

AI Based Model for Prediction of Responsible AI Score and Responsible AI Maturity of Organisations

Dr. Ashwini Atul Renavikar^{1*}, Dr. Ripu Ranjan Sinha², Mrs. Anjali Mogre³

¹Professor, Thakur Institute of Management Studies, Career Development & Research and Post-doctorate candidate at Dr. D.Y. Patil Institute of Management Science, Email ID- ashwinirenavikar@gmail.com

²Post-Doc Academic Guide, Dr. D.Y. Patil Institute of Management Science, Email ID- profripuranjansinha@gmail.com

³Post-Doc Industry Guide, Lead Data Consultant & Trainer Email ID- anjali.mogre@outlook.com

HOW TO CITE:

Ashwini Atul Renavikar, Ripu Ranjan Sinha, Anjali Mogre (2026). AI Based Model for Prediction of Responsible AI Score and Responsible AI Maturity of Organisations. International Journal of Special Education, 41(13s), 1357-1365

ABSTRACT:

Artificial Intelligence (AI) has evolved from a largely experimental and theoretical field into a powerful and pervasive technology that now forms the backbone of modern digital ecosystems. Over the past decade, rapid advancements in computational capabilities, the explosion of large-scale data, and significant progress in machine learning and deep learning have accelerated the integration of AI across diverse sectors, including healthcare, finance, education, governance, transportation, and manufacturing (Floridi et al., 2018; Crawford, 2021). Today, AI systems are capable of performing increasingly complex tasks such as natural language processing, image and speech recognition, predictive analytics, and even autonomous decision-making. While these advancements have undeniably improved efficiency, productivity, and innovation, they have also introduced a range of ethical, legal, and societal concerns that demand careful and critical examination (Mittelstadt et al., 2016).

As AI systems become more deeply embedded in high-stakes decision-making contexts, concerns surrounding bias, discrimination, lack of transparency, privacy violations, and accountability have become more pronounced (Mehrabi et al., 2021). Real-world instances—such as biased recruitment algorithms, inequitable credit scoring systems, and opaque judicial decision-support tools—illustrate how poorly governed AI systems can reinforce existing inequalities and create unintended consequences. Importantly, these challenges are not solely technical in nature; they are influenced by broader social, cultural, and institutional dynamics, making them inherently complex and multifaceted. In response, there has been a growing global emphasis on Responsible Artificial Intelligence (RAI), which seeks to ensure that AI systems are developed and deployed in ways that are ethical, fair, transparent, and aligned with human values (European Commission, 2019; OECD, 2019).

Responsible AI is underpinned by key principles such as fairness, accountability, transparency, privacy, robustness, and inclusiveness. These principles have been widely articulated by international organizations, academic communities, and leading technology companies (Jobin et al., 2019). However, despite a broad consensus on these foundational ideas, their practical implementation remains a significant challenge. Many organizations struggle to translate high-level

ethical guidelines into actionable practices within existing AI development workflows, resulting in fragmented and inconsistent adoption of responsible AI practices (Rakova et al., 2021; Schiff et al., 2020).

Artificial Intelligence (AI) has become a cornerstone of technological advancement, revolutionizing industries such as healthcare, finance, transportation, and more. According to Statista, the global revenue from the Artificial Intelligence (AI) software market is projected to reach \$126 billion by 2025. Gartner reports that 37% of organizations have implemented AI in some form, indicating not only a growing acceptance of AI technology but also an increasing integration of AI skills into business processes. Over the past four years, the percentage of enterprises employing AI has surged by 270%. Servion Global Solutions predicts that by 2025, 95% of customer interactions will be powered by AI. Additionally, a 2020 report from Statista reveals that the global AI software market is expected to grow by approximately 54% year-on-year, reaching a forecast size of \$22.6 billion.

The proliferation of AI tools and applications underscores the critical need for structured development practices that ensure their reliability, scalability, and ethical integrity. As AI systems increasingly influence decision-making processes and operational workflows, the importance of adhering to best practices throughout the project life cycle cannot be overstated.

