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A Dual-Level Rubric Design for Chemical Hazard Evaluation in Research Laboratories

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***Abstract*—Evaluation of chemical hazards in research laboratories must balance the requirements of regulatory frameworks with the need for tools that are usable by frontline staff. Systems such as the Globally Harmonized System (GHS), the European Union's CLP Regulation, OSHA's Hazard Communication Standard, and Malaysia's CLASS Regulations provide a common language for hazard communication but do not in themselves identify which chemicals in a laboratory inventory should be considered highest priority [3], [24]. This study introduces a dual-level rubric that combines a simplified tool for everyday use with a more detailed scoring framework for deeper analysis. Both rubrics feed into an Environmental Hazard Index (EHI) that integrates hazard categories with exposure-related dimensions such as quantity and frequency of use. The framework was applied to more than 500 records representing nearly 700 unique chemicals across research laboratories at Universiti Teknologi Malaysia (UTM) Kuala Lumpur. Results include a ranked list of Top 20 chemicals, per-laboratory profiles, distribution analyses, and hazard-type composition. The outputs not only enhance chemical safety management but also generate structured, auditable data suitable for AI-driven governance in laboratory safety.**

***Keywords*—Chemical hazard evaluation, Rubric design, Laboratory Safety, Risk Assessment**

I. INTRODUCTION

Universities and research institutions manage complex chemical inventories that often contain hundreds of different substances, each with varied hazards, storage requirements, and patterns of use. Accidents such as the fatal t-butyllithium fire at UCLA [14] and mercury spills in academic laboratories [1] underscore the consequences of inadequate hazard prioritisation. Although regulatory frameworks provide criteria for classification and labelling, they are rarely sufficient to guide day-to-day decisions about which chemicals deserve the most attention. In Malaysia, the CLASS Regulations and mandatory CHRA assessments offer important compliance structures, but case studies suggest they leave institutions with little guidance on prioritising across diverse inventories [20].

This study proposes a rubric-based approach designed to bridge that gap. By scoring chemicals along consistent dimensions—some focused on intrinsic hazard, others on contextual factors such as laboratory distribution—an institution can generate a transparent ranking of risk. More importantly, the data generated by such rubrics are explainable and auditable, aligning well with recent calls in AI governance for structured, traceable risk management frameworks [10], [17].

II. LITERATURE REVIEW

A growing body of research has highlighted the persistent challenge of transforming formal regulatory classifications of chemical hazards into practical tools that can support decision-making in laboratory environments. While comprehensive frameworks such as the European Union's CLP guidance and Malaysia's CLASS Regulations, supported by the Chemical Health Risk Assessment (CHRA) Manual, provide clear structures for hazard evaluation, they often stop short of offering prioritisation mechanisms that would allow institutions to rank risks and direct resources accordingly [3], [4], [5].This shortcoming is particularly evident in Malaysian academic laboratories where the HIRARC framework has been applied, but findings show that it lacks the ability to weigh hazards against contextual factors such as chemical volumes, frequency of use, or laboratory infrastructure [20]. The result is a gap between compliance-based assessment and the operational need to identify which chemicals represent the greatest cumulative risk.

In response, academic researchers have begun piloting semi-quantitative and rubric-based approaches that combine hazard data with laboratory-specific context. Fatemi *et al.* (2022) [6] demonstrated in Iranian universities that prioritisation frameworks can substantially improve mitigation effectiveness by helping laboratories target resources where they are needed most. Similar approaches have been applied elsewhere, such as the use of Failure Mode and Effects Analysis (FMEA) in laboratory safety evaluations [16] and semi-quantitative scoring systems to characterise occupational exposures in health science laboratories [8]. Other scholars have focused on adapting existing guidelines into structured ranking activities; for example, Denlinger *et al.* (2018) [2] and Schröder *et al.* (2020) [22] expanded on the National Research Council's *Prudent Practices* to provide more systematic methods for hazard identification and prioritisation. Related contributions include work by McCarthy *et al.* (2022) [15], who applied control-banding to decisions around laboratory ventilation, and Papadopoli *et al.* (2020) [18], who showed that even well-trained staff often lack awareness of chemical risks, highlighting the importance of tools that communicate prioritised hazards clearly.

