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The role of spatial distance to hazards in risk perception: A systematic literature review

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ABSTRACT

Introduction: The rapid change in climate and advancement in new materials and technologies are reshaping risk landscapes with more frequent and severe hazards, emergencies, and disasters. Spatial proximity to those hazards critically shapes risk perception, influencing safety decisions and behaviors. Though a few studies have investigated how people perceive and respond to risks based on different spatial exposure to hazards, the role of spatial distance in shaping risk perception remains conceptually fragmented. This systematic review aims to: (a) evaluate methodological approaches to distance and risk perception assessment; (b) examine human factors mediating proximity effects; and (c) identify patterns in distance-risk perception relationships. *Method:* A PRISMA-guided analysis of 54 studies from Scopus and Web of Science was conducted to examine the literature. *Results:* This review identified three distance-risk perception patterns: (a) increased risk perception with proximity (45 studies), largely attributed to sensory salience; (b) reduced perception near hazards (6 studies), linked to habituation; and (c) non-linear patterns (3 studies), influenced by familiarity and motivational trade-offs. The reviewed studies applied different methods to categorize and measure the distance to hazards, including Euclidean distance, zone-based classification, and real-time sensing. Risk perception was evaluated through diverse methodologies such as surveys, validated Likert-type scales, behavioral observations, and technology-driven tools like virtual reality simulations and physiological monitoring. This review also finds that human factors, such as age, gender, education, income, and prior experience, moderate proximity effects, with older adults and women exhibiting stronger sensitivity. *Practical applications:* This study contributes a unified overview of methodological variation and perceptual outcomes, offering new insight for risk communication, policy design, and hazard management.

1. Introduction

Risk perception is a critical factor influencing how individuals respond to hazards and make safety decisions (Slovic, 1987). It shapes preparedness levels, behavioral adaptations, and the effectiveness of risk communication strategies. For example, residents in flood-prone areas often base their evacuation decisions on perceived risk rather than objective danger levels (Zhou et al., 2022). Equally, when performing inherently dangerous tasks on construction sites, front-line workers rely heavily on their subjective appraisal of danger to decide whether to use protective equipment or comply with safety procedures (Priolo et al., 2025; Luo et al., 2016). Among the factors influencing risk perception, proximity (the state of being near a hazard in space) is a significant yet complex determinant. Empirical evidence shows that shorter distances to a threat systematically elevate perceived severity (Lindell & Hwang, 2008; Zhang & Liabsuetrakul, 2023) and trigger stronger affective responses such as fear and anxiety, which in turn shape protective or avoidant behavior (Zabini et al., 2021; Shi et al., 2020). A deeper understanding of these dynamics is crucial for designing targeted interventions, such as evacuation plans and disaster communication strategies, that effectively address immediate and long-term safety concerns.

Research has revealed that spatial distance shapes risk perception, but significant debates and uncertainties remain. Studies consistently demonstrate that individuals closer to hazards often exhibit heightened awareness and concern. For instance, Zhang and Liabsuetrakul (2023) found that residents living within 3 km of a waste incineration plant reported 35% higher risk perception than those living farther away. However, the relationship is not always linear, as some individuals near hazard zones report lower perceived risks. This counterintuitive finding

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is often attributed to cognitive dissonance—a psychological mechanism by which individuals downplay threats to maintain emotional equilibrium—or habituation, where prolonged exposure reduces sensitivity to potential risks (Chen et al., 2019). These contrasting patterns highlight ongoing debates in the literature: while proximity influences risk perception, the conditions under which these effects vary are still contested. This highlights the need for further exploration into how and why proximity interacts with risk perception across different contexts.

Human factors further complicate the relationship between distance and risk perception. Age, gender, income, and education significantly influence how proximity shapes perceived risks. A consistent body of empirical work shows that women and older adults tend to report higher subjective risk levels in environmental and industrial-hazard settings (Lohmann & Kontoleon, 2023; Lyons et al., 2020; Kim et al., 2022). Conversely, individuals with higher education levels may approach risks more analytically, mitigating the emotional impact of proximity (Chen et al., 2019). However, current findings are far from conclusive, with cultural contexts and prior hazard experiences adding further layers of complexity. These unresolved debates and uncertainties suggest the need for a more nuanced understanding of how human factors mediate or moderate the influence of distance. A systematic analysis of these factors could provide valuable insights for tailoring risk communication strategies.

Despite the growing body of research on risk perception, significant controversies persist, particularly regarding methodological inconsistencies and the scope of hazards considered. Distance is often measured inconsistently across studies, ranging from self-reported proximity estimates (perceived distance) to precise geocoded locations via Geographic Information System (GIS) analysis (Trumbo et al., 2011; Zhou et al., 2022). This variability has fueled debates about cross-study comparability and the generalizability of findings. Moreover, much of the existing literature is hazard-specific, focusing narrowly on floods or industrial risks without considering broader applications. Addressing these methodological and contextual uncertainties is crucial for developing a holistic understanding of how spatial distance influences risk perception.

These debates, controversies, and uncertainties emphasize the need for a comprehensive and systematic understanding of how proximity to hazards shapes risk perception. Gaps in the literature highlight the necessity of consolidating existing evidence, clarifying dynamics, and building a cohesive framework for future research. This study aims to provide a holistic view of how spatial distance to hazards influences risk perception. Specifically, it seeks to: (a) evaluate the methodological approaches used to measure distance and assess risk perception; (b) examine the human factors that mediate or moderate proximity effects; and (c) identify and synthesize recurring patterns in distance–risk-perception relationships. A systematic literature review was conducted by examining 54 papers published between 1978 and 2024. This study presents the findings about types of hazards and risks, distance categorization, distance measurement, risk perception evaluation, effects of distance on risk perceptions, and effects of human factors on the interaction between distance and risk perceptions.

2. Background

This section first clarifies how spatial distance is conceptualized in Section 2.1. Then, this section synthesizes the cognitive-affective mechanisms through which distance shapes risk perception and behavioral response in Section 2.2. Together, these two sub-sections establish the theoretical foundation for this review.

2.1. Distance and proximity

Distance is a multifaceted concept that significantly shapes human perception and behavior in risk contexts. It encompasses several dimensions, including spatial (or physical) distance, temporal distance, social distance, and experiential distance, with each influencing perception differently (Zhou et al., 2022). Spatial distance refers to the measurable geographical separation between entities (Zhou et al., 2022). Spatial distance significantly shapes human perception through its effects on sensory engagement, information accessibility, and cognitive processing (Zabini et al., 2021; Zhang et al., 2021; Zhou et al., 2022). Proximity often heightens awareness due to sensory cues and access to detailed hazard information. Temporal distance reflects the psychological perception of time between present, future, and past events (Zhang & Liabsuetrakul, 2023). This dimension influences how individuals prioritize risks, with distant threats often perceived as less urgent, while past events may inform current risk assessments (Zhang & Liabsuetrakul, 2023). Social distance pertains to the relational gap between individuals or groups (Zhang et al., 2021; Zhou et al., 2022). It affects factors such as empathy, trust, and collective responses to risks. For instance, closer social bonds often lead to stronger collaborative efforts in managing risks (Zhang et al., 2021). Experiential distance involves the distinction between direct and indirect exposure to an event (Zhou et al., 2022). Direct exposure typically enhances familiarity and understanding of hazards, whereas indirect exposure may lead to more abstract or mediated perceptions of risk (Zhou et al., 2022). These multiple dimensions of distance shape human interactions with risks in diverse ways.

Tobler's First Law of Geography, as proposed by Tobler in 1970, states that all things are interconnected, with closer entities having stronger relationships than those farther apart (Tobler, 1970). This principle forms the basis for spatial autocorrelation and distance-decay phenomena, where associations tend to be more pronounced at shorter distances and diminish as distance increases. Applied to hazards, this law suggests that factors such as visibility, attention, and perceived risk are often more closely associated with nearby sources compared to distant ones, holding all else constant. Recent interdisciplinary research has consistently observed distance-decay patterns across various domains including environmental exposure, mobility, and perception, indicating the widespread relevance of this principle. However, it is noted that specific contextual factors such as barriers, media dissemination, and variations in social and physical environments can modify these patterns (Dallas et al., 2024). As such, this review adopts Tobler's First Law as a theoretical framework to explore how spatial proximity influences perceptions and behaviors related to risk, without assuming any particular empirical outcomes.

Spatial distance, quantified through metrics such as Euclidean distance or network models, provides critical insights into hazard proximity and its influence on risk perception (Giordano et al., 2010; Sen et al., 2022; Ali et al., 2022; Lindell & Hwang, 2008). For instance, individuals living near industrial facilities or natural disaster zones frequently report higher perceived vulnerability than those farther away (Zhang et al., 2021; Zhou et al., 2022; Zhang & Liabsuetrakul, 2023). Although spatial distance is conventionally operationalized as an objective metric, behavioral responses are often driven by perceived rather than actual proximity (Ali et al., 2022; Lindell & Hwang, 2008; Zhou et al., 2022). Field studies show that residents who feel outside a floodplain may under-prepare even when their homes lie within the officially delineated hazard zone (Ali et al., 2022; Zabini et al., 2021). Conversely, intense media coverage or past trauma can create heightened perceived proximity in distant communities, amplifying worried and protective actions (Giordano et al., 2010; Zhou et al., 2022). Laboratory studies and post-event surveys further reveal systematic errors in distance estimation (up to 30%) under conditions of low visibility or high arousal (Lindell & Hwang, 2008). These dynamics highlight the critical role of spatial distance and human perceptions in shaping responses to risks.

Drawing on Construal Level Theory, various dimensions including temporal, social, and experiential distances, in addition to spatial distance, influence mental construal and risk assessments (Liberman & Trope, 2008; Trope & Liberman, 2010). Risk perceptions are also influenced by social systems, where media and networks can either amplify or diminish hazards, sometimes disconnecting perceived risk from physical proximity (Kasperson et al., 1988). These perspectives suggest that spatial closeness can be heightened by recentness, close social connections, or personal experience, while it can be diminished by time since the last event, framing by an out-group, or indirect experiences (Hertwig & Erev, 2009).

2.2. Risk perception

Risk perception is the lens through which individuals evaluate the potential impact of hazards. Classic work highlights cognitive heuristics (Slovic, 1987) and situational appraisal (Lindell & Hwang, 2008). More recently, a comprehensive review of wildfire research demonstrated that proximity-based cues interact with affective states and social trust to condition evacuation decisions (Kinateder et al., 2015). Together, these studies underscore that hazards are potential sources of harm, encompassing natural disasters, technological failures, and environmental threats (Lindell & Hwang, 2008). Risks quantify the likelihood and consequences of these hazards, integrating probabilistic assessments with impact evaluations (Lindell & Hwang, 2008). Uncertainty is critical in shaping risk perception, as individuals must often navigate incomplete or ambiguous information when assessing threats (Zhou et al., 2022; Zhang & Liabsuetrakul, 2023). This distinction provides a conceptual foundation for analyzing human responses to potential dangers.

Distance may influence risk perception through both cognitive and affective processes (Fig. 1) (Slovic, 1987; Lindell & Hwang, 2008; Shi et al., 2020; Zabini et al., 2021). The cognitive process comprises four interconnected components: awareness (Zhou et al., 2022), recognition (Slovic, 1987), assessment (Chen et al., 2019; Lindell & Hwang, 2008), and response (Zhou et al., 2022). Awareness is the preliminary recognition of a potential threat within the surrounding environment, serving as the foundation for subsequent stages (Zhou et al., 2022). Recognition extends this foundation by contextualizing the nature and consequences of identified hazards, enabling individuals to comprehend potential impacts (Slovic, 1987). Assessment integrates evaluations of probability, impact, and vulnerability into comprehensive judgments, employing multidimensional analyses to prioritize responses to hazards (Chen et al., 2019; Lindell & Hwang, 2008). Finally, responses translate these assessments into behavioral adaptations, such as protective actions and decisions. This stage also reflects the influence of cognitive and emotional factors, as observed in real-world hazard responses (Zhou et al., 2022). The affective process of risk perception operates through two distinct arousal states—high-arousal (e.g., fear and anxiety) and low-arousal (e.g., optimization)—that dynamically interact with distance to shape risk perception (Fig. 1).

High-arousal states (e.g., fear, anxiety) are triggered by acute sensory cues (e.g., visible floodwaters, emergency sirens) or perceived immediacy of threats. Proximity to hazards intensifies these emotions, leading to heightened risk salience and impulsive protective actions (Shi et al., 2020; Zabini et al., 2021). For instance, residents within 5–10 km of nuclear facilities exhibit elevated anxiety levels compared to those in immediate or distant zones, a phenomenon attributed to uncertainty and conflicting risk narratives (Giordano et al., 2010).