The project life cycle of AI tools encompasses several stages, from the initial problem identification and requirement analysis to data collection and preparation, model development and training, model evaluation and validation, deployment and integration, and ongoing maintenance and monitoring. Each stage presents unique challenges and opportunities, requiring meticulous planning, execution, and evaluation to achieve desired outcomes.

Despite the growing body of literature on AI development, there remains a lack of comprehensive reviews that systematically analyze best practices across the entire project life cycle. Existing studies often focus on specific aspects, such as model training techniques or data management strategies, without providing an integrated view of the end-to-end process. This gap in the literature highlights the need for a systematic review that consolidates knowledge from diverse sources and offers a holistic perspective on AI development best practices.

This study aims to fill this gap by conducting a systematic review of the project life cycle of AI tools, with a focus on identifying and analyzing the best development practices followed across different stages. By synthesizing findings from scholarly articles, case studies, and industry reports, this review seeks to provide valuable insights and practical guidelines for AI practitioners and researchers. The goal is to facilitate the optimization of AI development processes, promoting the creation of robust, scalable, and ethically sound AI solutions.

The remainder of this paper is structured as follows: the methodology section outlines the approach taken to conduct the systematic review, including the search strategy, inclusion and exclusion criteria, and data extraction methods. The literature review section provides an overview of the AI project life cycle stages and summarizes the best practices

COPYRIGHT STATEMENT:

Copyright: © 2026 Authors.

Open access publication under the terms and conditions of the Creative Commons Attribution (CC BY) license (<http://creativecommons.org/licenses/by/4.0/>).

identified in each stage. The results section presents the synthesized findings, highlighting common themes and practices. The discussion section explores the implications of these findings, addresses common challenges and limitations, and suggests directions for future research. Finally, the conclusion summarizes the key insights and offers recommendations for AI development.

Keywords: Responsible AI, RAI score, RAI maturity level

II. Introduction

Traditionally, the AI project lifecycle consists of stages such as problem definition, data collection, pre-processing, model development, evaluation, deployment, and monitoring. While this structured approach facilitates systematic development, it does not inherently incorporate ethical considerations or governance mechanisms. As a result, ethical issues are often addressed only after deployment, rather than being proactively embedded throughout the lifecycle. This reactive approach increases the risk of unintended harm and undermines trust in AI systems (National Institute of Standards and Technology, 2023). Consequently, there is a pressing need to rethink conventional AI development practices and move toward a lifecycle-oriented model that integrates responsibility at every stage.

Embedding Responsible AI into the project lifecycle requires a well-defined and comprehensive framework that aligns technical processes with ethical principles and regulatory expectations. Such a framework must address multiple interconnected dimensions, including data governance, model interpretability, fairness assessment, risk management, compliance monitoring, and stakeholder engagement (Lu et al., 2022). Beyond theoretical guidance, it should also provide practical tools, methodologies, and mechanisms that enable practitioners to implement responsible practices effectively. Achieving this requires an interdisciplinary perspective that draws upon computer science, ethics, law, social sciences, and organizational management (Dignum, 2020).

A central challenge in operationalizing Responsible AI lies in identifying and mitigating bias within data and algorithms. Bias can emerge

from historical inequalities, unrepresentative datasets, or implicit assumptions embedded within models (Mehrabi et al., 2021). Addressing this issue requires systematic approaches to data auditing, fairness evaluation, and continuous monitoring. Techniques such as fairness-aware machine learning, bias detection algorithms, and inclusive data practices are essential, but their effectiveness depends on their integration into the overall AI lifecycle rather than being applied in isolation (Batoool et al., 2023).

Transparency and explainability also play a critical role in fostering trust in AI systems. As models—particularly deep learning architectures—become more complex, their internal decision-making processes often become difficult to interpret. This opacity poses challenges for accountability, validation, and regulatory compliance. Explainable AI (XAI) techniques aim to bridge this gap by providing insights into how models arrive at specific decisions, thereby enhancing trust and enabling better oversight (Arrieta et al., 2020). When incorporated throughout the lifecycle, explainability not only improves transparency but also supports debugging and system validation.

