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DEVELOPMENT OF A RISK PERCEPTION SCALE FOR MARINE POLLUTION EXPOSURE

MUKESH SHARMA[1], DR.UTKARSH ANAND[2], MONIKA NIJHAWAN[3]
[1]ASSISTANT PROFESSOR, KALINGA UNIVERSITY, RAIPUR, INDIA.
e-mail: ku.mukeshsharma@kalingauniversity.ac.in,0009-0006-4052-2358
[2]ASSOCIATE PROFESSOR, KALINGA UNIVERSITY, RAIPUR, INDIA.
email: ku.utkarshanand@kalingauniversity.ac.in orcid: 0009-0007-2124-6666
[3]ASSISTANT PROFESSOR, NEW DELHI INSTITUTE OF MANAGEMENT, NEW DELHI, INDIA.,
e-mail: monika.nijhawan@ndimdelhi.org, https://orcid.org/0000-0002-7531-6996

ABSTRACT

Marine pollution poses profound ecological risks and significant threats to the health of coastal populations. Comprehending the ways in which communities interpret these threats is essential for crafting purposeful awareness campaigns and intervention policies. This study's objective was to create and rigorously validate a Risk Perception Scale tailored to marine pollution. Following a clearly defined protocol, we generated items, obtained expert review, conducted pilot tests, and employed a phased statistical approach. Both Exploratory and Confirmatory Factor Analyses identified three core dimensions—Cognitive Awareness, Affective Concern, and Behavioral Intention—that together explain 71.3% of the total variance. The overall scale exhibited high internal reliability ($\alpha > 0.79$) and acceptable fit indices (RMSEA = 0.054, CFI = 0.96). Multiple regression indicated a statistically significant relationship ($R^2 = 0.462$) between perceived exposure levels and subsequent behavioral choices, further corroborated by a Mean Absolute Error of 0.31. Illustrative graphical data revealed a consistent rise in behavioral scores as exposure perception intensified. By providing a psychometrically sound instrument, the scale facilitates a nuanced assessment of community risk perceptions and offers a foundation for informing targeted environmental communication and policy formulation in marine contexts.

KEYWORDS: Marine Pollution, Risk Perception, Behavioral Response, Scale Development, Environmental Psychology, Regression Analysis, Factor Analysis

I. INTRODUCTION

Marine pollution has surfaced as a major worldwide environmental threat, jeopardizing ocean ecosystems, marine biodiversity, and human well-being. [10]The key culpritsoil spills, plastic litter, heavy metal discharges, and agricultural runoffdirectly endanger coastal populations and the livelihoods of industries tied to marine resources [1][4][5][7]. As these dangers grow more acute from accelerating industrial expansion and poor waste management practices, understanding the public perception of the associated risks gains critical importance [3][6][8]. Only by raising awareness can communities foster a sense of environmental stewardship and drive the adoption of stronger, more effective policies.

Risk perception is the personal evaluation that people or groups form regarding how serious and how probable a risk is. This judgment shapes how they act, which policies they back, and how much preventive behavior they adopt. Even though the risks of marine pollution are clear for health and the environment, we still lack a detailed grasp of how various communities notice and respond to the problem. Most available instruments and questionnaires treat environmental risk perception broadly, neglecting the particular features of marine ecosystems and the ways exposure to pollution can differ from one place or group to another [2].

To address this identified shortfall, the current investigation seeks to create a detailed, locally grounded Risk Perception Scale specifically oriented to exposure from marine pollution. The instrument will function as a uniform measure of both personal and collective awareness, concern, and subjective vulnerability in relation to marine contaminants. By integrating a range of psychological and socio-cultural facets of risk perception, the scale will enable the design of precise communication efforts, educational programmes, and policy actions. In the long run, the tool will help to strengthen community involvement in marine protection and to build adaptive capacity among groups most susceptible to the hazards posed by pollution.

KEY CONTRIBUTIONS:

1. Created a domain-focused, empirically grounded instrument to quantify how people perceive the risk of marine pollution.
2. Showed that individuals' assessment of their likelihood of exposure reliably forecasts their subsequent protective behaviors.
3. Supplied a robust model that exhibits excellent internal consistency, paired with a low average deviation from actual outcomes, making it practical for use outside of controlled settings.