Low-arousal states (e.g., optimism) emerge from prolonged exposure or psychological adaptation. Communities adjacent to recurrent hazards (e.g., floodplains, industrial zones) often normalize risks, reducing preparedness despite objective vulnerability (Navarro et al., 2021; López-Fletes et al., 2022). Cognitive dissonance further suppresses risk perception, as seen in populations rationalizing chronic industrial exposure through optimistic bias (Lyons et al., 2020).

Several foundational frameworks have tried to explain and understand risk perception. The psychometric paradigm examines how individuals evaluate risks based on characteristics such as familiarity, voluntariness, and severity, which influence perceived acceptability and concern (Slovic, 1987). Cultural theory emphasizes the role of societal values and norms in shaping collective interpretations of risks, highlighting variability across cultural contexts. The social amplification of risk framework explores how media, institutional trust, and social communication amplify or attenuate perceptions, shaping public responses and policy outcomes (Zhou et al., 2022). Together, these frameworks provide critical insights into risk perception's cognitive, social, and cultural dimensions.

Human factors play a crucial role in influencing the relationship between proximity and perceived risk. Existing research has demonstrated that cognitive and affective processes significantly impact risk assessments. For instance, the availability heuristic suggests that events that are more vivid or easily recalled tend to be perceived as more risky (Tversky & Kahneman, 1973; Lichtenstein et al., 1978). Moreover, the affect heuristic associates negative emotions with higher perceived risk and reduced perceived benefits (Finucane et al., 2000; Slovic, 1987). Biases such as optimism bias and probability neglect also contribute to systematic distortions in risk perception (Sharot, 2011; Sunstein, 2002). Individual traits and dispositions, such as sensation seeking as measured by SSS-V (Zuckerman, 1994), risk propensity (Meertens & Lion, 2008), and domain-specific risk patterns assessed by DOSPERT (Blais & Weber, 2006), further influence risk judgments. The Balloon Analogue Risk Task (BART) is also highlighted as a behavioral measure that complements self-report assessments (Lejuez et al., 2002). Specific emotions and emotion-regulation strategies, such as fear versus anger (Lerner &

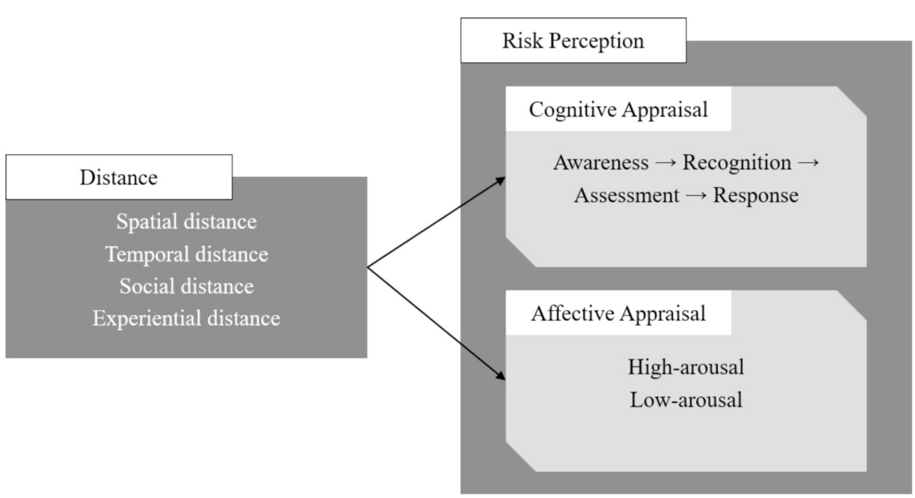

Fig. 1. A conceptual distance–risk-perception framework.

Keltner, 2001; Lerner et al., 2003) and reappraisal versus suppression (Gross, 1998, 2002), also play a role in shaping risk perceptions. Additionally, social norms and cultural contexts impact how signals of danger are either amplified or normalized within social networks (Weber & Hsee, 1998; Dryhurst et al., 2020). These various factors suggest that the impact of proximity on risk perception can vary depending on individual states and traits. Therefore, it is essential to consider the extent to which these factors were accounted for in previous studies and how they interact with proximity to influence risk perception.

The literature presents the complex underlying mechanisms of risk perception, yet the interplay of spatial distance with risk perception is still fragmented. A clear understanding of this knowledge, with summarized evidence, is needed.

3. Methods

This study aims to provide a holistic view of how spatial distance to hazards influences risk perception. We conducted a systematic literature review following the method proposed by Khan et al. (2003) to provide a comprehensive understanding of the role of spatial distance to hazards in risk perception. The method consists of five steps: formulating research questions, identifying relevant studies, assessing the quality of the studies, summarizing the evidence, and interpreting the research findings. The first three steps are reported in this section, and the rest are presented as results and discussion in Section 4 and Section 5.

3.1. Formulating research questions

To achieve the research aim, we have formulated the following six research questions (RQ):

RQ1: What types of hazards and risks have been investigated for the effects of distance on risk perception?
RQ2: How is distance categorized to reveal its influence on risk perception?
RQ3: What are the methods for measuring the distance to hazards?
RQ4: What are the methods for evaluating risk perception?
RQ5: What are the effects of distance to hazards on risk perception?
RQ6: What human factors influence the effects of distance on risk perception?

Identifying hazard types (RQ1) establishes foundational context, as risk perception dynamics may differ among different hazard types. This enables a comparative analysis of how proximity effects vary across hazard characteristics. Distance categorization (RQ2) determines how proximity is operationalized in risk models. And we delimit our analysis to spatial distance. Evaluating measurement methods (RQ3 and RQ4) clarifies how methodological choices influence observed proximity-risk relationships. Synthesizing distance effects (RQ5) builds on these foundations to reveal overarching patterns. Finally, human factors (RQ6) are positioned to investigate their role in yielding divergent risk perceptions across demographics, cultures, and lived experiences. In addressing RQ6, we also considered common human factors associated with risk perception and risk-taking propensity, as measured by established instruments such as the SSS-V, RPS, DOSPERT, and BART scales. We systematically coded the following information where available: (a) instrument name and version, (b) item and response format, (c) reported psychometric properties such as Cronbach's alpha, (d) analytical role (predictor, outcome, control, or moderator of distance), and the examination of a Distance X Instrument interaction. Unspecified generic 'risk' scales are categorized as such. Detailed summaries of the study-level coding details can be found in Appendix S2 (Blais & Weber, 2006; Lejuez et al., 2002; Meertens & Lion, 2008; Zuckerman, 1994).

3.2. Identify relevant studies

We searched for relevant studies using two academic databases: Scopus and Web of Science, accessed in January 2025. Scopus is the largest abstract and citation database of peer-reviewed literature, while Web of Science is a major database for peer-reviewed literature in science and engineering (Chadegani et al., 2013). We used the following keyword string to capture relevant studies: *(distance OR proximity)* AND *("risk perception" OR "hazard perception" OR "threat perception" OR "danger perception")*.

We conducted a search on the Web of Science Core Collection and Scopus to identify peer-reviewed studies published in English. While these databases offer comprehensive, curated coverage across multiple disciplines, it is important to note that they may not capture all relevant literature, particularly from non-English and regionally indexed sources, potentially introducing geographic bias. For transparency, we present the locations of the studies in Table 1. When analyzing regional trends, we exercise caution (Page et al., 2021; Tennant, 2020; Mongeon & Paul-Hus, 2016).

The first keyword group consisted of distance and proximity, which are often used interchangeably in the literature. The second keyword group covered the synonyms for risk perception. The search was not restricted by time to ensure the broadest possible range of publications.

The search initially yielded a total of 3,078 results, including 2,622 from Scopus and 1,086 from Web of Science. After removing 778 duplicates, we conducted a systematic filtering process in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework (Page et al., 2021), as shown in Fig. 2. The papers were filtered using predetermined inclusion and exclusion criteria. At the screening stage, we scanned the titles and abstracts to exclude papers that did not fit the following criteria:

(i) the study investigates the effect of distance on risk perception; and
(ii) the study focuses on humans as the subject instead of animals, microorganisms, plants, or other non-human entities.

After the screening, 230 papers remained. Then, we examined the full text to confirm the eligibility of the remaining papers. Papers that satisfied both of the following criteria were included:

(i) the study presents testing, evaluation, experimentation, or data collection to demonstrate the effect of distance on risk perception; and
(ii) the distance discussed in the study refers to spatial distance rather than social, temporal, or experiential distance. Finally, 54 papers remained eligible for this review.

The full list of the eligible papers is presented in Table 1.

3.3. Assessing the quality of studies

Following the completion of the last group of qualifying studies identified by the authors through the PRISMA workflow, we performed a quality assessment to evaluate the extent to which each study addressed the six research questions. It is important to note that this assessment is distinct from the study selection process and does not impact decisions regarding inclusion or exclusion.

We utilized a 3-point Likert scale to assess each criterion (1 = low, 2 = moderate, 3 = high) along three dimensions: (a) topical relevance to the review focus; (b) alignment of the study design/cases with the review questions; and (c) appropriateness of reported results for addressing those questions. The scores were aggregated, resulting in a total score ranging from 3 to 9. This scoring process was conducted manually. To enhance transparency and scalability, we also generated AI-assisted ratings using ChatGPT-4o, based solely on the study title and

Table 1
Hazard types.

Hazard Types	Descriptions	Counts of occurrence	Study location (Country/region)	References
Natural Hazards	To evaluate the effect of proximity to natural events, such as floods and earthquakes, on risk perception and behavioral responses.	38.5% (25)	Pakistan, Italy, United Kingdom, Bangladesh & Nepal, Nigeria, India, United States, Pakistan, France, Malaysia, China, Colombia, Ireland, Mexico	(Zabini et al., 2021),(Wei & Lindell, 2017),(Trumbo et al., 2011),(Sherman-Morris et al., 2022),(She et al., 2012),(Shah et al., 2024),(Santoro et al., 2022),(Ruz et al., 2020),(Rasool et al., 2022),(Qasim et al., 2015),(O'Neill et al., 2016),(Navarro et al., 2021),(Masud et al., 2019),(López-Fletes et al., 2022),(Lohmann & Kontoleon, 2023),(Liu et al., 2019),(Lindell & Hwang, 2008),(Grover et al., 2022),(Gray-Scholz et al., 2019),(Gavilanes-Ruiz et al., 2009),(Faruk & Maharjan, 2023),(Ekoh et al., 2022),(Casareale et al., 2023),(Arias et al., 2017),(Ali et al., 2022)
Industrial Hazards	To investigate the influence of industrial activities, such as waste incineration and power plants, on public safety and environmental health concerns.	24.6% (16)	India, Thailand, South Korea, Mexico, China, Australia, Germany, Netherlands, United States, Italy	(Zhou et al., 2022),(Zhang & Liabsuetrakul, 2023),(Severtson & Burt, 2012),(Sen et al., 2022),(Porsius et al., 2015),(Mueller et al., 2017),(Maderthaner et al., 1978),(Lyons et al., 2020),(López-Fletes et al., 2022),(Lindell & Hwang, 2008),(Kim et al., 2022),(Hüppe & Weber, 1999),(Giordano et al., 2010),(Freudenstein et al., 2015),(Chen et al., 2019a),(Catalán-Vázquez et al., 2010)
Environmental Health Hazards	Risks from pollutants/contaminants affecting human health (air, water, electromagnetic).	24.6% (16)	South Korea, Thailand, China, Mexico, Iraq, United States, New Zealand, Canada	(Zhou et al., 2022),(Zhang & Liabsuetrakul, 2023),(Wei & Lindell, 2017),(Ward & Wilde, 1996),(She et al., 2012),(Makki et al., 2019),(López et al., 2020),(Li, 2019),(Li et al., 2021),(Li et al., 2016),(Li, 2019),(Barton Laws et al., 2015),(Kim et al., 2022),(Kim & Kang, 2024),(Kim & Kang, 2021),(Freudenstein et al., 2015)
Transportation Hazards	To examine risks related to road safety, including pedestrian-vehicle interactions, driver behavior, and vehicle collisions.	12.3% (8)	China, Germany	(Zhang et al., 2021),(Ward & Wilde, 1996),(Makki et al., 2019),(López et al., 2020),(Frings et al., 2014),(Feng et al., 2024),(Duan et al., 2013),(Ding et al., 2019)
Total		100% (65*)		

* This number is higher than the number of eligible articles because some articles included multiple studies and hazards.

abstract in conjunction with our evaluation criteria. Notably, the AI model did not have access to full texts or any confidential information. The AI-generated outputs were not determinative for study inclusion; rather, they were used for validation purposes to confirm the alignment of already selected studies with the review criteria.