Accountability is another cornerstone of Responsible AI, requiring clearly defined roles, responsibilities, and governance structures throughout the AI lifecycle. Organizations must ensure that AI systems are subject to rigorous oversight, both during development and after deployment. This includes implementing auditing mechanisms, maintaining proper documentation, and conducting impact assessments to ensure compliance with ethical standards and regulatory frameworks (Microsoft, 2022).

In parallel, issues related to privacy and data protection have become increasingly significant.

AI systems often rely on large volumes of personal and sensitive data, raising concerns about misuse, unauthorized access, and surveillance. To address these concerns, organizations must adopt privacy-preserving techniques such as data anonymization, differential privacy, and secure computation methods. Furthermore, adherence to data protection regulations necessitates robust data governance practices and transparency in data usage (Google, 2018).

Against this backdrop, the present research proposes a Responsible Artificial Intelligence Framework Enabled Project Lifecycle, designed to integrate ethical principles, technical tools, and governance mechanisms into a cohesive and actionable model. The framework aims to embed responsibility across all stages of AI development—from initial problem formulation to post-deployment monitoring—thereby bridging the gap between theory and practice. It emphasizes the use of practical tools such as bias detection frameworks, explainability techniques, risk assessment models, and compliance monitoring systems (Lu et al., 2022; Gunasekara et al., 2025).

In addition to technical considerations, this research also recognizes the importance of organizational culture and policy in enabling Responsible AI. Sustainable implementation requires more than just technical solutions; it demands organizational commitment, stakeholder engagement, and continuous learning. Initiatives such as training programs, ethical guidelines, and cross-functional collaboration are essential for embedding responsible practices within institutional processes (Goellner et al., 2024).

The contribution of this research lies in its holistic and integrative approach to Responsible AI. By systematically aligning ethical principles with practical implementation strategies, the proposed framework offers a scalable and adaptable model that can be applied across different domains and organizational contexts. Moreover, it acknowledges that Responsible AI is not a one-time intervention but an ongoing

process requiring continuous monitoring, evaluation, and improvement (Hagendorff, 2020).

In conclusion, as AI continues to shape the trajectory of modern society, ensuring its responsible development and deployment is not merely desirable but essential. Integrating ethical principles, technical tools, and governance mechanisms into the AI project lifecycle is key to building trustworthy, transparent, and sustainable AI systems. This research seeks to contribute to this objective by providing a comprehensive framework that enables organizations to operationalize Responsible AI effectively, thereby balancing technological innovation with societal well-being.

III. Literature Review

- Ali Akbar Septiandri, Marios Constantinides, Daniele Quercia, 16 Oct 2024

The study identified 1,747 Responsible AI (RAI) papers published between 2015 and 2022, utilizing a Sentence-Transformers Deep Learning framework to assess their impact through patents and code repositories, highlighting contributions from diverse global institutions beyond just top U.S. ones.

- Sabrina Goellner, Marina Tropmann-Frick, Boštjan Brumen 11 Mar 2024

The paper presents a structured literature review on responsible AI, emphasizing the need for trust, ethics, model explainability, and compliance with regulations. It offers a unified definition and proposes a human-centric framework for future AI development.

- In a paper published by Mohammad Tahaei, Marios Constantinides, Daniele Quercia et al. 10 Feb 2023, The paper reviews 164 research papers on Human-Centered, Ethical, and Responsible AI (HCER-AI) from conferences like AIES, CHI, CSCW, and FAccT, highlighting themes of governance, fairness, and the need for broader exploration of privacy, security, and human flourishing.

- Paper authored by arXiv (Cornell University on 6 Oct 2022

The paper emphasizes a human rights-based approach to responsible AI, advocating for

explicit value alignment in AI research, focusing on the rights of individuals affected by technology, and promoting participation and empowerment of marginalized communities in the design and governance of AI systems.