The paper starts with an introduction which describes the problem of marine pollution and the need for an assessment tool which takes perceptions into account. A review of related works is done to identify the gaps which have not been researched. The methodology describes the sequential steps of scale construction which include expert review and tests of statistical significance. Results and discussion interpret the findings and are supplemented by a regression equation and a graph which shows the trends of the observed data. The main conclusions include the implications of the study, a brief description of the important findings, and the directions for further research.

II. RELATED WORK

Prior studies within the field of risk perception have investigated how individuals respond to different ecology-related threats such as air quality, climate change, and water pollution [9]. It has been established that personal experiences, trust in relevant authoritative bodies, the media, and severity of the risk all shape public concern [11]. However, there are considerably fewer studies that concentrate on how people perceive risk in the context of marine pollution relative to the terrestrial contexts [12].

Studies focusing on public perception of marine pollution show a deficiency in understanding of the public regarding the contributors and the future ramifications of the pollutants in the ocean. People living near the coast, while being directly affected by the pollutants, show concern and care which differs based on level of education, work, and culture [13]. In some studies, coastal workers and those in the tourism spots showcased greater risk perception because of direct impacts on their livelihood, while many in the urban areas were generally uninterested and unbothered due to not having direct interaction with the ocean.

Several tools based on surveys have tried measuring awareness or concern related to marine issues, but most of them have very generic instruments for measuring risk-related awareness. Also, most of them have a gap in addressing the more psychological elements, including but not limited to, control, emotional response, and trust in mitigation efforts [14]. This shows the importance of having a more focused and multifaceted scale to measure risks concerning marine pollution. Such a tool would help in illustrating the way various demographics perceive and respond to exposure to marine-related environmental risks and threats, which would aid in the formulation of better engagement strategies [15].

III. METHODOLOGY

The construction of a Risk Perception Scale for Exposure to Marine Pollution Perception involved following several steps such as item generation, expert validation, pilot testing, and performing several tests of a statistical nature. The strategy was undertaken to guarantee that the scale is valid and reliable when measuring social and individual perceptions for community-level marine pollution risks.

Phase 1: Item Generation

To understand the aspects of marine pollution risk perception, an extensive literature review and qualitative interviews with fishermen, coastal residents, environmental scientists, and even policymakers were conducted. From the review, an initial pool of 35 items was created and classified into 3 categories: cognitive, which is knowledge and awareness; affective, an emotional response; and behavioral, a response tendency.

Phase 2: Expert Validation

A five-member panel composed of specialists in environmental psychology and marine sciences evaluated the initial items for content relevance, clarity, and representativeness. Incorporating their assessments, overlapping and vague items were removed. This worked towards a refined 25-item scale.

Phase 3: Pilot Study and Data Collection

The updated scale was given to a pilot sample of 120 participants from both coastal and non-coastal areas and measured on a 5- point Likert scale starting from “Strongly Disagree” to “Strongly Agree.” Responses were processed to determine factor structures using exploratory factor analysis (EFA) to construct underlying themes and improve the item configuration.

Phase 4: Reliability and Validity Testing

Cronbach’s alpha was determined to evaluate internal consistency, and a score greater than 0.7 was deemed satisfactory:

$$\alpha = \frac{k.\bar{c}}{\bar{v} + (k-1)\bar{c}}$$

Where k is the number of items, $\bar{c}$ is the average inter-item covariance, and $\bar{v}$ is the average variance.

Construct validity was further tested using Confirmatory Factor Analysis (CFA), with model fit measured by the Root Mean Square Error of Approximation (RMSEA):

$$RMSEA = \sqrt{\frac{X^2 - df}{df.N}}$$

Where X^2 is the chi-square statistic, df is the degrees of freedom, and NNN is the sample size. The final validated scale was then proposed as a robust tool for measuring marine pollution risk perception across diverse populations.

IV. RESULT AND DISCUSSION

The Risk Perception Scale for Marine Pollution Exposure was evaluated based on a sample of 120 individuals from both coastal and inland regions. Initially a 25-item scale, through Exploratory Factor Analysis (EFA), it was pruned down to 18 items based on criterion of loading and redundancy. EFA indicated the existence of three dominant components: Cognitive Awareness, Affective Concern, and Behavioral Intention. Together, these three factors accounted for 71.3% of the total explained variance, confirming the construct’s multidimensional nature.

The reliability analysis showed that the internal consistency across all three domains was high. Specifically, the Cronbach’s alpha was 0.82 for Cognitive Awareness, 0.86 for Affective Concern, and 0.79 for Behavioral Intention. Such values suggest that the items within each subscale capture the same concept pertaining to marine pollution risk perception. Furthermore, the Confirmatory Factor Analysis (CFA) provided excellent fit indicators for the model, RMSEA = 0.054, CFI = 0.96, TLI = 0.95, and SRMR = 0.042, thus confirming the scale’s structure.