Control-banding itself continues to evolve as a flexible approach to managing uncertainty in the absence of complete toxicological data. Zalk and Swuste (2020) [26] introduced the concept of "barrier banding" to deal with a wider range of hazard scenarios, while Ramos *et al.* (2023) [19] and Jankowska *et al.* (2023) [13] advanced control-banding methods for nanomaterials, where data gaps are common. These innovations reinforce the logic behind rubric-based tools, which share the same underlying philosophy of grouping and ranking risks in a way that can guide immediate action. Beyond occupational safety, the need to integrate environmental considerations has grown more urgent. International monitoring has documented the persistence of organic pollutants across ecosystems (UNEP, 2019) [24], and recent policy and toxicological analyses of per- and polyfluoroalkyl substances (PFAS) argue strongly for hazard indices that account for persistence and bioaccumulation alongside acute toxicity [9][11]. By including these dimensions, laboratory-level indices such as the Environmental Hazard Index (EHI) reflect global concerns while still addressing local institutional needs.

These technical and methodological advances are increasingly being framed within the wider discussion of AI governance. New standards such as ISO/IEC 23894:2023 on AI risk management and the NIST AI Risk Management Framework emphasise the importance of explainability, transparency, and traceability in risk assessment processes [10][17]. Ethical initiatives such as AI4People [7] and comparative surveys of international AI ethics guidelines [12] likewise highlight accountability and the need for structured, auditable methods. Scholars such as Stahl *et al.* (2021) [23] and Whittlestone *et al.* (2019) [25] have argued that responsible AI in environmental and occupational contexts requires methodologies that can be interrogated and adapted across institutions and jurisdictions. In this respect, rubric-based scoring systems serve not only as pragmatic tools for chemical safety but also as exemplars of how structured data can bridge the gap between regulatory compliance and intelligent, accountable institutional governance.

III. METHODS

A. Dataset and Pre-processing

The construction of the Environmental Hazard Index (EHI) and its underlying rubric scores was achieved through a deliberate triangulation of three distinct data streams, ensuring a robust and context-aware assessment of risk.

The chemical inventory masterlist compiled from UTM Kuala Lumpur contained approximately 1,150 entries. After cleaning duplicate records and consolidating units, the dataset was reduced to 698 unique chemicals. This ensured that hazard scoring and Environmental Hazard Index (EHI) calculations were based on a non-redundant set of substances, while still retaining information on laboratory distribution and total quantities. Quantity fields were parsed from text entries (e.g., "500 mL"), and numeric values were extracted for scoring. Frequency was defined as the number of laboratories in which a chemical appeared, while modal laboratory assignment captured the most common location for each entry.

The second foundational hazard classifications were systematically extracted from Safety Data Sheets (SDS), with a specific focus on Section 2 and its standardized Globally Harmonized System of Classification and Labelling of Chemicals (GHS) hazard statements (H-phrases); these designations, such as H350 for carcinogenicity or H225 for flammability, provided a consistent, internationally recognized basis for scoring a substance's intrinsic health and physical dangers. To further refine the environmental component, particularly for persistence and bioaccumulation, these SDS-derived codes were supplemented by cross-referencing authoritative international databases like the European Union's Registration, Evaluation, Authorization and Restriction of Chemicals (REACH) Substances of Very High Concern (SVHC) list and the United Nations Environment Programme's (UNEP) inventories on Persistent Organic Pollutants (POPs), thereby anchoring the scoring within global regulatory discourse.

The third and final dimension incorporated infrastructure readiness, a factor evaluated through formal laboratory safety audits that assessed the adequacy of engineering controls like fume hoods and ventilation, as well as administrative measures and safety equipment. They were all benchmarked against international's best practices such as the Control of Substances Hazardous to Health (COSHH) guidelines. This integrative methodology ensures the final risk evaluation is tempered by the specific context of its local use and the mitigating infrastructure in place, aligning with demands for transparent, auditable, and reproducible decision-support systems.

B. Rubric and scoring

We employed a two-tiered rubric system to ensure a comprehensive yet practical evaluation of chemical risk. The initial, simplified rubric was designed for rapid triage and incorporated six core factors: Health, Physical, and Environmental hazards, alongside Quantity, Frequency, and Infrastructure. Each factor was assigned a score on a transparent one-to-five scale. Crucially, the Infrastructure score was independently assessed through structured laboratory safety audits; these evaluations considered the real-world adequacy of engineering and administrative controls, including the presence and functionality of fume hoods, the suitability of chemical storage, overall ventilation efficacy, and the availability of essential safety equipment like spill kits and fire suppression systems, drawing on established best practices from leading safety organizations (ACS, 2016; HSE, 2019).

