. Meanwhile, the manpower and material dimensions demonstrate moderate error lengths with 0.134 and 0.102, reflecting a standard level of analytical dispersion within the operational parameters. Notably, the process method dimension possesses the shortest error bar with the lowest value of 0.089 in Figure 7, which demonstrates a high degree of consensus among engineering experts regarding stability and predictability.

In conclusion, the visual synthesis corroborates the quantitative findings derived from the risk matrix, which emphasize that the mechanical equipment and external environmental disturbances constitute the two foremost systemic threats to wastewater treatment plants. In contrast, material and manpower present moderate, controllable risks, whereas the processing method remains basically secure. Based on the discussion above, the findings in this study indicate that to optimize the lifecycle stability of biochemical systems, project management must implement a differentiated on-site control strategy, prioritizing predictive mechanical maintenance and environmental early-warning mechanisms.

4. Conclusions

Including Local Weight (LW), Total Weight (TW), Impact Factor (IF), and Adjusted Total (AT) scores, this study integrated the 4M1E framework with a dual-layer hierarchical weighting analysis and Risk Matrix to establish a multidimensional quantitative risk assessment paradigm for biochemical systems in WWTPs. By translating qualitative expert evaluations into quantifiable engineering metrics, this study provides a valuable reference in civil and environmental engineering risk management, particularly regarding the systemic risk propagation during equipment installation, commissioning, and operational stages. The quantitative framework in this study mitigates subjective scoring bias through hierarchical calibration, providing an objective, scalable, and reproducible analytical basis for identifying core vulnerability factors in the operations of WWTPs.

The comprehensive empirical evaluation across the five dimensions revealed an overall risk hierarchy: Machine ($R = 0.590$) > Environment ($R = 0.515$) > Material ($R = 0.510$) > Manpower ($R = 0.481$) > Method ($R = 0.396$). Mechanical equipment and external environmental factors represent the primary risk drivers, characterized not only by higher mean risk levels but also by the widest risk fluctuation spans and standard deviations. Specifically, in cases such as sewage pumps (AT = 79.950, LW = 0.242), continuous hydraulic power devices, and critical aeration systems constitute the principal operational failure points, where equipment breakdowns lead to severe process disruptions. Environmentally, influent flow rates (AT = 65.273, LW = 0.242) and temperature variations (AT = 64.194, LW = 0.238) exhibit strong site-specificity and extreme risk volatility under adverse conditions ($R_{\text{TA-5}} = 0.862$). On the other hand, with the smallest standard deviation, the Method dimension demonstrated the lowest overall risk and the highest expert evaluation consensus, indicating that mature biochemical process designs possess intrinsic stability and resilience under conventional operating conditions.

The quantitative findings and risk fluctuation profiles derived from this study offer valuable data-driven references for implementing the 4M1E management framework in WWTPs. By quantifying dimension-specific risk thresholds and variability, managers and plant operators can transition from reactive maintenance to frontline proactive risk prevention. The findings in this study emphasized that prioritized resource allocation should be directed toward routine preventive maintenance of hydraulic machinery and early-warning monitoring for external environmental fluctuations, while standardizing reagent quality and operator competencies. Based on the 4M1E framework, the multidimensional assessment approach is expected to reduce operational uncertainty, optimize lifecycle operation and maintenance (O&M) expenditures, and ensure sustained biochemical stability with effluent compliance of wastewater treatment infrastructure.

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Author Contributions

Conceptualization: M.S.; Methodology: M.S., N.F., and X.Y.C.; Software: M.S.; Validation: M.S., and N.F.; Formal analysis: M.S.; Investigation: X.Y.C., and N.F.; Resources: M.S., and N.F.; Data curation: M.S., N.F., and X.Y.C.; Writing—original draft preparation: M.S.; Writing—review and editing: M.S., and S.G.K.; Visualization: M.S.; Supervision: S.G.K., and X.X.H.; Project administration: M.S.; Funding acquisition: M.S. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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Appendix A. Items of the Survey

Indicator	Questionnaire Title
Manpower	Impact of operator turnover or unavailability on the wastewater treatment process. Impact of inaccurate or delayed water quality laboratory analysis on the wastewater treatment process. Impact of delayed fault response by equipment maintenance and electrical personnel on the wastewater treatment process. Impact of improper sludge dewatering and drying operations by sludge treatment personnel on the wastewater treatment process. Impact of incorrect process planning and decision-making by technical and managerial personnel on the wastewater treatment process.
Material	Impact of excessive breakage rate, excessive mud content of anthracite filter media, or improper particle size gradation of quartz sand filter media on the wastewater treatment process. Impact of insufficient adsorption capacity or failure of activated carbon and carbon fiber adsorption media on the wastewater treatment process. Impact of inadequate biofilm formation on elastic and combined packing media on the wastewater treatment process. Impact of quality fluctuations in flocculants (e.g., PAC and PAM) on the wastewater treatment process. Impact of fiber breakage or membrane fouling in membrane separation materials (e.g., MBR, MF, and RO) on the wastewater treatment process.
Machine	Impact of reduced separation efficiency of grit removal equipment on the wastewater treatment process. Impact of wastewater lifting pump failure or insufficient pumping capacity on the wastewater treatment process. Impact of blockage of sludge return pumps, transfer pumps, or conveying systems on the wastewater treatment process. Impact of aerator blockage or mechanical damage leading to insufficient dissolved oxygen (DO) in the wastewater treatment process. Impact of insufficient dissolved-air generation efficiency in the dissolved air flotation (DAF) system on the wastewater treatment process.
Method	Impact of inappropriate parameter settings in pretreatment processes (screening and grit removal) on the wastewater treatment process. Impact of insufficient hydraulic retention time during primary sedimentation on the wastewater treatment process. Impact of the mismatch between secondary biological treatment process selection and influent wastewater characteristics of the wastewater treatment process. Impact of improper control of sludge concentration and sludge retention time (SRT) in biological treatment systems on the wastewater treatment process. Impact of unreliable sludge treatment and disposal process routes on the wastewater treatment process.
Environment	Impact of influent flow fluctuations exceeding the designed regulation capacity on the wastewater treatment process. Impact of insufficient efficiency of odor collection and treatment systems on the wastewater treatment process. Impact of chlorine or chlorine dioxide leakage risk and inadequate control of disinfection by-products in chlorination facilities in the wastewater treatment process. Impact of failure of noise insulation and vibration isolation measures for blowers and pumping units, resulting in excessive noise levels in the wastewater treatment process. Impact of abnormal water temperature (low or high temperature) on microbial activity in the wastewater treatment process.

Appendix B

B1. Impact Factor Scoring Scale

Score	Impact Level	Description
1	Negligible impact	No operational adjustment needed
2	Mild impact	Minor localized adjustments required
3	Moderate impact	Noticeable disturbance, recoverable within a short period
4	Severe impact	Significant operational delays or financial overruns
5	Critical impact	Complete failure of the biochemical treatment process

B2. Occurrence Probability Scoring Scale

Score	Frequency Level	Description
0.03	Extremely low frequency	Rarely occurs in lifecycle
0.10	Low frequency	Occurs every few years
0.20	Medium frequency	Occurs annually
0.50	High frequency	Occurs frequently, e.g., monthly
1.00	Extremely high frequency	Routine operational disturbance