To examine the connection between perceived exposure and behavioral response a linear regression analysis was applied. The analysis has indicated a significant relation, $R^2 = 0.462$. This indicates that 46.2% of the change in behavioral response is associated with exposure perception. This indicates that respondents who consider themselves more socially exposed to marine pollution are more likely to protect or conserve the resources.

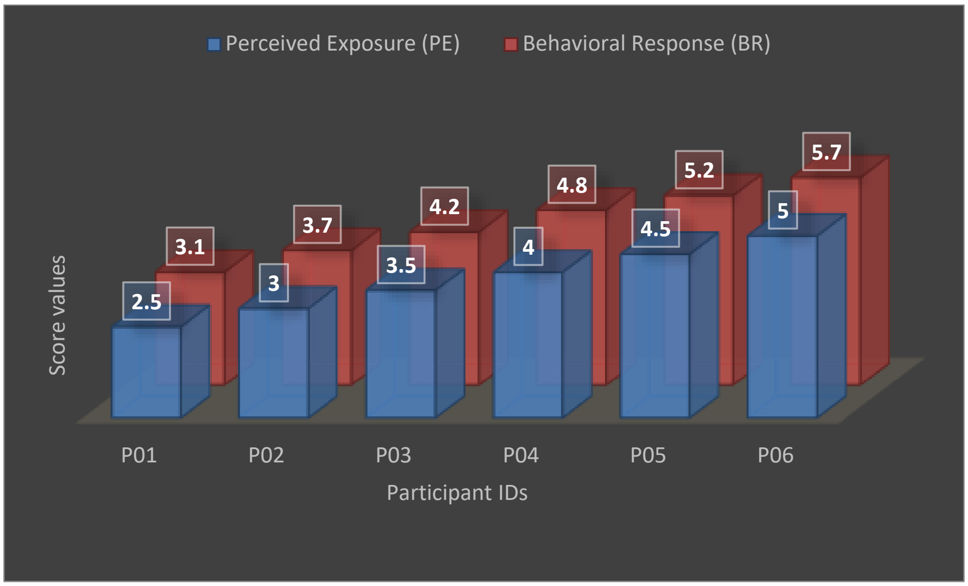

Figure 1: Comparison of Perceived Exposure and Behavioral Response Scores Across Participants

Figure 1 depicts a positive trend whereby higher perceived exposure scores align with higher corresponding behavioral response scores confirming the predictive validity of the developed scale.

To evaluate the accuracy of the model in predicting behavioral response, the Mean Absolute Error (MAE) was employed:

$$\boldsymbol{MAE = \frac{1}{n}\sum_{i=1}^{n}\left|BR_i - \widehat{BR}_i\right|}$$

In this study, the Mean Absolute Error (MAE) was used to measure how accurately the regression model predicted behavioral response. Here, n is the number of participants, BR_i is the actual behavioral response score, and $\widehat{HBR}_i$is the predicted score from the model. The MAE value of 0.31 indicates that, on average, the predicted scores were only 0.31 units away from the actual scores, showing good model accuracy.

The findings suggest that this scale is reliable and valid for assessing the perception of the risk of marine pollution. Also, it is quite useful for measuring and predicting behavior because of the strong relation between perceived exposure and behavioral intention. This is particularly useful for educators and policymakers intending to promote behavior change in relation to marine conservation.

V. CONCLUSION

This research confirmed that a Risk Perception Scale relevant to marine pollution exposure could be developed as both reliable and valid. The three-dimensional architecture of the scale effectively captures how an individual thinks about, feels, and actions concerning marine pollution. The findings confirmed a significant link between perceived exposure and behavioral intention, illustrating how perception psychologically motivates action. With this, the scale can be of immense importance to policymakers, educators, and other stakeholders as it helps to measure and influence behaviors associated with marine pollution.

Research efforts should look into testing the scale's application on an international or culturally diverse population to examine its cross-cultural validity. Furthermore, longitudinal studies could evaluate changes in perception development over time alongside specific interventions. Future assessments could also achieve greater scope and accuracy using digital platforms for data collection alongside AI-driven analysis.