While the final eligible set (n = 54) sustained a suitable size for manual scoring, we deliberately trialed GPT-assisted scoring as a validation measure rather than a replacement for human assessment. GPT functioned as a standardized, rubric-based co-rater following set prompts and decision criteria, offering an independent consistency assessment and highlighting potentially ambiguous cases for targeted human reassessment. This trial also demonstrates the potential scalability of this approach across broader systematic literature reviews and enables a specific evaluation of AI-human concordance in relevance assessment. Importantly, GPT ratings did not influence inclusion or exclusion decisions; any discrepancies were resolved through human verification, with human ratings taking precedence. Across the entire set of 54 studies, there was substantial agreement between GPT-generated and finally human-verified total scores (linear-weighted Cohen‘s $k = 0.726$, $SE = 0.129$, 95% CI [0.657, 0.796], $p < 0.01$; see Appendix S1).

The model was provided with a detailed prompt comprising: (a) the objective of assessing the study's relevance to the review questions; (b) three criteria along with definitions and boundary examples; (c) explicit constraints: exclusion not recommended, inference limited to title and abstract, scoring range of 1–3 per criterion and 3–9 in total, accompanied by a justification of up to 60 words linked to the criteria; and (d) a predefined output format (criterion1, criterion2, criterion3, total, justification). The complete prompt template and a sample input and output are available in Appendix S1.

A three-round calibration process was carried out on a subset of 15 papers, involving both human raters and artificial intelligence (AI) scoring in parallel. In cases where there was a discrepancy of one point or more in any criterion, we revised the wording of the prompts (e.g., by providing clarification on boundary cases) and reevaluated the scores until the differences were within one point for at least 80% of the subset. The final scores in the dataset underwent verification by human raters. Instances where there was a difference of two points or more between the AI and human scores necessitated a mandatory reevaluation by human raters, with the human scores taking precedence. Detailed summaries of inter-rater agreement are provided in Appendix S1. The distribution of quality scores for the eligible studies is shown in Fig. 3.

4. Results

This section provides the results extracted from the eligible papers to answer the research questions presented in Section 3.1. The results cover six key themes: hazards and risks, distance categorization, distance measurement, risk perception evaluation, effects of distance on risk perception, and human factors. Fig. 4 shows the global distribution of the included studies, while detailed findings for each theme are presented in the following subsections.

4.1. Hazards and risks

This review identifies diverse hazards that have been studied for the association between distance and risk perception across various fields (Table 1). The investigated hazards span four major areas, including natural hazards (25 counts), industrial hazards (16 counts), environmental health Hazards (16 counts), and transportation hazards (8 counts). The total count of hazards exceeds the number of eligible articles because some articles included multiple case studies and hazards.

Natural hazard studies within the reviewed literature primarily

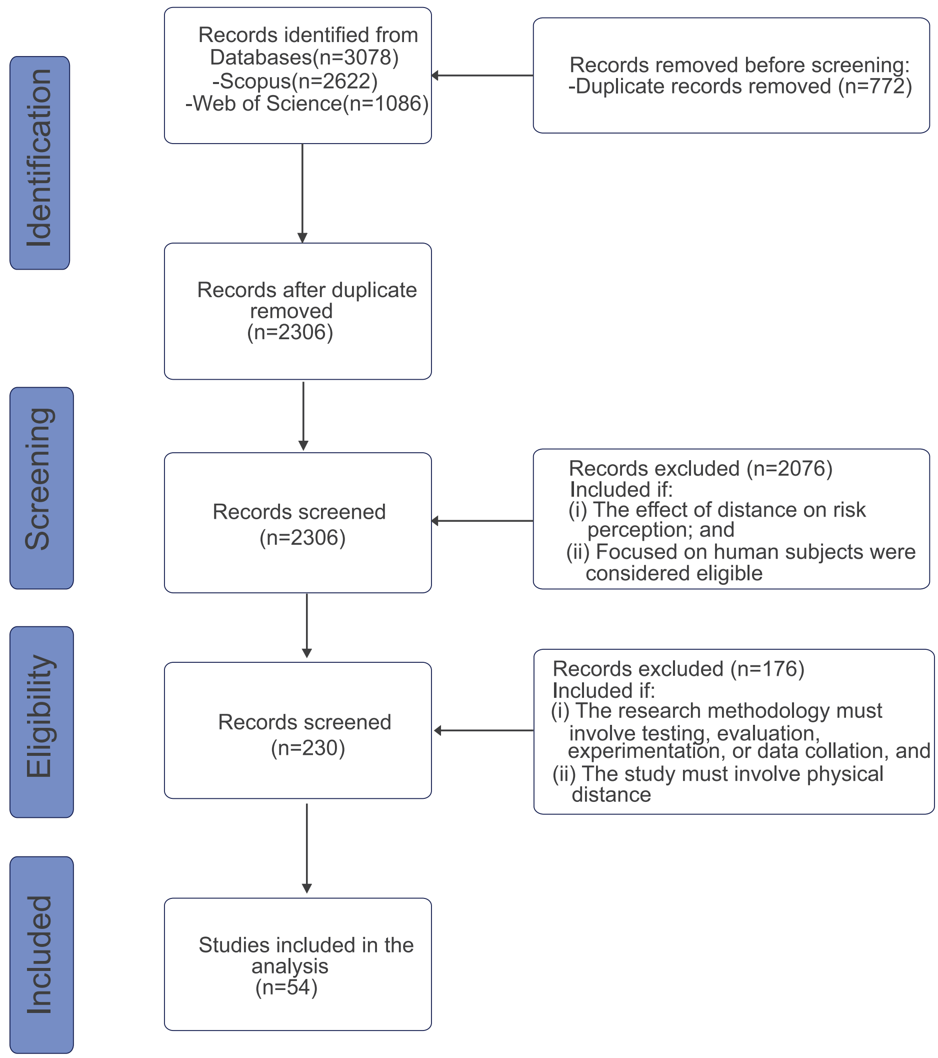

Fig. 2. Study selection process.

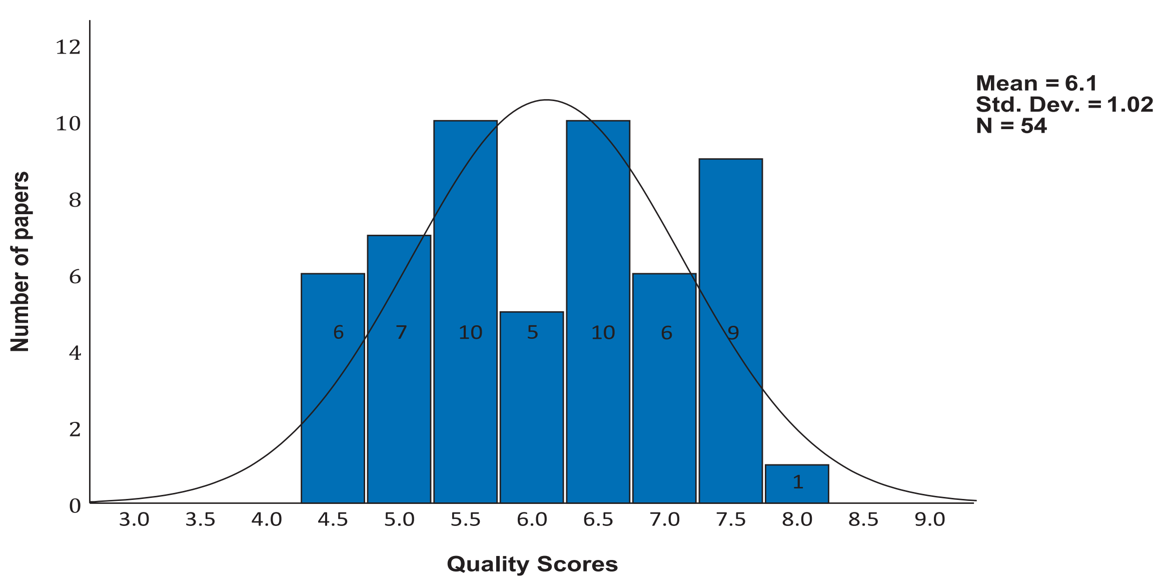

Fig. 3. Quality scores for eligible papers.

address flooding events (n = 18). Notable studies include spatial analyses of flood risk perceptions in river basins of South Asia (Ali et al.,

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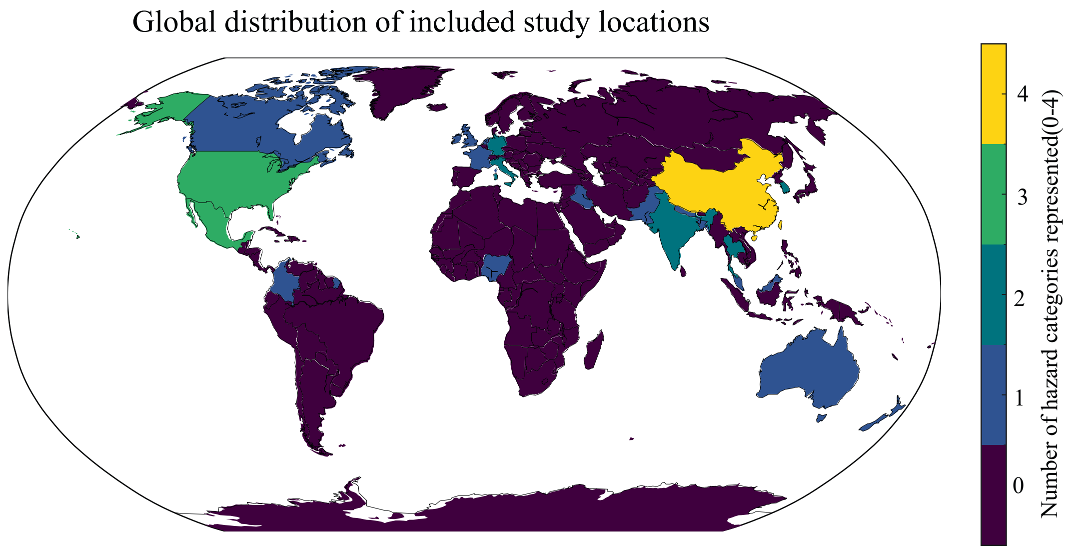

Fig. 4. Global distribution of included studies.

2022; Faruk & Maharjan, 2023) and floodplains across North America (Grover et al., 2022). Geological (n = 5) and meteorological hazards (n = 2) constitute a secondary focus, as seen in volcanic risk perception studies near Mt. Rainier (Wei & Lindell, 2017) and hurricane preparedness analyses along the U.S. Gulf Coast (Lindell & Hwang, 2008). A subset of studies (n = 5) intentionally integrates multiple hazard types. One notable example is Lindell and Hwang's (2008) examination of flood-hurricane-industrial risk interactions. These studies address two underexplored dimensions. First, they consider cumulative exposure effects in communities facing concurrent threats. Second, they explore behavioral trade-offs in allocating protective resources between spatially overlapping hazards. An example of such trade-offs is evacuation priority conflicts in flood-chemical hazard zones (Lindell & Hwang, 2008; United Nations Office for Disaster Risk Reduction Global assessment report on disaster risk reduction, 2024).

Industrial hazard studies (n = 16) predominantly examine three categories. The first category includes waste processing infrastructure, specifically incineration plants, across three studies (Kim et al., 2022; Zhang & Liabsuetrakul, 2023; Zhou et al., 2022). The second category involves energy production facilities, notably nuclear plants in five studies (Chen et al., 2019; Giordano et al., 2010; Hüppe & Weber, 1999; Lyons et al., 2020; Maderthaner & Guttmann, 1978), and high-voltage lines in two studies (Mueller et al., 2017; Porsius et al., 2015). The third category covers industrial emissions, spanning heavy metal exposure in mining communities (Catalán-Vázquez et al., 2010), atmospheric pollutants affecting smelter-adjacent populations (Barton Laws et al., 2015; Li, 2019; Li et al., 2016; Li et al., 2021), radiofrequency radiation (Freudenstein et al., 2015), and chemical releases (Lindell & Hwang, 2008).

