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Ethical AI and Data Engineering: Building Transparent and Accountable Systems - A Systematic Review

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Abstract - **We conducted a systematic review of 19 peer-reviewed articles focused on the key developments in ethical artificial intelligence and ethical data engineering spanning 2021 and previewing 2025. We review new frameworks, initiatives, and technologies that are being developed to enhance the transparency and accountability of AI systems. We find evidence of a move from algorithmic ethics to a data-centric paradigm, complemented by increasing attention to metrics of fairness and explainability. This enables steps towards bridging the gaps between practice and ethical theory requirements as well as in cross-cultural and small-scale deployments, despite progress in the development of technical solutions. The review identifies differences in ethical demand across contexts and proposes that future work on ethical demand be directed toward longitudinal outcomes, forms of stakeholder engagement, and adherence to shifting regulatory demands. In sum, we present an integrated approach that addresses ethical considerations across the data engineering life cycle.**

Keywords: Data-centric Ethics, AI Transparency, Algorithmic Accountability, Ethical Data Engineering, Fairness Metrics.

I. INTRODUCTION

Artificial intelligence technologies have come to wield ever more influence over the most central aspects of society, from medical diagnosis to the extension of credit to student evaluation and hiring staff. Their pervasive use prompts urgent questions of fairness, transparency, accountability and moral responsibility. As businesses adopt AI for mission-critical functions, the distance between ethical intent and technical delivery has emerged as a key challenge for both researchers and practitioners.

The field has shifted quite dramatically from an algorithmic to a data-centric approach to ethical AI. The shift recognizes that most ethical issues are seeded in the data engineering, or data life cycle process of collection, preparation and processing as opposed to the model design or deployment phase. Recent works show that at data level biases permeate through the AI systems and tends to escalate social asymmetries, despite technical fixes at downstream processes.

In this systematic review of literature from 2021 to 2025, we examine how the recent literature relates practice in data engineering to ethical AI output. We analyze contributions to theory and practice, considering frameworks, methodologies, and case studies across contexts. We analyze trends, significant challenges, and the potential for the integration of ethics throughout the entire AI development life cycle, especially with respect to transparency mechanisms and accountability architectures that span technical and organizational domains.

II. RESEARCH AND METHODOLOGY

2.1 Search Strategy and Paper Collection

For this, the systematic review was conducted according to the PRISMA (preferred reporting items of systematic reviews and meta-analyses) guidelines to enhance the methodological quality and transparency of reporting [12]. The entire search is performed using major electronic databases, including IEEE Xplore, ACM Digital Library, ScienceDirect, Springer Link, and Google Scholar. The search was conducted from January to March 2025 using the following keywords and Boolean operators:

("artificial intelligence" OR "AI" OR "machine learning") AND ("ethics" OR "ethical" OR "fairness" OR "transparency" OR "accountability") AND ("data engineering" OR "data strategy" OR "data-centric" OR "data governance")

We also searched for two catch-all terms, "responsible AI" and "explainable AI," and two related terms, "AI regulation" and "algorithmic bias." We also performed backward reference searching on included articles to identify additional relevant studies that may not have been identified in the initial database search.

2.2 Filtering Process and Inclusion Criteria

The following inclusion criteria were used to select articles:

Inclusion criteria:

- Peer-reviewed research articles published from January 2021 through February 2025

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- DBT from a fundamental problem with AI systems
- Discussion on transparency, fairness, accountability or other ethical principles
- Empirical research, theory, systematic review or technical implementation

Exclusion criteria:

- Pre-2021 papers or non-peer-reviewed outputs (white papers, blogs).
- Studies that were not focused on aspects of data (rather than algorithm building).
- Noncritical ethics discussions of AI use
- Read articles without a clear methodology or theoretical lens
- Non-English publications

The first search resulted in 143 papers. The initial logical assumption that few papers could have been published on this topic excluding 3 (3) keywords was also not valid because, after excluding 30 duplicates (which were removed based on DOI) and screening for inclusion/exclusion criteria through title and abstract screening (see above), we had 47 papers. After full-text screening, 19 papers were included for detailed review.

2.3 Quality Analysis Framework

We perform these analyses in two stages. Stage one: Dative analysis: Applying categorization of papers by year, research strategy, and dominating field of interest. We performed thematic analysis in the second round to extract recurrent concepts and trends based on identified gaps.