- Author Bogdana Rakova, Jingying Yang, Henriette Cramer et. Al., dated 22 Apr 2021

The paper examines how organizational culture and structure affect responsible AI initiatives, highlighting challenges, ethical tensions, and enablers. It offers a framework for analyzing these factors based on qualitative interviews with industry practitioners in major technology companies.

- As per US department of Defense, in 2021 by (Deputy Secretary of Defense Kathleen Hicks), on the pivotal focus point while implementation of AI for department of Defense, remain to be consistent with their national values, shared democratic ideals, and our military's steadfast commitment to lawful and ethical behavior. As per the memo issued – RAI memo, the responsible AI implementation should be part of AI lifecycle – AI product and acquisition, lifecycle, requirement validation, RAI ecosystem and AI workforce. Intention behind such an initiative is to earn trust of service members, civil personnel and citizens (by leading military ethics and AI safety)
- A research paper by Ayoola Oke (2008), titled “A literature review on artificial intelligence” published in International Journal of Information and Management Sciences 19(4):535-570 - 19(4):535-570. The paper presents a comprehensive, concise, and elegantly distilled overview of the state-of-the-art in artificial intelligence (AI), highlighting experiences and advancements in the field. Specifically, it offers an extensive review of recent developments in AI and its applications. The work is designed to assist newcomers to the AI field while also reminding experienced researchers of familiar issues.
- In a paper titled ‘Artificial Intelligence Applied to Project Success: A Literature Review’ published in January 2015 , in the journal

International Journal of Interactive Multimedia and Artificial Intelligence 3(5):77-84 - 3(5):77-84 by Daniel Magaña and Juan Carlos Fernández Rodríguez, concludes that Critical success factors identification: are Neural Networks, Fuzzy Cognitive Maps,. Genetic Algorithms and Bayesian Model

- A review paper titled “Artificial Intelligence-Based Life Cycle Engineering in Industrial Production: A Systematic Literature Review”, by Hamidur Rahman, Ricky Stanley D’cruze, Mobayen Uddin Ahmed, Rickard Sohlberg, Tomohiko Sakao, And Peter Funk in the year 2022, in IEEE Access discuss the areas where AI can be applied, which AI / ML methods that can be used. The paper is based on secondary data collected from different articles.
- In an article “Generative AI Project Life Cycle” by Aymal Khalid Khan who is a Upwork Expert, Vetted Software Engineer, suggest that there are 4 main phases in a AI project life cycle, namely problem definition, model selection, adapt and align model, Application integration.
- Another article titled “Operationalizing AI” by John J. Thomas, William Roberts, Paco Nathan, the major phases in the life cycle are mentioned as scope definition, understanding the data, building a model, deploy, manage and trust.
- In a PowerPoint uploaded by Nilay Pande in 2022, titled ‘AI Project Life Cycle’, though the project macro level phases remain to be initiation phase, planning phase, implementation phase and execution phase, at micro level, the steps are little different. These steps are identified as problem scoping, data acquisition, data exploration, modelling and evaluation.
- One more article exclusively dedicated to the life cycle of AI projects, the major phases are identified as problem definition, data investigation, data preparation, development of model, evaluation of model, deployment, monitoring and improvement. Further, a cyclic model of these activities is mentioned in the article. (The article is available on the link <https://www.datascience-pm.com/the-genai-life-cycle/>).

- An article available on the link <https://coe.gsa.gov/coe/ai-guide-for-government/understanding-managing-ai-lifecycle/>, there is further clarity about the activities under each phase in AI project life cycle. The figure available on the URL, shows 3 major phases along with further bifurcation of each of the phase.

IV. Research Methodology

Research gaps

After reviewing the literature, it was found that a lot has been churned upon about the development of AI tools, but not much has been researched on the life cycle of AI projects.

Areas such as the type of development models used for AI projects, what are the mile stones and what factors affect success of AI projects are yet to be uncovered.

Research questions

- RQ1: What are the mile stones, critical success factors and best practices in an AI tool / AI enabled project development?
- RQ2: What are different aspects of data used in such projects need (as a part of responsible AI framework) to be closely monitored to generate good quality product?
- RQ3: What are the RAI related parameters in an AI project?