Environmental health hazards encompass electromagnetic fields, air pollution, water contamination, and infectious diseases. Some papers focus on electromagnetic fields, examining radio frequency or extremely low-frequency sources and their influence on perceived health risks (Freudenstein et al., 2015; Porsius et al., 2015). Research on air pollution has investigated both industrial and urban contexts. In industrial settings, studies have explored how proximity to emission sources, such as smelting operations, shapes public concern about environmental pollution (Barton Laws et al., 2015; Li et al., 2016; Li, 2019). Urban-focused research primarily emphasizes the health implications of air pollutants and community perceptions of associated risks (Kim et al., 2022; Zhou et al., 2022; Zhang & Liabsuetrakul, 2023). Infectious diseases, including COVID-19, also draw attention. Scholars investigate how psychological distance, and crowding perceptions guide public health actions (Kim & Kang, 2021, 2024; Li et al., 2021). Other studies expand the concept of health hazards to waste incineration byproducts (Kim et al., 2022; Zhou et al., 2022; Zhang & Liabsuetrakul, 2023) and toxic metal exposure (Catalán-Vázquez et al., 2010). This broad scope underscores the range of hazards that can affect health and well-being.

Transportation hazards were examined in eight studies across different scenarios, including car-following interactions (n = 3), pedestrian-vehicle conflicts (n = 2), cyclist overtaking maneuvers (n = 1), railway crossings (n = 1), and lane-change scenarios (n = 1) (Ding et al., 2019; Duan et al., 2013; Feng et al., 2024; Frings et al., 2014; López et al., 2020; Makki et al., 2019; Ward & Wilde, 1996; Zhang et al., 2021). These studies mainly focus on spatial gaps (e.g., headway, lateral, and rear), crossing distances, or stopping distances among road users in different transportation and traffic scenarios. These hazards are characterized by specific spatial configurations, such as headway distances between vehicles, lateral clearances during overtaking, and crossing or stopping gaps at intersections. For instance, car-following hazards involve proximity interactions between vehicles, while pedestrian-vehicle conflicts focus on narrow crossing distances in urban settings. Cyclist overtaking hazards highlight the risks associated with limited lateral space, and railway crossings emphasize proximity to moving trains. Lane-change scenarios, on the other hand, involve abrupt spatial adjustments in traffic flow.

A comprehensive analysis of hazards reveals a complex interplay of risks, spanning health, economic, environmental, technological, and societal domains (World Economic Forum, 2020). Health risks, such as respiratory illnesses and allergic reactions, are frequently linked to proximity to industrial facilities, as evidenced by higher health risk perceptions among residents living within 3 km of waste incineration plants (Zhou et al., 2022; Kim et al., 2022). Economic risks, including property damage and livelihood disruptions, are prominent in flood-prone areas, where spatial proximity to rivers significantly increases perceived financial vulnerability (Ali et al., 2022; Grover et al., 2022). Environmental risks, such as air and water pollution, are exacerbated by proximity to industrial emissions, with studies documenting elevated risk perceptions within 5 km of smelters and incinerators (Li et al., 2016; Zhou et al., 2022). Technological risks, exemplified by nuclear power plant accidents and chemical spills, demonstrate non-linear proximity effects, with heightened anxiety observed at moderate distances (3–8 km) due to uncertainty and incomplete hazard familiarity (Giordano et al., 2010; Hüppe & Weber, 1999). Societal risks, including inequitable access to hazard preparedness resources and community-level distrust, are particularly pronounced in marginalized populations living near industrial zones, where socioeconomic disparities amplify spatial vulnerability (Barton Laws et al., 2015; Sen et al., 2022). This interconnected risk landscape underscores the need for holistic hazard management frameworks that integrate spatial proximity with spanning health, economic, environmental, technological, and societal domains.

4.2. Distance categorization

This review shows that studies classify distance in different ways. Some use zones, such as 0–3 km, 3–8 km, and beyond, to assess how proximity influences risk perception (Ali et al., 2022; Kim et al., 2022; Shah et al., 2024; Sen et al., 2022; Sherman-Morris et al., 2022). Others measure distance as Euclidean distance (Giordano et al., 2010; Zhou et al., 2022). Figs. 5 and 6 illustrate the two predominant approaches to distance categorization across hazard types: zone-based (discrete spatial ranges) and Euclidean distance (continuous linear measurements). This review reveals distinct methodological choices across different hazard categories.

Natural hazard studies predominantly employed zone-based distances (n = 22), segmenting proximity into discrete risk zones. Flood-related studies (n = 18) typically defined high-risk areas as 0–5 km from water bodies. Only three studies utilized Euclidean distance for assessment, primarily for volcanic hazards (Wei & Lindell, 2017), coastal erosion (Sen et al., 2022), and nuclear facilities (Giordano et al., 2010).

Industrial hazard research favored zone-based distances (n = 12), establishing common classifications at 0–3 km (high-risk), 3–10 km (moderate), and over 10 km (low). Four industrial hazard studies employed Euclidean distances, documenting linear changes in perceived risk for industrial hazards (e.g., power lines) (Mueller et al., 2017).

Ten environmental health studies utilized zone-based distances. They classify and define critical zone-spatial ranges where hazard exposure and risk perception are most pronounced based on hazard type and intensity, for instance, 0–5 km for air pollution sources (Li et al., 2016) and 0–1 km for water contamination (She et al., 2012). Studies employing Euclidean distances (n = 16) focused on quantifying exposure or pollutant gradients, such as decreasing heavy metal concentration per kilometer (Catalán-Vázquez et al., 2010).

In contrast to other categories, transportation hazard studies predominantly utilized Euclidean distances (n = 6), with precise metrics for vehicle interactions (e.g., less than 2-second following gaps; Zhang et al., 2021) and pedestrian safety (less than 1.5-meter clearance; Feng et al., 2024). The minority using zone-based distances (n = 2) established "critical proximity" thresholds, such as 50-meter zones at rail crossings (Ward & Wilde, 1996).

4.3. Distance measurement

Section 4.2 demonstrates the diverse categorization of distance associated with different hazards. Consequently, various methods have been applied for measuring these distances (Fig. 7), including Global Navigation Satellite System (GNSS) and GIS technologies (n = 25), maps (n = 14), surveys and subjective measures (n = 4), and real-time detection (n = 11). The most popular one was GNSS, which could provide precise spatial data to measure distance. GIS was also frequently used to measure the distance between individuals and sources of hazards on a large scale of physical space, such as communities close to rivers, coastlines, volcanoes, and industrial facilities (Shah et al.2024; Sen et al., 2022; Grover et al.2022; Gray-Scholz et al. 2019). Additionally, three studies combined GIS with GNSS coordinates, providing more accurate distance measurements of spatial relationships between individuals and potential hazards (Li et al., 2021; Navarro et al., 2021; Giordano et al., 2010).

While GIS and GNSS offer precise digital data, some studies have relied on traditional maps. For example, in studies by Faruk and Maharjan (2023), Santoro et al. (2022), and Mueller et al. (2017), maps were provided to participants to help visualize their residential areas and the locations of hazards. These maps allowed for spatial distance measurement by delineating affected areas and representing proximity through visual zoning (e.g., close, medium, or far), enabling a clear interpretation of distance to a hazard (Trumbo et al., 2011; Severtson & Burt, 2012; Ruz et al., 2020; López-Fletes et al., 2022). This approach facilitated a more intuitive assessment of spatial relationships between individuals and hazard sources compared to non-visual or self-reported proximity estimates, enhancing participants' understanding of their risk exposure. By translating abstract distances into tangible visual categories, maps reduced ambiguities inherent in verbal descriptions (e.g., "near" vs. "far") and improved the consistency of risk interpretations across diverse populations.

In transportation studies, real-time detection methods were widely used, including tools such as driving simulators, roadside cameras, and laser rangefinders to measure distance among vehicles or road users. By providing real-time detection measurements of headway distance, lateral clearance, or stopping distance, these tools are crucial for evaluating road user behavior and perception under complex conditions.

In addition to objective measurements, surveys and subjective measures were also used to indicate hypothetical or perceived spatial distance to hazards, along with participants' intentions and willingness based on perceived risks (Kim & Kang, 2024; Kim & Kang, 2021; Liu et al., 2019). For instance, Kim et al. (2022) asked participants to indicate how close they were willing to live near hazards (e.g., less than 1 km, 1–5 km, 5–10 km, 10–20 km, and more than 20 km). In the study conducted by Kim and Kang (2024), participants estimated the distance with other people in daily life, such as intimate space (0–0.45 m),

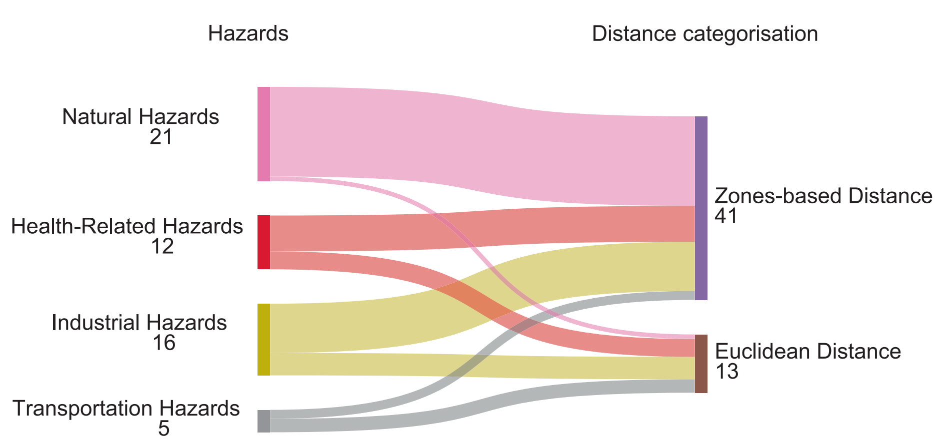

Fig. 5. Relationships among hazards and distance categorisation.

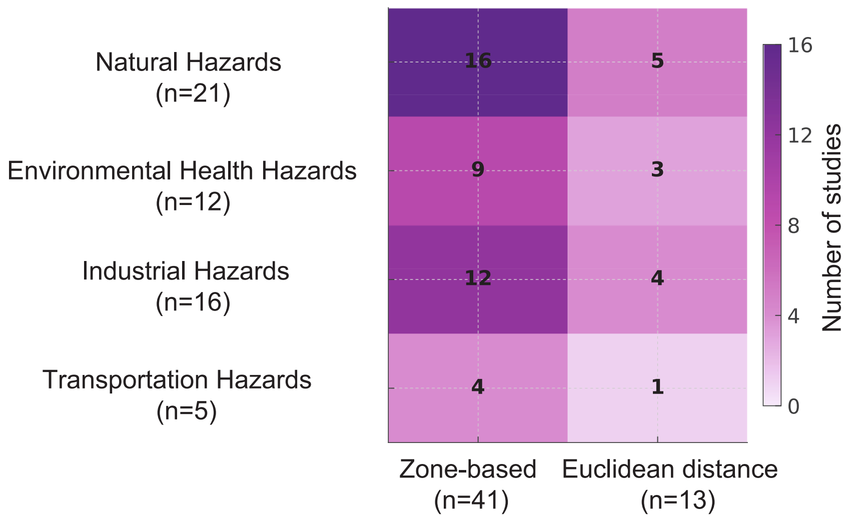

Fig. 6. Hazard landscape contrasting distance metrics (zone-based vs. continuous Euclidean).

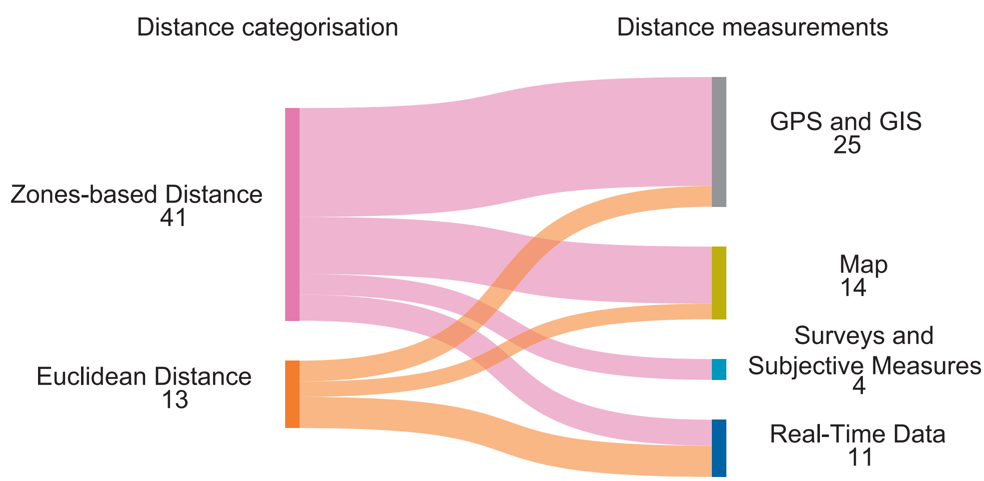

Fig. 7. Relationships among hazards, Distance measurement.

personal space (0.45–1.2 m), social space (1.2–3.5 m), and public space (beyond 3.5 m) to assess their perception of risk exposure and safety in different spatial contexts (Freudenstein et al., 2015).