A second, detailed rubric was applied, expanding the hazard evaluation into nine specific sub-categories: Acute Toxicity, Carcinogenicity, Reproductive Toxicity, Mutagenicity, Flammability, Corrosivity, Reactivity, Persistence, and Bioaccumulation, each also rated on a one-to-five scale based on standardized hazard statements from sources like the European Chemicals Agency [4]. This dual-level approach allowed the study to balance operational efficiency with analytical depth, enabling both institution-wide screening and detailed, substance-level profiling where it mattered most.

C. Environmental Hazard Index (EHI)

EHI = (Environmental + Persistence + Bioaccumulation) X (Quantity + Frequency)

Values were normalized to a 0–100 scale for comparability

IV. RESULTS & DISCUSSIONS

A. Chemicals by EHI

The initial application of simplified rubric produced a Top 20 list of chemicals, confirming that a scoring framework combining Health, Physical, and Environmental hazards with practical exposure metrics such as Quantity and Frequency can highlight high-priority substances (Table I). Unsurprisingly, widely used solvents and acids featured prominently, reflecting both their extensive distribution across laboratories (high Frequency bands) and the large volumes in which they are stored (high Quantity bands). This finding underscores a critical insight: institutional risk is often shaped not by rare, exotic toxicants but by familiar reagents that accumulate significance through sheer prevalence and volume. Such outcomes are consistent with earlier reports that showed everyday laboratory chemicals frequently dominate cumulative risk burdens [6], [20].

The detailed rubric added further resolution (Table II), disaggregating broad hazard categories into sub-classes such as carcinogenicity, flammability, and environmental persistence. This revealed differences in chemical profiles: while some substances maintained moderate scores across multiple categories, others, including strong acids and heavy metal salts, reached elevated totals due to the combination of acute toxicity and persistence. This layered approach offers institutions both a wide-angle view of operational risks and the ability to identify long-term environmental liabilities—an alignment with calls to integrate persistence and bioaccumulation into prioritization frameworks [9][11][24].

TABLE I. SIMPLIFIED RUBRICS TABLE

Chemical Name	Hea	Phy	Env	Q band	F band	Infr	Total
Lead (II) nitrate	3	2	4	4	3	3	19
Lead (II) chloride	3	2	4	3	2	3	17
Cadmium nitrate tetrahydrate	3	2	4	4	1	3	17
Boric acid	3	2	4	3	3	3	18
Perchloric acid	3	2	4	4	2	3	18
Acetic acid	3	2	4	3	2	3	17
Sulphuric acid	3	2	4	2	3	3	17
Trichloroacetic acid	3	2	4	4	1	3	17

(Hea = Health, Phy = Physical, Env = Environmental, Q = Quantity, F = Frequency, Infr = Infrastructure)

Using the Environmental Hazard Index (EHI) produced a clear ranking of chemicals as illustrated in Fig. 1. The diagram showed a steep gradient at the top of the distribution, suggesting that a relatively small group of substances disproportionately influences the overall institutional risk. Chemicals such as lead salts, cadmium compounds, and strong acids occupied these top positions. This pattern aligns with Pareto-style dynamics in risk management, where a minority of agents account for most of the hazard potential [21].

TABLE II. A DETAILED RUBRICS TABLE

Chem.	Ac	Ca	Re	Mu	Fl	Co	Re	Pe	Bi	Qu	F	To
Lead (II) nitrate	3	2	1	1	4	2	2	2	2	4	3	26
Lead (II) chloride	3	2	1	1	4	2	2	2	2	3	2	24
Cadmium nitrate tetrahydrate	3	2	1	1	4	2	2	2	2	4	1	24
Boric acid	3	2	1	1	4	2	2	2	2	3	3	25
Perchloric acid	3	2	1	1	4	2	2	2	2	4	2	25
Acetic acid	3	2	1	1	4	2	2	2	2	3	2	24
Sulphuric acid	3	2	1	1	4	2	2	2	2	2	3	24
TCA	3	2	1	1	4	2	2	2	2	4	1	24

(Chem = Chemical, Ac = acute, Ca = carcinogen, Re = reproductivity, Mu = Mutagenicity, Flam = flammability, Co = Corrosivity, Re = Reactivity, Pe = Persistence, Bi = Bioaccumulation, Qu = Quantity, F = Frequency, To = Total)

This ranking provides a practical foundation for targeted interventions. For example, procurement reviews could focus on reducing unnecessary duplication of high-ranking chemicals across laboratories, while storage protocols could be adjusted to prioritize segregation or containment of the most hazardous compounds. Substitution may also be considered for compounds that are both high-scoring and non-essential, thereby directly reducing risk without impeding research activities.