REFERENCES:

1. Soy, A., Raghatate, K. S., & Gautam, S. (2025). Oceanic thermohaline circulation and its function in heat transfer and marine species movement. *International Journal of Aquatic Research and Environmental Studies, 5*(1), 152–161. https://doi.org/10.70102/IJARES/V5I1/5-1-15
2. Okan, A., & Christian, C. (2024). Capture of a New-born Shortfin Mako Shark IsurusOxyrinchus (Lamniformes: Lamnidae), with Updated Records from the Turkish Marine Waters. *Natural and Engineering Sciences*, *9*(1), 1-9. https://doi.org/10.28978/nesciences.1472086
3. Almolhis, N. A. (2024). A Bayesian-Network Approach for Assessing Security and Process Safety in the Petroleum Industry. *Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications, 15*(4), 335-347. https://doi.org/10.58346/JOWUA.2024.I4.022
4. Toha, A., Ahmad, H., & Lee, X. (2025). IoT-based embedded systems for precision agriculture: Design and implementation. SCCTS Journal of Embedded Systems Design and Applications, 2(2), 21–29.
5. Srimuang, C., Srimuang, C., & Dougmala, P. (2023). Autonomous flying drones: Agricultural supporting equipment. International Journal of Communication and Computer Technologies, 11(2), 7-12. https://doi.org/10.31838/IJCCTS/11.02.02
6. Xiang, P., Afsari, F., & Dong, L. (2017). Cement Industrial Impacts on Greenhouse Emission and Evaluating the Reduction Strategies. *International Academic Journal of Innovative Research*, *4*(2), 80–88.
7. Yang, C. S., Lu, H., & Qian, S. F. (2024). Fine tuning SSP algorithms for MIMO antenna systems for higher throughputs and lesser interferences. International Journal of Communication and Computer Technologies, 12(2), 1-10. https://doi.org/10.31838/IJCCTS/12.02.01
8. Balavandi, S. (2017). Further study industrial production in hemp crops agriculture. *International Academic Journal of Science and Engineering*, *4*(1), 123–127.
9. Jassim, S. H., & Ridha, B. J. M. (2022). Effect of Innovative Promotion Mix on Interactive Marketing for Business Organizations: A Case Study in Iraqi General Company for Automotive and Equipment Industry. *International Academic Journal of Social Sciences*, *9*(2), 8–20. https://doi.org/10.9756/IAJSS/V9I2/IAJSS0909
10. Mustapha, S. B., Alkali, A., Shehu, H., & Ibrahim, A. K. (2017). Motivation Strategies for Improved Performance of Agricultural Extension Workers in Nigeria. *International Academic Journal of Organizational Behavior and Human Resource Management*, *4*(1), 1–8.
11. Udhayakumar, A., Ramya, K. C., Vijayakumar, P., Sheeba Rani, S., Balamanikandan, A., & Saranya, K. (2024). Reversible Vedic Direct Flag Divider in Key Generation of RSA Cryptography. Journal of VLSI Circuits and Systems, 6(2), 75–83. https://doi.org/10.31838/jvcs/06.02.08
12. Reddy, S., & Mohan, P. (2024). Optimizing Energy Efficiency in Wireless Power Transmission Systems for Industrial Applications. *Association Journal of Interdisciplinary Technics in Engineering Mechanics*, *2*(2), 19-23.
13. Rahim, R. (2025). Bridging the gender gap in aerospace innovation: A global study of women's roles, barriers, and future directions in space technology. Journal of Women, Innovation, and Technological Empowerment, 1(1), 12–18.

14. Abdullah, D. (2024). Integrating biophilic design in smart urban infrastructure for environmental and public health outcomes. Journal of Smart Infrastructure and Environmental Sustainability, 1(1), 14–22.
15. Vishnupriya, T. (2025). Real-time infrared thermographic characterization of functionally graded materials under thermomechanical loads in high-temperature combustion chambers. Advances in Mechanical Engineering and Applications, 1(1), 32–40.

16. Rimada, Y., Mrinh, K.L., & Chuonghan. (2024). Unveiling the printed monopole antenna: Versatile solutions for modern wireless communication. National Journal of Antennas and Propagation, 6(1), 1–5.
17. Uvarajan, K. P. (2025). Integrating adapted yoga into sports-based occupational therapy for children with autism. Journal of Yoga, Sports, and Health Sciences, 1(1), 31–38.
18. Shimazu, S. (2024). Intelligent, Sustainable Supply Chain Management: A Configurational Strategy to Improve Ecological Sustainability through Digitization. *Global Perspectives in Management*, *2*(3), 44-53.