4.4. Risk perception evaluation

The reviewed studies mainly employed four methods to evaluate risk

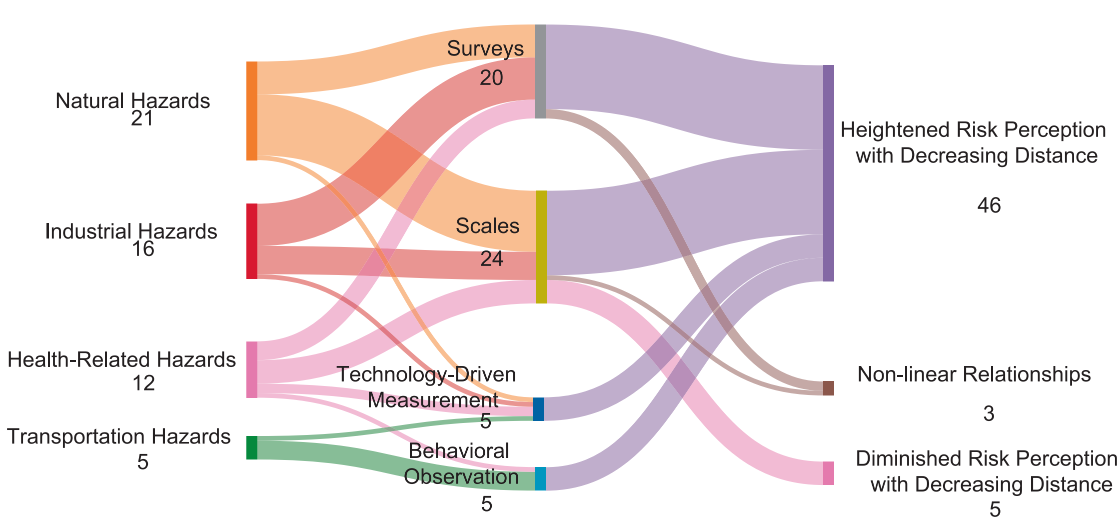

Fig. 8. Relationships among hazards, risk perception evaluation, and effects of distance to hazards on risk perception.

perception: surveys, scales, behavioral observation, and technology-driven measurement (Figs. 8 and 9). These methods reflect the diversity of tools used to assess how spatial proximity influences perceived risks across hazard contexts.

Surveys, representing 37.2% of the reviewed studies (n = 20), relied on non-standardized questionnaire tools that were not uniformly designed or validated across studies to capture subjective risk perceptions. While many studies created unique sets of questions tailored to their specific research contexts (e.g., Trumbo et al., 2011; Chen et al., 2019), several incorporated or adapted existing survey questions or frameworks. For example, Lohmann and Kontoleon (2023) utilized the UK Household Longitudinal Study (UKHLS) to evaluate flood risk perceptions, and Arias et al. (2017) drew on Lindell and Perry's (2012) risk perception and action model. Others, such as Masud et al. (2019), applied Bird's (2009) framework to assess flood risk awareness in community surveys.

Scales dominated the literature (n = 24), utilizing validated frameworks to quantify risk perception systematically. Likert-type scales were prominent, with tools adapted from seminal works. For instance, Kim and Kang (2024) modified scales by Heberlein and Vaske (1977), Vaske et al. (1986), and Knowles et al. (1973) to measure crowding risks, while Zhou et al. (2022) integrated Liu et al. (2018) and Colquitt's (2001) constructs to evaluate concerns on waste incineration. Semantic differential scales, such as Ali et al.'s (2022) bipolar dimensions for flood risks—informed by Rana et al. (2020) and Sato et al. (2020)—and Navarro et al.'s (2021) Coastal Flooding Risk Perception (CFRP) scale Lerner et al. (2003), provided nuanced insights into perceived threat severity. Navarro et al. (2021) further combined the CFRP scale with López et al. (2020) and López-Fletes et al. (2022) Environmental Risk Coping Scale to contextualize behavioral responses.

Behavioral observation methods (n = 5) analyzed risk perception through real-time interactions and actions. For instance, driving simulators tracked car-following behaviors under low visibility (Zhang et al., 2021), motion capture systems monitored pedestrian-vehicle gaps at crossings (Feng et al., 2024), and cyclist overtaking maneuvers were recorded to assess lateral clearance preferences (Frings et al., 2014). These methods emphasized objective behavioral data, avoiding reliance on self-reported biases.

Technology-driven measurement methods (n = 5) integrated advanced tools for objective risk assessment. Physiological measurements captured stress responses to proximate hazards, such as eye-tracking (Frings et al., 2014) and heart rate monitoring (López et al., 2020). Makki et al. (2019) deployed roadside cameras and laser rangefinders to assess pedestrian-vehicle conflicts at intersections, focusing on stopping distances under low-visibility conditions. Emerging tools like virtual reality (VR) simulated hazardous environments, enabling precise tracking of evacuation decisions under controlled spatial conditions (Shi et al., 2020). Masud et al. (2019) first geocoded household-level survey scores (1 = very low to 5 = very high perceived flood risk) to each respondent's centroid address. In ArcGIS, the point data were aggregated to 500-m grid cells and Empirical-Bayes smoothed; Global Moran's I ($I = 0.42$, $p < 0.01$) and Getis-Ord Gi hot-spot analysis then produced z-scores that "quantified" spatial clustering of high- and low-perception areas. Kernel-density maps visualized these disparities, revealing risk-perception hot spots within 1 km of the river channel and cold spots on higher terraces.

Out of the 54 studies analyzed, a few incorporated neurophysiological measures, including EEG/ERP indices (e.g., frontal midline theta, N2/P3) and peripheral physiology (e.g., electrodermal activity, heart-rate variability), in addition to self-report and behavioral assessments. Specifically, EEG/ERP investigations within this subset associated frontal midline theta activity with cognitive control and effort, while N2/P3 responses were linked to conflict detection, salience, and attentional allocation. The late positive potential was indicative of sustained affective engagement with risky stimuli. Some studies also utilized peripheral physiological measures such as electrodermal activity and heart-rate variability, as well as eye-tracking and pupillometry to assess arousal and visual attention during risk assessment. Consistent with our findings, existing neuroscience literature supports these associations: frontal midline theta, control/effort (Cavanagh & Frank, 2014); N2/P3: conflict/salience/attention (Folstein & Van Petten, 2008; Polich, 2007); LPP: sustained emotional processing (Hajcak et al., 2010). Furthermore, fMRI studies implicate the amygdala/insula (threat), anterior cingulate and lateral prefrontal cortices (monitoring/control), and ventromedial prefrontal cortex/striatal systems (valuation/choice) in risk evaluation (Paulus et al., 2003; Preuschoff et al., 2008; Bartra et al., 2013; Shackman et al., 2011). Real-time assessment of arousal and attention through peripheral physiology and ocular metrics, increasingly integrated with virtual reality tasks, offer valuable insights (Critchley, 2002; Thayer et al., 2009; Beatty, 1982). While this review focuses on spatial distance, these methodologies are directly transferable to proximity studies, enabling the quantification of how Distance and Distance X Time influence salience, affect, and control.

4.5. Effects of distance to hazards on risk perception

The reviewed articles reveal complex and multifaceted effects of distance to hazards on risk perception, varying across different contexts.

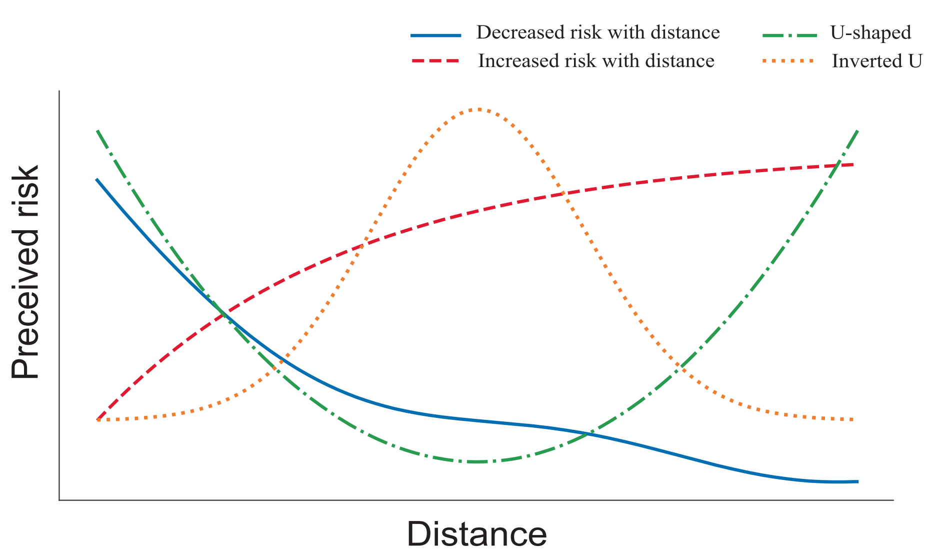

Fig. 9. Distance-risk relationships.

Other factors, such as environment, individual characteristics, and psychological mechanisms, may also influence the effects. Distance is a key element that affects how individuals perceive various hazards. In general, three patterns were exposed by this review: heightened risk perception with decreasing distance, diminished risk perception with decreasing distance, and a non-linear relation between distance and risk perception. The following subsections explore these effects in greater detail.

Most studies (n = 46) reported that the closer to a hazard, the higher the perceived risks. This effect was particularly pronounced for natural hazards and industrial hazards, where proximity intensified the perceived immediacy of threats, often leading to heightened awareness and concerns (Lohmann & Kontoleon, 2023; Rasool et al., 2022). For example, Zabini et al. (2021) found a significant correlation between proximity to rivers and perceived flooding risks, with those living within 0–5 km of flood-prone areas expressing substantially higher concerns than residents farther away. Similarly, Kim et al. (2022) reported that individuals residing within 1 km of waste incinerators perceived elevated environmental pollution and health risks, such as allergic rhinitis, compared to those beyond 3 km. Regression analyses in these studies confirmed that spatial distance inversely predicted risk perception scores. While the majority of findings focused on natural and industrial contexts, a few studies explored proximity effects in other settings. For instance, Kim and Kang (2024) demonstrated that reduced personal and social space amplified crowding-related risk perceptions in recreational environments. Overall, the dominant pattern—heightened risk perception with decreasing distance—held consistently across hazard types, reinforcing the critical role of spatial proximity in shaping public risk evaluations.

In contrast, five studies have identified an inverse effect, where closer proximity to hazards resulted in lower risk perception due to habituation or familiarity (Shah et al., 2024; Ali et al., 2022; López-Fletes et al., 2022; Li et al., 2021; Lyons et al., 2020). These studies suggest that residents who live near hazardous sites may develop coping mechanisms or adaptations to risks, making them perceive fewer risks. For instance, Lyons et al. (2020) found that individuals living near nuclear reactors perceived lower risk levels than those living farther away. This was attributed to cognitive dissonance and psychological coping strategies; thereby, frequent exposure to the hazard reduced concerns. Similarly, López-Fletes et al. (2022) observed that some residents living near flood-prone coastal areas downplayed their perception of flooding risks due to strong emotional attachment to their surroundings, indicating that familiarity with an environment may sometimes suppress risk perception.

Interestingly, another three studies present a non-linear relation between proximity and risk perception, where risk perception did not heighten or diminish in a simple linear way with a change in distance (Giordano et al., 2010; Hüppe & Weber, 1999; Zhou et al., 2022). Specifically, Giordano et al. (2010) analyzed data from 450 residents who lived near nuclear facilities, revealing an inverted U-shaped pattern. The perceived risk peaked at a moderate distance of 5–10 km (mean risk score = 4.2 on a 5-point scale), compared to lower scores from residents within 0–3 km (mean = 3.1) and beyond 15 km (mean = 2.4). Similarly, Hüppe and Weber (1999) found that individuals who lived 3–8 km from a nuclear plant reported 35% higher anxiety levels than those living within 1 km. Zhou et al. (2022) identified a U-shaped pattern near waste incineration plants. Risk perception scores declined when the distance increased from within 1 km (7.8) to 5–6 km (5.2), then sharply rose to 6.5 when the distance was beyond 6 km. A regression model also indicated a U-shaped curve, further confirming this border zone effect. These studies suggest that proximity-risk relationships may be mediated by both psychological adaptation and environmental uncertainty, resulting in a non-linear pattern.