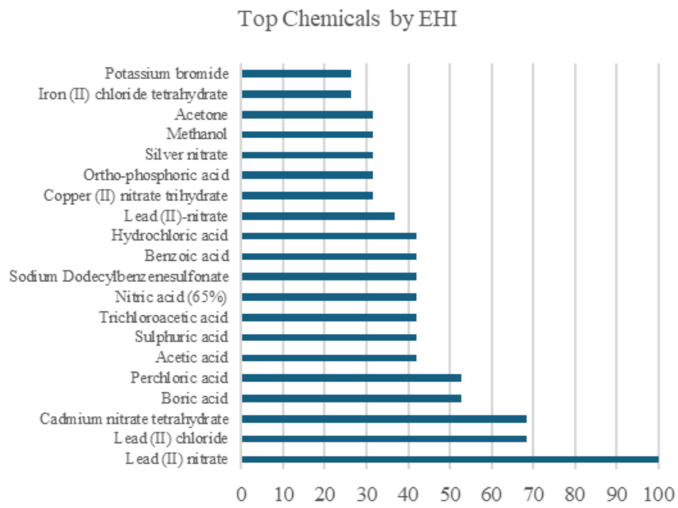

Fig. 1. Top chemicals by Environmental Hazard Index (EHI).

B. *Hazard-Type Composition*

The hazard-type composition of the Top 20 chemicals (Fig. 2) revealed that the majority fell within the medium hazard band (15 chemicals), while three were classified as high hazard and two as low. The dominance of the medium band suggests that institutional risk is not solely driven by extreme outliers but by a substantial group of moderately hazardous substances whose collective presence is significant. This finding reinforces the idea that risk governance must extend beyond the obvious “red flag” chemicals and consider the cumulative impact of widely distributed medium-risk substances.

Moreover, the composition shows that high-scoring entries tend to be substances with environmental and chronic health implications, particularly persistent and bioaccumulative agents. This resonates with global policy trends, where regulators emphasise long-term environmental hazards such as PFAS and other persistent organic pollutants [9][24]. By incorporating these dimensions explicitly, the rubric mirrors global regulatory discourse at the institutional scale.

C. *Distribution of EHI scores*

The overall distribution of EHI scores across the dataset (Fig. 3) displayed a positively skewed profile, with most chemicals concentrated in the low-to-medium range and a long tail of high-risk substances. This statistical pattern strongly supports a prioritisation strategy that focuses on the relatively small group of high-impact chemicals. From a management perspective, concentrating resources—such as advanced containment systems or specialised training—on this limited group represents an efficient use of finite safety budgets while still addressing the bulk of the hazard potential.

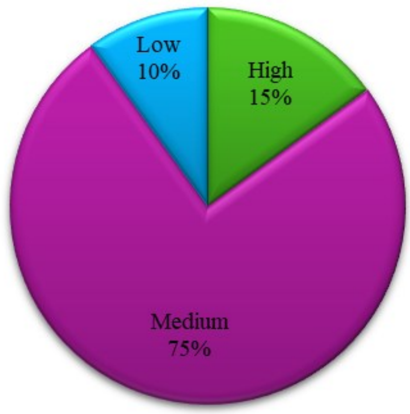

Fig. 2. Hazard-Type Composition of Top Chemicals

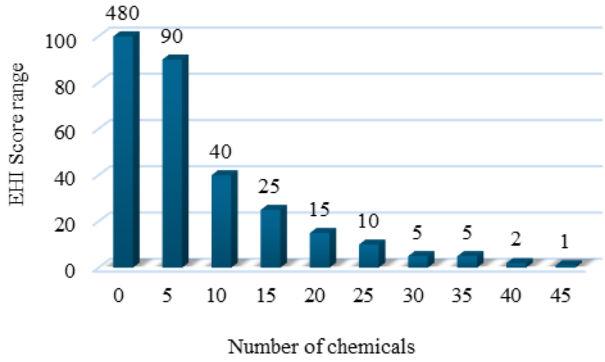

Fig. 3. Distribution of Environmental Hazard Index (EHI) scores

D. *Laboratory Risk Profiles*

EHI averages varied across laboratories, reflecting the heterogeneity of research activities within the institution. Teaching and undergraduate laboratories produced lower averages, whereas research-focused facilities with high solvent turnover or heavy metal usage produced significantly higher scores. This mirrors observations by Papadopoli *et al.* (2020) [18], who found that chemical risk awareness and distribution are uneven even within the same institution.