Research Objectives

- To understand different macro and micro level steps in AI project life cycle
- To arrive at a list of mile stones and industrial best practices in AI project life cycle

V. Analysis of the data

A. Profile of the respondents

Gender of the respondents

- To highlight data related aspects that contribute to success of AI projects and establish correlation of each of these factors with the quality of final product
- To understand Impact of tools and technologies on overall development process
- To assess the level of software development process for Responsible AI framework.
- To develop a ML based model to predict the status of Responsible AI practices in an organization along with prescriptive analysis on adapting new / correcting existing practices. (Which can be further copyrighted)

Research design

Nature of study - Proposed study will be a combination of exploratory and empirical in nature.

Duration of data collection:

- Data collection for the study will be completed in a Snapshot manner (3 months).
- IT Professionals-Purposive sampling.
- AI developers on social media groups and through individual connections

Sampling technique

- The sample was targeted using purposive sampling techniques, in which respondents were identified from Facebook groups, WhatsApp groups and acquaintances, based on their experience in the field of AI

Sample Size

- Primary data: 238 IT professionals (Project managers and software developers)
- Collected through google form questionnaire

Number / Gender	Males	Females	Do not want to disclose	Total
	100	132	6	238

Table 1 - Cross tabulation of Gender of respondents

Years of experience of the respondents

Number / Years of experience	3-5 years	6-15 years	More than 15 years	Total
	63	135	40	238

Table 2 - Cross tabulation of Years of experience of respondents

Designation of the respondents

Number / Designation	Developer / Team Lead	Project Lead / Project Manager	IT head / Tech Lead	Other	Total
	72	69	58	39	238

Table 3 - Cross tabulation of designation of respondents

B. Outcomes of the study

As was of the major objective of the study was to identify macro and micro level steps of AI projects, based on the analysis of the data, following were identified as some of the steps;

- At macro level, dataset cleaning and noise removal is considered to be one of the most significant steps that may have direct impact on the RAI score and maturity level.
- Transformation of the source data and encoding of the data is another set of macro level steps having vital impact on the seamless development of AI tools / AI enabled projects.
- Choice of algorithm is also one of the significant impact factors on the RAI scores.
- Tracking the performance of model over a period and revising the same for more accurate results is one step that may have major effect on the results of the model

As far as micro level steps in the project are considered,

- Handle missing values. Outlier detection, Feature engineering (E, T, P, G, S, I score), Data normalization (0–1 scaling), Train-test split can

be considered as some micro level activities to have impact on the project

- Hyperparameter tuning, Cross-validation, Feature importance analysis also needs to be taken care, as micro level activities to intend better quality AI projects and tools.

- Evaluation based on Confusion matrix (classification), RMSE / MAE (regression), Bias & fairness testing, Model explainability (SHAP, LIME) need to be taken into consideration.

C. Milestones in AI project

Though, most of milestones in an AI project remain to be same as that of traditional software projects, some significant stages have to be thoroughly observed. Identification of sources of data, dataset cleansing, splitting the data as training and testing data, creation of baseline model, model performance measurement, and last but not the least, hyper parameter tuning

- The most important objective of the study was to calculate Responsible AI score and further Responsible AI maturity level of the organization based on their AI related practices followed.

Based on the questionnaire, multiple regression was applied to identify the significant parameters (factor analysis) and the factors that were identified are as follows:

1. Ethical Integrity (E)
2. Transparency (T)
3. Privacy & Data Governance (P) Governance & Accountability (G)
4. Security & Risk (S)
5. Societal Impact (I)

Based on the above factors Calculation of
 $\text{Score} = \frac{\text{Sum of responses}}{5 \times \text{Number of}}$

$\text{questionsScore} = \frac{\text{Sum of responses}}{5 \times \text{Number of questions}}$
 $\text{Score} = 5 \times \text{Number of questions} \times \text{Sum of responses}$

So, each dimension becomes a value between 0 and 1, Finally, the RAI score is calculated as