4.6. Human factors

The reviewed articles have suggested that human factors, including age, gender, education level, income, knowledge, past experiences, household size, employment status, homeownership, risk tolerance, and cultural background, may play a crucial role in shaping risk perception in relation to proximity to hazards. Although these factors have been identified in the literature, empirical studies have largely focused on five variables—age, gender, education, income, and experience. Other factors (e.g., cultural background, family size) have limited quantitative data available for synthesis, despite their theoretical relevance. Table 2 summarizes the moderating effects of all human factors discussed in the literature.

The reviewed studies demonstrate that human factors systematically moderate spatial risk perception through cognitive and behavioral pathways. Cultural attainment fundamentally shapes awareness mechanisms. Collective norms and shared worldviews can dampen—or amplify—how spatial cues translate into perceived risk. In some collectivist communities, for example, social cohesion and deference to local institutions have been shown to attenuate pollution-risk recognition even when residents live in close proximity to emission sources (Laws et al., 2015). Such findings highlight that culture shapes the very first stage of hazard awareness, conditioning whether objective distance is noticed and interpreted as threatening.

As depicted in Table 2, age is a critical determinant of risk perception in proximity to hazards. Studies have consistently shown that older individuals tend to perceive more significant risks than younger ones when living near hazardous areas (Lyons et al., 2020; Zabini et al., 2021). Research on populations near flood zones (Zabini et al., 2021) and nuclear power plants (Lyons et al., 2020) reveals that residents aged over 65 exhibit 27%–33% higher perceived vulnerability scores compared to those under 35, likely due to heightened somatic sensitivity to environmental stressors, cumulative exposure to hazard narratives through life-course experiences, and mobility constraints amplifying perceived evacuation barriers (Casareale et al., 2023), resulting in increased perceived severity of hazards. While older individuals often exhibit greater risk awareness, they do not always engage in protective actions. Some studies indicate that older individuals are less likely to evacuate during disasters, despite recognizing the risks associated with proximity to hazards (Shah et al., 2024). This reluctance may be attributed to physical limitations, attachment to home environments, or a tendency to normalize risks over time. These findings suggest that increased risk awareness does not necessarily lead to higher preparedness or response rates, particularly among older populations.

Gender differences can shape how individuals perceive risks in proximity to hazards. Studies indicate that women implement 26% more household flood adaptations than males (Casareale et al., 2023) and temporary workers near industrial zones showing 18% lower evacuation

Table 2
Moderating Effects of Key Human Factors on Proximity-Risk Perception Relationships.

Human Factor	Total Studies	Amplifying the effect of distance on risk perception	Downplaying the effect of distance on risk perception
Age	17	12 (70.6%)	4 (23.5%)
Gender	10	5 (50%)	5 (50%)
Education	11	9 (81.8%)	2 (18.2%)
Income	13	8 (61.5%)	5 (38.5%)
Experience	10	7 (70%)	3 (30%)
Household Size	2	1 (50%)	1 (50%)
Employment Status	3	2 (66.7%)	1 (33.3%)
Homeownership	4	3 (75%)	1 (25%)
Risk Tolerance	5	3 (60%)	2 (40%)
Cultural Background	2	1 (50%)	1 (50%)

compliance despite equivalent perceived risks (Lyons et al., 2020). For instance, women residing near geological hazards (e.g., landslides and volcanic activity) express greater concern about these specific risks than men. Conversely, men tend to prioritize meteorological hazards (e.g., hurricanes and floods) as more threatening than women, even when spatially distant (Casareale et al., 2023). This divergence suggests that gendered risk perceptions are context-dependent, influenced by hazard type and perceived controllability. Women's heightened sensitivity to localized geological risks may stem from caregiving roles or community attachment, while men's focus on meteorological events may reflect societal expectations of risk management in broader environmental contexts (Casareale et al., 2023).

Education levels significantly moderate how spatial proximity influences risk perception. Studies indicate education amplified technical risk appraisal for low-probability and high-impact events (Zhou et al., 2022). Sherman-Morris et al. (2022) found that highly educated residents near tornado-prone areas perceived heightened risks within 1–3 km of hazard zones. In contrast, less-educated individuals showed minimal sensitivity to distance changes. Similarly, Ali et al. (2022) observed that educated floodplain populations linked closer proximity (0–5 km) to higher likelihoods of disaster impact, often proactive relocation. However, education can also attenuate proximity effects in contexts where technical knowledge overrides spatial cues. Navarro et al. (2021) reported that engineers living near volcanic hazards discounted physical proximity, relying on geological data to assess risks. This reduced the effect of distance on risk perception. This suggests that education does not uniformly strengthen or weaken proximity-risk relationships but interacts with hazard types and cognitive framing.

Income shapes proximity-risk relationships through resource-influenced risk perception dynamics. For instance, Sen et al. (2022) discovered that lower-income populations (less than $25 k/year) within 5 km of industrial clusters exhibit 32% higher risk perception scores than high-income populations (over $75 k/year) at equivalent distances. The effect of distance on risk perception may be amplified through three key pathways: limited capacity for protective investments (e.g., flood-proofing renovations), dependence on hazard-zone employment, and constrained relocation options (Grover et al., 2022). Conversely, wealth can mitigate the effects of proximity. High-income residents living within 1 km of floodplains demonstrated 41% lower evacuation intention than low-income groups residing 3–5 km away (Lohmann & Kontoleon, 2023). This difference arises from variations in resource utilization. Insurance coverage reduces perceived financial risk, while private monitoring systems lessen reliance on public warning mechanisms. Higher-income individuals are more likely to depend on private systems, whereas lower-income groups rely on public warnings. As a result, wealthier individuals tend to perceive lower risk and demonstrate reduced evacuation intentions (Liu et al., 2019).

Previous exposure to hazardous events can also influence how individuals perceive risks based on proximity to similar hazards. Studies indicate that individuals who have experienced disasters in the past tend to have heightened sensitivity to risks and are more likely to engage in precautionary behaviors when living near high-risk areas (Ali et al., 2022; Santoro et al., 2022). For example, individuals living near flood-prone areas with past flood experiences are more likely to anticipate future risks and take preventive measures than those in the same areas without previous exposure to floods (Wei & Lindell, 2017). Some research suggests prolonged exposure to hazards can result in risk normalization, where individuals downplay potential threats despite proximity (Navarro et al., 2021). This finding implies that past experiences can either increase risk perception or lead to habituation, depending on how individuals process previous exposure. Understanding how experience shapes risk awareness and responding behaviors is essential for developing effective risk communication and intervention strategies.

Other human factors associated with risk perception and risk-taking propensity were identified in the studies. These factors have been measured by various instruments. Canonical trait/behavioral tools were infrequently utilized, with the SSS-V tool mentioned in only 1 out of the 54 studies (Zuckerman, 1994), while the DOSPERT tool (Blais & Weber, 2006) and BART tool (Lejuez et al., 2002) were not utilized in the studies analyzed. In contrast, measures identified as 'risk propensity' were present in 17 out of the 54 studies. However, many of these scales did not explicitly reference Meertens and Lion (2008) and were categorized as 'unspecified' (see Appendix S2).

Various human-factor covariates and moderators were frequently considered in the studies. For instance, education was found to enhance sensitivity to nearby hazards, leading to increased perceived risk within approximately 1 to 5 km, while professional or technical expertise sometimes mitigated distance-related gradients by shifting the evaluation towards analytical indicators. Socioeconomic factors such as income and disadvantage exhibited consistent trends: individuals with lower incomes residing closer to industrial clusters tended to report higher perceived risk compared to wealthier individuals at similar distances, reflecting resource limitations that amplify the effects of proximity. The analysis commonly involved examining interactions between distance and human-factor variables, with 42 out of 54 studies incorporating such analyses. Many studies reported significant interactions, such as social or attitudinal factors heightening risk perceptions at shorter distances, while others observed a reduction in risk perception when knowledge or resources replaced spatial cues. One study, utilizing the SSS-V scale, investigated the role of sensation seeking in relation to distance to explore whether individuals with a higher propensity for stimulation exhibit diminished risk signals based on proximity (Zuckerman, 1994). Detailed information on this study's methodology, outcomes, and all moderator classifications (including unspecified 'risk propensity' scales) can be found in Appendix S2. Furthermore, a summary of expanded moderator analyses including age, gender, education, income, and experience is presented in Table 2 (refer also to Blais & Weber, 2006; Lejuez et al., 2002; Meertens & Lion, 2008 for instrument details).

Human factors influencing risk perception are not independent of spatial context; rather, they are intricately linked to specific locations and spatial configurations (Cutter, Boruff, & Shirley, 2003; Montello et al., 2018). The concept of place attachment, characterized by emotional connections to one's home and community, plays a crucial role in shaping the impact of proximity on risk perception. Specifically, heightened attachment is associated with increased preparedness and protective behaviors in situations of perceived high risk and efficacy. However, in certain neighboring communities, strong place attachment and local identity can mitigate perceived threats and maintain daily routines, thereby diminishing the sense of danger despite close proximity (Lewicka, 2011a; Qing et al., 2022; Scannell & Gifford, 2010b; Wang et al., 2021; Parreira & Mouro, 2023). Recent research and literature reviews have highlighted these dual pathways in the context of both coastal and inland hazards (Parreira & Mouro, 2023; Lie et al., 2023).

Spatial segregation leads to the concentration of disadvantaged populations in areas with higher exposure to environmental hazards, such as industrial emissions and heavy traffic, while limiting access to amenities. This exacerbates the impact of proximity effects and restricts potential responses. Recent studies across multiple cities and cohorts have established a connection between segregation, pollution exposure, and disparities in environmental quality (Kind & Buckingham, 2018; Neier, 2023; Zewdie et al., 2025).

Cultural context varies geographically, influencing risk perception and protective behavior through factors such as individualism-collectivism and uncertainty avoidance. This variation is evident in cross-national surveys and studies conducted during the pandemic. The inclusion of cross-level cultural indicators, as demonstrated in studies by Dryhurst et al. (2020) and Fischer and Karl (2021), aids in elucidating the spatial differences in patterns of distance-risk relationships. Data from the World Values Survey Association (2017-2022) further support these findings.

5. Discussion

5.1. Spatial distance and its measurement

The reviewed studies predominantly focused on macro-level spatial distances, typically measured between residential zones and large-scale hazards such as industrial facilities or floodplains. These investigations often utilized geospatial tools like GIS and GNSS to quantify proximity, providing robust insights into community-level risk awareness (Zhou et al., 2022; Sen et al., 2022). Zone-based and Euclidean distance metrics were frequently applied to map hazard exposure gradients. For instance, high-risk zones were defined as 0–5 km from floodplains or industrial emissions sources (Ali et al., 2022; Li et al., 2014).

While macro-level distances dominated the literature, a subset of studies explored micro-level proximity, emphasizing precision in measuring immediate hazards. For example, transportation safety research employed laser rangefinders and driving simulators to quantify vehicle–pedestrian gaps (Feng et al., 2024) or car-following headways (Zhang et al., 2021), with thresholds such as less than 1.5 m for pedestrian crossings and less than 2-second temporal gaps for collision risks. Similarly, Luo et al. (2016) used motion sensors on construction sites to measure workers' proximity to falling objects, identifying a critical threshold of 2 m for triggering avoidance behaviors. These micro-level studies highlight the value of real-time detection technologies (e.g., LiDAR, motion capture) in capturing dynamic spatial interactions, complementing traditional macro-scale GIS approaches.

Though less commonly addressed, vertical proximity emerged in contexts where elevation directly correlated with hazard exposure. For example, construction safety studies operationalized "height" as a vertical distance metric, with elevated work platforms (over 0.65 m) linked to increased fall risks and physiological stress responses (Zhu et al., 2023). Here, elevation served as a measurable spatial variable akin to horizontal distance to assess proximity-related hazards. However, this dimension remains underexplored compared to horizontal distance analyses.