To contextualise these differences, laboratories were divided into high, medium, and low-risk clusters using terciles (Fig. 4). This relative classification avoids arbitrary thresholds and ensures that each laboratory’s score is interpreted in relation to its peers. As expected, specialised research laboratories dominated the high-risk cluster, while teaching spaces clustered at the low-risk end. Such classification offers administrators a clear framework for prioritising interventions, whether through enhanced audits, infrastructure upgrades, or targeted training.

E. *Pareto Analysis of Chemicals Based on Environmental Hazard Index (EHI)*

Fig. 5 illustrates a Pareto analysis of chemicals ranked according to their Environmental Hazard Index (EHI). The blue bars represent the individual EHI scores of each chemical, arranged from the highest to the lowest hazard level. The red line shows the cumulative percentage contribution of these chemicals to the overall environmental hazard as additional substances are considered.

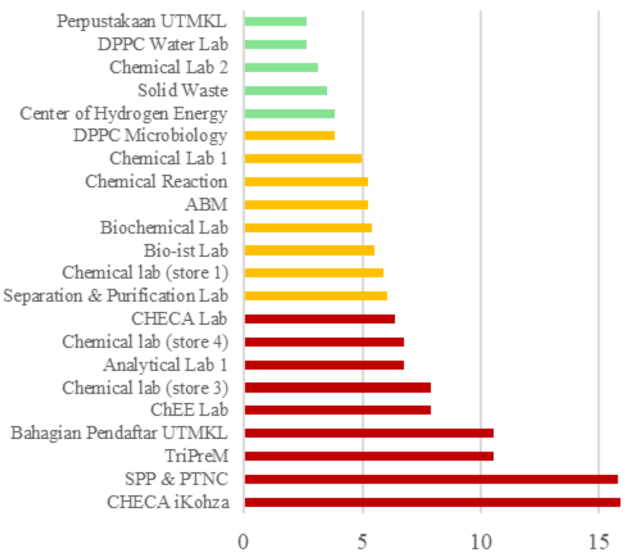

Fig. 4. Lab clusters by average Environmental Hazard Index (EHI).

Figure 5 demonstrates that only a small number of chemicals contribute significantly to the total environmental hazard. In particular, lead (II) nitrate, lead (II) chloride, and cadmium nitrate tetrahydrate record the highest EHI values, indicating that these substances pose relatively greater environmental risks compared to the other chemicals in the inventory. As more chemicals are moving from left to right, the cumulative contribution gradually increases until it reaches the total hazard profile.

The dashed vertical line indicates the approximate point where the most hazardous chemicals account for a substantial share of the total environmental impact. This pattern reflects the Pareto principle, where a limited number of factors contribute to a large proportion of the overall outcome.

Overall, the figure suggests that focusing risk management efforts on the highest-ranked chemicals could meaningfully reduce the environmental hazard associated with the laboratory's chemical inventory. Prioritizing these substances allows for more efficient safety management and supports a practical, risk-based approach to chemical handling and storage.

F. Method Comparison with Chemical Health Risk Assessment (CHRA)

A natural point of comparison is Malaysia's Chemical Health Risk Assessment (CHRA), mandated under USECHH Regulations 2000 and guided by CLASS 2013. While both the CHRA and the rubric seek to systematize hazard evaluation, they differ fundamentally in orientation. The CHRA is primarily occupational, focusing on worker exposures through inhalation or dermal contact and ensuring compliance with regulatory limits [3]. By contrast, the rubric casts a wider net by including environmental endpoints such as persistence and ecotoxicity, alongside infrastructural readiness, situating risk within a broader sustainability context.