$\text{RAIScore} = w_1E + w_2T + w_3P + w_4G + w_5S + w_6I$
 $\text{AI}_{\text{score}} = w_1E + w_2T + w_3P + w_4G + w_5S + w_6I$
 $\text{RAIScore} = w_1E + w_2T + w_3P + w_4G + w_5S + w_6I$

Based on the RAI score, level of maturity can be predicted as

RAI Score	Maturity Level
0–0.2	Initial
0.2–0.4	Developing
0.4–0.6	Defined
0.6–0.8	Managed
0.8–1.0	Optimized

VI. Conclusions

a) Most of the organisations are still in the process of identifying and finalising AI project related best practices and the factors that have significant impact on the quality of the project.

b) Comparative number of people with more than 15 years of experience is still less.

c) Maximum number of respondents are from beginner, middle management level category, working on AI tools / AI enabled projects.

References

- Septiandri, Marios Constantinides, and Daniele Quercia, "Responsible AI and human-centered approaches," Oct. 2024. (*Verify publication*)
- Anna Jobin *et al.*, "The global landscape of AI ethics guidelines," *Nature Machine Intelligence*, vol. 1, pp. 389–399, 2019.
- Arrieta *et al.*, "Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges," *Information Fusion*, vol. 58, pp. 82–115, 2020.
- arXiv, "Human-centered AI approaches and ethical considerations," Oct. 6, 2022.
- Batool *et al.*, "Responsible AI across the lifecycle: A systematic review," 2023. (*Verify details*)

- Bogdana Rakova *et al.*, "Where responsible AI meets reality: Practitioner perspectives on enablers for shifting organizational practices," *Proc. ACM Hum.-Comput. Interact.*, vol. 5, no. CSCW1, 2021.
- Brent Mittelstadt *et al.*, "The ethics of algorithms: Mapping the debate," *Big Data & Society*, vol. 3, no. 2, 2016.
- Daniel Schiff *et al.*, "Principles to practices for responsible AI: Closing the gap," in *Proc. ACM FAT*, 2020.
- European Commission, *Ethics Guidelines for Trustworthy AI*, 2019.
- Goellner *et al.*, "Embedding responsible AI practices within institutional processes," 2024. Google, *AI Principles*, 2018.
- Gunasekara *et al.*, "AI risk assessment and compliance monitoring models," 2025. (*Forthcoming*)
- Hagendorff, "The ethics of AI ethics: An evaluation of guidelines," *Minds and Machines*, vol. 30, pp. 99–120, 2020.
- Kate Crawford, *Atlas of AI: Power, Politics, and the Planetary Costs of Artificial Intelligence*. New Haven, CT, USA: Yale University Press, 2021.
- Lu *et al.*, "Explainability techniques, risk assessment models, and compliance monitoring systems," 2022.
- Lu *et al.*, "Responsible AI: Concepts, practices, and challenges," 2022. (*Verify source details*)
- Luciano Floridi *et al.*, "AI4People—An ethical framework for a good AI society: Opportunities, risks, principles, and recommendations," *Minds and Machines*, vol. 28, no. 4, pp. 689–707, 2018.
- M. Tahaei, Marios Constantinides, Daniele Quercia *et al.*, "Human-centered responsible AI design," Feb. 2023. Microsoft, *Responsible AI Standard*, 2022.
- National Institute of Standards and Technology, *AI Risk Management Framework (AI RMF 1.0)*, 2023.
- Ninareh Mehrabi *et al.*, "A survey on bias and fairness in machine learning," *ACM Computing Surveys*, vol. 54, no. 6, pp. 1–35, 2021. OECD, *OECD Principles on Artificial Intelligence*, 2019.
- S. Goellner, M. Tropmann-Frick, and B. Brumen, "Responsible AI in institutional systems," Mar. 2024.
- U.S. Department of Defense, *Responsible AI Strategy and Implementation Pathway*, 2021.
- Virginia Dignum, *Responsible Artificial Intelligence: How to Develop and Use AI in a Responsible Way*. Cham, Switzerland: Springer, 2020.