Methodologically, many studies employed GIS, GNSS, maps, or real-time detection methods to provide precise distance data. Some students also used surveys and subjective measures. However, the understanding and investigation of discrepancies between perceived and actual distances are overlooked. There is a need to investigate the factors leading to such discrepancies and their consequences. For example, Shi et al. (2020) used VR to simulate road-crossing decisions and found that visual barriers made participants perceive hazards as farther away, leading to reduced urgency in making a response. Similarly, Skjermo et al. (2024) observed that participants in a VR road tunnel underestimated the proximity of black smoke, delaying their evacuation actions. These findings heighten the need to incorporate distance perception errors into risk assessment frameworks, especially for those hazards at a close range.

Spatial distance measurement involves considerations of scale, heterogeneity, and verticality. The definition of spatial distance is inherently influenced by scale, with choices such as spatial resolution and zoning impacting proximity effects, a phenomenon known as the modifiable areal unit problem (MAUP). Therefore, findings based on distance should include explicit scale and sensitivity assessments (Chen, 2022; Deng, Li, & Liu, 2024). In addition to horizontal Euclidean or network distance, vertical metrics (e.g., elevation above flood level, floor height, building verticality) play a significant role in flood and construction hazards, potentially altering near-field patterns (Tuitjer, 2021; Emamgholian et al., 2021). Environmental heterogeneity, including topography, urban form, and land use, can impact exposure pathways, visibility, egress, and effective path length. In such contexts, measures based on network/cost distance or visibility may more accurately reflect perceived proximity compared to straight-line distance (Rincón, Khan, & Vescovi, 2018; Monkkonen & Manville, 2024).

Assessing spatial structure using Moran's I is essential in analyzing distance effects in risk-perception data (Masud et al., 2019). Researchers are advised to employ Global Moran's I to determine overall clustering or dispersion and, when applicable, Local Moran's I (LISA) to pinpoint hot spots, cold spots, and spatial outliers. It is recommended to define spatial weights (such as contiguity, distance-band, or k-nearest neighbors), present the I statistic along with z- or pseudo-p values, and, for LISA maps, address issues related to multiple testing while clearly distinguishing local clusters from random variation (Esri, n.d.; Cai, Fan, Lian, & Zhou, 2021). In the case of survey or experimental point data, Moran's I can be utilized for both outcomes (e.g., perceived risk scores) and residuals to assess residual spatial structure post distance adjustment. Although our review does not conduct such analyses, we advocate for future studies to: (a) routinely incorporate Moran's I diagnostics when exploring proximity–risk associations and (b) if significant autocorrelation is identified, consider employing spatially informed models (e.g., spatial lag/error models or other relevant techniques) and scale-aware methodologies to mitigate bias in estimated distance effects (Esri, n.d.; Chen, 2022; Deng et al., 2024; Cai et al., 2021).

5.2. Interactions between spatial and non-spatial distance

The findings from the analyzed studies reveal that only a small number of studies focused on the relationship between temporal distance and spatial proximity. Specifically, these studies observed changes in perceived risk near hazardous events over time, with initial heightened risk perception near the hazard decreasing gradually. Conversely, areas located farther away occasionally experienced temporary increases in risk perception coinciding with media coverage cycles. Modeling time elapsed since the event indicated a decrease in proximity effects as time passed, while distant regions displayed transient significance that diminished as media coverage waned.

The interaction between social distance and spatial distance was examined in studies that assessed ingroup versus outgroup framing or local trust and identification. Strong local identification tended to normalize nearby hazards, reducing spatial gradients, while low trust or salient outgroup narratives heightened proximity effects, leading to steeper near-field gradients. Similarly, the interplay of experiential distance and spatial distance was investigated in studies that differentiated between direct experience (e.g., routine, low-harm exposures) and indirect exposure (e.g., narrative or media descriptions). Findings indicated that direct, repeated experiences could habituate local individuals to nearby hazards, thereby reducing the gradient. In contrast, indirect, affect-laden exposure sometimes increased the salience of distant hazards, resulting in transient far-field peaks.

The observed patterns align with established theories of psychological distance and risk perception. Temporal distance interacts with spatial proximity through construal and salience dynamics: recent events amplify immediate risks that diminish over time, while distant hazards may gain short-term salience due to media coverage (Liberman & Trope, 2008; Trope & Liberman, 2010; Tversky & Kahneman, 1973; Lichtenstein et al., 1978). Social distance, characterized by ingroup/outgroup distinctions, shared norms, and trust levels, influences whether proximity is normalized or magnified; cohesive, high-trust environments mitigate spatial gradients, whereas low trust or outgroup dominance accentuates them (Weber & Hsee, 1998; Dryhurst et al., 2020). Experiential distance, distinguishing between direct and indirect exposure, corresponds to the effects of firsthand experience versus descriptions: direct, frequent, low-harm exposure may lead to habituation and reduced immediate risks, while emotionally charged narratives can heighten the salience of distant risks (Hertwig & Erev, 2009; Kasperson et al., 1988; Small et al., 2007).

We propose four hypotheses for future investigations: (a) Temporal X Spatial Interaction: Proximity to significant events leads to a temporary increase in perceived risk, which then diminishes overtime; in contrast, perceived risk at a distance shows brief spikes corresponding to media coverage cycles (Liberman & Trope, 2008; Lichtenstein et al., 1978; Trope & Liberman, 2010; Tversky & Kahneman, 1973); (b) Social X Spatial Interaction: Strong local trust or group identification reduces spatial variations in risk perception, while low trust or outgroup identification amplifies these differences (Weber & Hsee, 1998; Dryhurst et al., 2020); (c) Experiential X Spatial Interaction: Direct, frequent, low-consequence experiences lessen perceived risk in close proximity through habituation; however, indirect, emotionally charged exposures can heighten risk perception at a distance (Hertwig & Erev, 2009; Kasperson et al., 1988; Small et al., 2007); (d) Scale Dependence: The effects of these interactions differ across micro, meso, and macro spatial scales, necessitating multilevel research designs to assess scale-specific influences.

5.3. Temporal dynamics of proximity–risk perception

A subset of studies within the reviewed studies examined the evolution of risk perceptions over time frames (e.g., weeks or months following significant events) while considering spatial proximity. Findings include the following patterns: (a) Post-event decay near the source: Following prominent local cues (e.g., visible impacts, alarms, official notices), perceived risk is initially higher in close proximity to the hazard and diminishes as these cues diminish over time. Distant locations exhibit weaker or short-lived changes in perceived risk; (b) Transient far-field salience: Some studies observe temporary increases in perceived risk further away from the hazard shortly after events, often coinciding with information dissemination cycles (e.g., news coverage), with these peaks diminishing over time; (c) Habituation under repeated low-harm exposure: Communities experiencing regular, low-harm exposures show stabilized or reduced perceived risk in close proximity over repeated observations, despite consistent physical proximity to the hazard; (d) Laboratory/immersive recency effects: Experimental or immersive studies manipulating recency levels across trials reveal heightened urgency and risk assessments immediately following prominent cues, with a decrease in intensity over subsequent uneventful trials.

The aforementioned reviewed studies patterns are in accordance with established theories of availability and affect and social amplification/attenuation. Proximity to a risk event typically leads to an initial increase in perceived risk followed by a decrease over time, whereas risks that are more distant may exhibit transient spikes in salience coinciding with media cycles (Finucane et al., 2000; Lichtenstein et al., 1978; Small et al., 2007; Tversky & Kahneman, 1973). These patterns also correspond to distinctions between experiential and descriptive information, where repeated exposure to benign events can lead to habituation to nearby risks, while vivid narratives can heighten awareness of more remote hazards (Hertwig & Erev, 2009).

Subsequent research should incorporate explicit time measurements (e.g., time elapsed since the event, repeated observations) and incorporate Distance X Time variables, utilizing multilevel structures in the presence of spatial clustering. This addresses the current scarcity of studies within our dataset that have integrated repeated or post-event assessments and would enhance the accuracy of estimating temporal variations in proximity effects.

5.4. Risk perception and its evaluation

The reviewed articles demonstrate that spatial distance significantly influences risk perception across diverse hazard contexts. In large-scale hazards, such as natural disasters and industrial accidents, proximity is pivotal in shaping risk awareness and behavioral responses (Zhou et al., 2022; Chen et al., 2019). For example, individuals closer to flood-prone areas exhibit higher evacuation intentions due to the perceived immediacy of risk (Ali et al., 2022). Conversely, residents near nuclear power plants often develop psychological adaptations, such as habituation and cognitive dissonance, to rationalize their risk exposure (Hüppe & Weber, 1999). These findings suggest the interplay between environmental visibility, sensory engagement, and hazard-specific exposure patterns in shaping risk perception.

The effect of distance to hazards on risk perception does not always follow a linear pattern. For instance, a U-shaped pattern (Border Zone Effect) was revealed: risk perception declines from proximal zones (e.g., less than 1 km) to moderate distances (5–6 km) before sharply rising beyond 6 km (Zhou et al., 2022). Communities in these moderate distances experience heightened uncertainty due to conflicting risk signals. Proximity-driven vigilance diminishes without direct sensory cues, yet media narratives may amplify the risk perception among these communities. For instance, waste incineration risks were perceived as lowest at 5–6 km but resurged beyond 6 km, reflecting spatial heterogeneity in hazard visibility and trust in institutional controls. This effect is attributed to uncertainty, reduced familiarity with the hazard, and reliance on external information sources (e.g., media coverage).

Another pattern is the inverted U-shaped pattern: perceived risk peaks at moderate distances (5–10 km) and declines at both closer and farther ranges. For example, residents near nuclear facilities exhibited heightened anxiety at intermediate distances (3–8 km), reporting 35% higher risk perception than those within 1 km and 28% higher than those over 8 km, likely due to incomplete hazard familiarity and reliance on ambiguous external information (Hüppe & Weber, 1999; Giordano et al., 2010). This pattern contrasts with risk normalization observed in populations residing closest to hazards, where prolonged exposure fosters habituation and cognitive dissonance (Santoro et al., 2022).

Environmental factors further complicate these dynamics. For instance, obstructed visibility due to terrain, buildings, or vegetation can reduce risk perception among nearby residents. At the same time, those at moderate distances may perceive higher risk due to increased visual exposure and media influence (Shi et al., 2020). Additionally, hazards such as air pollution and radiation exhibit spatially variable risk profiles, with exposure intensity peaking at specific distances, further challenging linear proximity-risk assumptions (Zhou et al., 2022). These findings collectively challenge simplistic distance-risk perception models, emphasizing the need to account for psychological adaptation, environmental mediators, and informational asymmetries.

Methodologically, the reviewed articles often rely on retrospective self-report methods, such as surveys and interviews, to understand risk perception. These methods can capture general risk perceptions but fail to detect real-time cognitive processes and physiological responses (Shi et al., 2020). Also, the retrospective methods are susceptible to memory biases and rationalization processes, potentially compromising the validity of self-reported data. To address these limitations, researchers have increasingly adopted real-time detection assessment tools, such as VR and motion capture technologies. For example, Luo et al. (2016) utilized motion sensors to analyze workers' responses to falling objects, demonstrating that distance significantly influences hazard avoidance behaviors. Similarly, Zhu et al. (2023) combined eye tracking and motion capture to reveal that stress responses are closely linked to distance misjudgments in virtual environments. These studies highlight the importance of objective and real-time detection assessments to comprehensively understand proximity-based risk perception (Shi et al., 2020).

While spatial proximity remains central to risk perception frameworks, emerging evidence highlights the need to integrate psychological and social dimensions into these analyses. Risk assessment extends beyond physical distance alone, with cognitive biases, emotional states, and cultural contexts introducing additional layers of complexity (Giordano et al., 2010). For instance, individuals with prior hazard experience may exhibit heightened sensitivity to risks, while those with strong emotional attachments to their environment may downplay potential threats (Navarro et al., 2021). Future research should explore these psychological and social factors to develop more holistic risk perception models.

5.5. Human factors as moderators of proximity-risk links

Table 2 categorizes human-factor moderators into five domains: demographics and socioeconomics (age, gender, education, income), expertise and experience with the hazard, social attitudes (trust, norms, crowding, and PMT components), cognitive and affective heuristics (availability, affect, optimism bias, probability neglect), and instrumented risk propensity (SSS-V, RPS, DOSPERT, BART). The observed patterns align with a structured moderation of proximity gradients. Specifically, higher education and knowledge often intensify sensitivity to nearby risks, leading to increased perceived risk at short distances. Conversely, specialized expertise can mitigate distance gradients by directing evaluation toward analytical cues rather than spatial closeness (see Table 2 for education/knowledge vs. professional expertise).