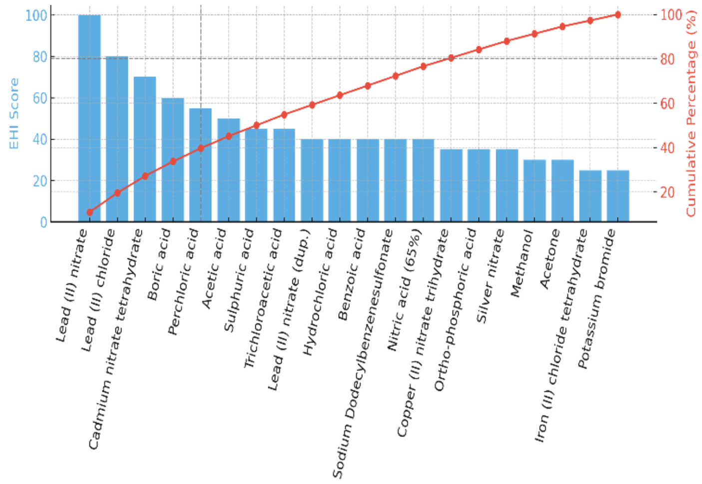

Fig. 5. Pareto curve with top chemicals by Environmental Hazard Index EHI

Their data foundations also diverge. The CHRA relies on direct sampling and observational studies of work practices, whereas the rubric builds on existing institutional data, such as SDS codes, inventory records, and audit findings, thus making it inherently more scalable for institution-wide screening. Consequently, the CHRA outputs qualitative classifications of risk for specific roles or tasks, while the rubric generates ranked lists of chemicals and laboratories with normalized scores that lend themselves to dashboards and cross-laboratory benchmarking.

In this sense, the two approaches are complementary rather than competing. The CHRA provides the prescriptive regulatory assessment necessary for compliance, while the rubric functions as a flexible management tool designed for continuous monitoring, prioritization, and integration into AI-driven governance systems.

V. LIMITATIONS AND FUTURE WORK

One of the notable strengths of the dual-level rubric is its ability to generate transparent and traceable outputs. Because every risk ranking can be broken down into its underlying scores, the framework directly addresses the demand for explainability that has become central to modern AI governance standards [10][17]. This structured, auditable approach contrasts sharply with the often subjective and time-consuming review of individual Safety Data Sheets, offering instead a systematic way to triage large inventories that may contain hundreds of chemicals. Importantly, the rubric can be integrated into existing risk management systems such as ISO 14001 and ISO 45001 by feeding directly into environmental and occupational health registers. At the national level, the framework also shows strong alignment with Malaysian protocols, including the DOSH CHRA process and DOE environmental impact assessment guidelines [3]. By embedding persistence and bioaccumulation as scoring criteria, the approach additionally ensures that local laboratory risk management remains connected to global debates on persistent organic pollutants and other chemicals of emerging concern [9][11][24].

Despite these advantages, several limitations must be acknowledged. Hazard scoring in this study relied on name-based heuristics, which, although practical, lack the precision of assessments linked directly to CAS registry numbers and structured Safety Data Sheet databases. The method of parsing chemical quantities also introduces a margin of error, as unit expressions are not always consistent, and frequency was treated as a proxy for presence rather than actual usage intensity. Furthermore, the Environmental Hazard Index (EHI) is a relative measure: its distribution depends on the composition of the dataset, which makes comparisons across institutions less straightforward.

These limitations point towards clear directions for future development. Integrating authoritative hazard databases will provide greater accuracy and reduce reliance on heuristics. Linking rubric scores with incident reports and waste management records will allow validation against real-world outcomes, strengthening the framework's predictive capacity. Finally, the structured datasets generated here are well-suited for digital dashboards. By visualising ranked chemical lists, laboratory clusters, and score distributions in real time, institutions can move beyond static compliance towards dynamic risk monitoring. Over time, these data streams could power machine learning models capable of predicting emerging hazards from procurement trends or flagging anomalies in laboratory inventories, enabling a shift from compliance-driven oversight to proactive, preventive safety management.

VI. CONCLUSION

This study demonstrated the feasibility of a dual-level rubric combined with an Environmental Hazard Index as a practical, explainable, and AI-ready tool for laboratory hazard evaluation. By applying the framework to a dataset of nearly 700 unique chemicals across UTM laboratories, we showed how rubric scoring can highlight priority chemicals, characterize laboratory risk profiles, and produce structured outputs suitable for integration into AI-driven governance systems. The approach complements regulatory tools such as CHRA by providing an institution-wide perspective on hazard prioritization, bridging compliance with intelligent, accountable decision-making.

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CONFLICT OF INTEREST

The authors agree that this research was conducted in the absence of any self-benefits, commercial or financial conflicts and declare the absence of conflicting interests with the funders.

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