Furthermore, income disparities often result in stronger proximity effects, with lower-income groups residing closer to hazard clusters perceiving higher risk compared to wealthier groups at similar distances. This suggests that resource limitations may amplify the significance of local risks (see Table 2 for income data). Additionally, social and attitudinal factors frequently moderate these effects: levels of trust can either mitigate or exacerbate the relationship between distance and perceived risk based on the perceived credibility of institutions or actors, while crowding tends to heighten perceived risk near hazardous areas (refer to Table 2 for trust and crowding data). Moreover, individual risk tendencies exhibit consistent patterns: individuals with high sensation-seeking tendencies (SSS-V) or a greater inclination towards risk-taking (RPS/DOSPERT) may attenuate the influence of proximity-based risk signals by assigning less weight to hazard cues. Conversely, heightened neuroticism may amplify local risk assessments (Blais & Weber, 2006; Meertens & Lion, 2008; Zuckerman, 1994). Although the presence of Behavioral Approach Task (BART) and DOSPERT measures was limited in our dataset, their inclusion underscores the importance of integrating self-reported data with behavioral or context-specific metrics (Blais & Weber, 2006; Lejuez et al., 2002).

In the realm of cognitive-affective processes, seminal studies have shown that the availability and affect heuristics amplify the significance of vivid or negative local events, thereby intensifying perceived risks in close proximity (Tversky & Kahneman, 1973; Lichtenstein et al., 1978; Finucane et al., 2000; Slovic et al., 2007). Conversely, optimism bias and probability neglect may either mitigate or amplify perceptions of distant hazards, contingent upon the emotional context (Sharot, 2011; Sunstein, 2002). Emotionally, fear and anger can lead to divergent evaluations, with employing reappraisal instead of suppression being conducive to mitigating exaggerated responses to proximal threats (Lerner & Keltner, 2001; Lerner et al., 2003; Gross, 1998, 2002). On a social and cultural level, norms, trust, and cultural viewpoints influence whether proximity is normalized or accentuated, while network diffusion and media channels can attribute comparable significance to distant hazards, thereby altering spatial gradients (Weber & Hsee, 1998; Dryhurst et al., 2020).

In summary, based on the data presented in Table 2 and Appendix S2, we propose a comprehensive conceptual synthesis: (a) individual personality traits and inclinations towards risk-taking may either reduce (e.g., sensation seeking) or heighten (e.g., neuroticism) proximity gradients (Blais & Weber, 2006; Meertens & Lion, 2008; Zuckerman, 1994); (b) cognitive tendencies can magnify risks in close proximity and, through media exposure, increase the significance of distant threats (Finucane et al., 2000; Lichtenstein et al., 1978; Small et al., 2007; Tversky & Kahneman, 1973); (c) emotions and regulatory mechanisms influence the strength and direction of these gradients (Lerner & Keltner, 2001; Lerner et al., 2003; Gross, 1998, 2002); and (d) societal norms and cultural/trust frameworks determine whether proximity is socially accentuated or diminished (Weber & Hsee, 1998; Dryhurst et al., 2020). We advocate for the use of pre-registered Distance X Trait/State models (e.g., Distance X SSS-V; Distance X reappraisal; Distance X trust) and multi-level, scale-sensitive methodologies to investigate the scale-dependent nature of human-factor moderation.

5.6. Place attachment and spatial embeddedness

Place attachment refers to emotional, cognitive, and social connections to particular locations, developed through identity, social relationships, care, and daily habits (Brown & Perkins, 1992; Lewicka, 2011b; Scannell & Gifford, 2010a). By contextualizing human influencers geographically, place attachment elucidates that identical physical distances can elicit varied perceptions based on individuals' level of attachment to the location and the significance they attribute to it (Devine-Wright, 2009; Scannell & Gifford, 2010a).

Attachment plays a crucial role in habituation and normalization processes in proximity to hazardous environments. Repeated exposure to relatively low-risk situations, such as living near industrial facilities or flood-prone areas, can lead to decreased perceived risk due to factors like familiarity, established coping mechanisms, and shared narratives. This phenomenon results in a reduction of the perceived risk of hazards in close proximity, thereby weakening the relationship between proximity and risk assessment (Kasperson et al., 1988; Lewicka, 2011). Conversely, when attachment is lacking—characterized by short residency duration, weak neighborhood identification, fragile social connections, or viable exit strategies—the salience of environmental cues in close proximity to hazards remains high, leading to sharper proximity-risk gradients (Hidalgo & Hernández, 2001; Kyle et al., 2004).

Cultural perspectives play a crucial role in shaping the interaction between Distance X Attachment dynamics. In societies where rootedness is integral to one's sense of self or essential for sustenance, physical proximity may be redefined as manageable, thereby reducing perceived risks despite close proximity. Conversely, in settings characterized by low institutional trust or rigid mobility norms, the same proximity can heighten perceived risks (Devine-Wright, 2009; Dryhurst et al., 2020a). This variability elucidates the presence of non-linear patterns, such as peaks in border areas, where the strength of emotional attachment and the interpretation of land use undergo transitions (Scannell & Gifford, 2010; Lewicka, 2011).

For future research, it is advisable to directly assess place attachment using validated concise scales or proxies such as residence duration, homeownership, and local participation. Additionally, it is recommended to gather exposure histories to differentiate habituation from mere proximity. When modeling the interaction between Distance and Attachment, it is crucial to explicitly define neighborhood boundaries and scale, considering the scale-dependent nature of attachment effects (Kyle et al., 2004; Lewicka, 2011a; Scannell & Gifford, 2010a).

5.7. Future research directions

Building on the insights and limitations discussed in the previous sections, this review identifies a few possible directions for future research to enhance the understanding of how distance to hazards shapes risk perceptions.

While spatial distance remains foundational to risk perception frameworks, future models must better account for its interplay with psychological and sociocultural variables. For instance, demographic factors (e.g., age, education) and cultural norms (e.g., societal trust) systematically moderate how proximity translates into perceived risk (Chen et al., 2019). A promising approach involves synthesizing insights across hazard types—such as industrial accidents, natural disasters, and workplace risks—to identify universal patterns and context-specific divergences in proximity-risk relationships. This cross-hazard integration could enhance predictive accuracy while testing the generalizability of theoretical frameworks.

Geospatial technologies (e.g., GIS, GNSS) provide robust tools for quantifying objective distances but require complementary methods to capture subjective perceptions. Emerging technologies, such as VR and motion capture, offer the potential for real-time detection assessments of behavioral and physiological responses (Zhu et al., 2023; Shi et al., 2020). Future studies may also integrate physiological metrics (e.g., stress responses or gaze patterns) to understand reactions under time constraints and stress. Longitudinal studies tracking risk perception across varying distances and time could reveal how psychological and social factors evolve with prolonged exposure to hazards.

The "border zone effect" (Zhou et al., 2022) is a U-shaped non-linear relationship where risk perception is lowest at a moderate distance before rising again beyond that point. This highlights the need to investigate spatial heterogeneity in hazard exposure. Environmental features, such as physical barriers (e.g., terrain, infrastructure) and hazard intensity gradients (e.g., pollutant dispersion patterns), may explain why communities at intermediate distances experience either heightened or diminished risk perception compared to those closer to hazards. For example, air pollution studies in urban versus rural settings could clarify how visibility and population density amplify or attenuate proximity-based perceptions. Similarly, radiation risk studies near nuclear facilities might reveal how hazard-specific exposure profiles (e.g., directional fallout patterns) interact with spatial variability to shape risk judgments.

Collective factors like media narratives and institutional trust critically mediate proximity effects. Comparative studies across cultural contexts could explore how societal norms amplify distance-risk perception relationships. For instance, communities with low trust in authorities may perceive greater risks at moderate distances due to reliance on informal information networks. In contrast, cohesive societies might exhibit aligned risk perceptions across spatial zones. Tailoring risk communication strategies to these dynamics, particularly in regions with conflicting narratives, could improve preparedness in spatially vulnerable populations.

While large-scale hazards dominate current research, high-frequency risks (e.g., workplace accidents and traffic collisions) remain underexplored despite their cumulative societal impact. Micro-level proximity scenarios, such as machinery failures in construction sites or sudden vehicle–pedestrian interactions, demand distinct behavioral adaptations compared to rare disasters. Future studies should examine how immediate spatial threats (e.g., less than 2-meter gaps) trigger rapid risk assessments, bridging the gap between macro-scale proximity models and real-time decision-making.

Neuroscientific approaches for proximity research should incorporate a variety of methods to enhance understanding. Among the 54 studies analyzed, only a limited number utilized neurophysiological techniques. To address this gap, we propose the integration of EEG/ERP measures (such as frontal theta, N2/P3, LPP), peripheral physiological indicators (e.g., electrodermal activity, heart-rate variability), and eye-tracking/pupillometry. Ideally, these measures should be implemented within virtual reality (VR) environments or controlled field settings to capture rapid fluctuations in salience, affect, and cognitive control in relation to Distance and Distance X Time. Employing such multimodal methodologies would not only enhance the depth of mechanistic insights but also complement traditional self-report and behavioral assessments. Key references supporting this approach include Cavanagh and Frank (2014), Folstein and Van Petten (2008), Polich (2007), Hajcak et al. (2010), Critchley (2002), Thayer et al. (2009), Beatty (1982), Paulus et al. (2003), Preuschoff et al. (2008), Bartra et al. (2013), and Shackman et al. (2011).

6. Conclusion

This study systematically examines the role of distance in shaping risk perception across various hazard contexts. Through analyzing 54 articles published between 1978 and 2024, this study provides evidence from the literature by investigating different hazards and risks, distance categorizations, distance measurements, risk perception evaluations, and human factors.

This study identifies three key patterns that significantly advance our understanding of spatial risk perception. First, heightened risk perception correlates with decreasing distance, particularly for natural and industrial hazards, driven by sensory immediacy and threat salience. Second, diminished risk perception is observed in populations residing close to hazards, attributable to psychological adaptation mechanisms such as habituation and cognitive dissonance. Third, complex non-linear relationships emerge across contexts: (a) an inverted U-shaped pattern, where perceived risk peaks a moderate distance due to uncertainty and incomplete hazard familiarity; and (b) a U-shaped "border zone effect," where risk perception is lowest at an intermediate distance before increasing again beyond that point, driven by conflicting information and heightened environmental vigilance (Zhou et al., 2022). These findings highlight the need to move beyond linear assumptions and incorporate contextual heterogeneity into risk models.

This study contributes to the body of knowledge by synthesizing the patterns of distance-risk perception relations. Also, this study reveals that psychological mechanisms, such as habituation, cognitive dissonance, and familiarity, alter risk perception near hazards. Last, this study identifies inconsistencies and challenges in measuring distance and risk perception, suggesting the potential of innovative methods to provide a more accurate and comprehensive understanding. As hazard landscapes continue to evolve, integrating the insights and knowledge into practical applications is essential for improving individual safety and public resilience.

This study holds several limitations. First, the scope of analysis was restricted to spatial proximity, omitting other dimensions of distance such as temporal (e.g., time until hazard impact), social (e.g., relational closeness to affected groups), and experiential (e.g., direct vs. indirect exposure) factors. A multidimensional framework integrating these aspects could offer a more holistic understanding of how distance shapes risk perception. Finally, reliance on Scopus and Web of Science databases, though methodologically rigorous, may have excluded regionally focused or non-English publications. Incorporating grey literature and interdisciplinary repositories could mitigate potential selection biases and enrich the evidence base.

7. Declaration of generative AI and AI–assisted technologies in the writing process

During the preparation of this manuscript, the authors used OpenAI's GPT-4o to support quality-assessment screening phases of our systematic review. Specifically, GPT-4o was iteratively prompted—three calibration cycles, no model fine-tuning—to score candidate studies against a 1-to-3 Likert rubric (thematic relevance, methodological alignment, analytical rigour). Discordant scores identified by human raters prompted prompt-refinement and re-testing until agreement was reached. Only study titles, abstracts, and the scoring rubric were supplied to the model, ensuring compliance with journal confidentiality policies.

After using the tool, the authors reviewed and edited all AI outputs and take full responsibility for the integrity and accuracy of the published work.

CRediT authorship contribution statement

Lei Liu: Writing – original draft, Visualization, Methodology, Formal analysis, Conceptualization. **Zhenan Feng:** Writing – review & editing, Validation, Supervision, Project administration. **Daniel Paes:** Writing – review & editing, Visualization, Supervision. **Ruggiero Lovreglio:** Writing – review & editing, Validation, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jsr.2026.03.012.

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