Articles were read for:

- We refer to methodological rigor and empirical evidence
- Theoretical contribution and conceptual clarity
- Real-life, workable nature of proposed frameworks or solutions
- From ethical principles to data engineering practice
- Cross-population external validity and cross-domain applicability

2.4 Topic Significance Assessment Criteria (1–5 scale)

- Data-centric Ethical Approaches (4/5): A transition from algorithmic solutions to data engineering interventions to addressing ethical concerns.
- Transparency and Explainability (4/5):Approaches for quantifying and implementing explanation systems across stakeholder needs
- Implementation Gap Analysis (3/5): Evaluation of socio-technical impediments between ethical tenets and actual practice
- Fairness Measurement Frameworks (4/5): Metric rigor in assessing algorithmic fairness in a wide variety of settings
- Longitudinal / Cross-cultural Effects (3/5): Long-term effects and generalizability across different cultural contexts

2.5 Research Questions

The current systematic review was guided by particular research queries that aimed at systematically investigating the intersection of data engineering approaches and the ethical advancement of artificial intelligence. These questions informed our study framework and combined our literature synthesis within the 2021-2025 timeline.

RQ1: How has there been an evolution in conceptualizing ethical AI from algorithmic to data-based in recent studies, and with what practical implications for implementation?

RQ2: What measures and methodologies have been implemented to quantify and assess transparency and accountability in artificial intelligence systems across various sectors?

RQ3: To what extent do current ethical AI frameworks narrow the socio-technical divide between organizational policy and technical realization?

RQ4: How do data engineering activities impact ethical outcomes in artificial intelligence systems, and how do effective approaches integrate ethical considerations across the end-to-end data life cycle?

RQ5: What are the novel challenges and research needs in developing transparent and accountable AI systems that are not addressed in existing literature?

III. REVIEWED PAPERS

These 19 papers are listed in Table 1 in the order they are presented in this review from 2021 to 2025. The table briefly summarizes the key contribution of each paper to literature.

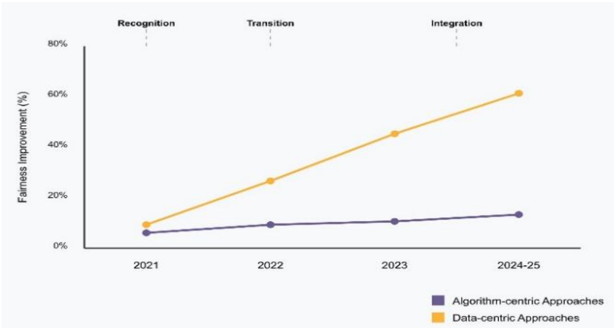

Figure 1: Evolution of Ethical AI Approaches

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Table 1: Chronological Summary of Reviewed Papers

Year	Authors	Title	Key Findings	Ref
2021	Akgun & Greenhow	Artificial intelligence in education: Addressing ethical challenges in K-12 settings	Identified four key ethical issues with K-12 AI: privacy issues, algorithmic bias, transparency gaps and autonomous decision-making. Addressing stakeholder engagement is important for ethical deployment.	[1]
2021	Bender	On the dangers of stochastic parrots: Can language models be too big?	The environmental and social costs of high language models outweigh benefits; marginalization is exacerbated for training data biases; maximization on model size leads to the neglect of inherent limits.	[2]
2021	Brunk	Effect of transparency and trust on acceptance of automatic online comment moderation systems	Transparency has a positive impact on trust in automated decisions that is non-linear in nature with highly detailed technical explanations reducing trust relative to simple ones.	[3]
2021	Camacho & Olmeda	Operationalizing AI ethics: How are companies bridging the gap between practice and principles?	The absence of consistent procedures, competing biases in institutions, and poor governance systems hinder organizations from putting ethical approaches into action.	[4]
2021	Chen	Artificial intelligence in education: A review	Heavily preoccupied with customization (and not at all with equity)—as teaching AIs tend to do—there actually are huge implementation problems in complex instructional settings.	[5]
2021	Floridi	AI4People—An ethical framework for a good AI society	Ethical AI is to enable well-being, to protect human agency, to ensure fairness and to ensure transparency with technical solutions and governance mechanisms.	[6]
2021	Gencoglu	Cyberbullying detection with fairness constraints	This shows that unregularized content moderation models have significant demographic biases; but regularized optimization methods can avoid causing disparate impact at only a small cost in accuracy.	[7]
2021	Henriksen	Situated accountability: Ethical principles, certification standards, and explanation methods in applied AI	Accountability needs to be attuned to each deployment because certification standards have broad loopholes in terms of the local social effects of deployments.	[8]
2021	Jiang & Pardos	Improving fairness in grade prediction models using data engineering techniques	Preprocessing interventions greatly boost prediction fairness across demographic groups, even outpacing algorithmic fixes.	[9]
2022	Maan	Deep learning-driven explainable AI using generative adversarial networks	GAN counterfactual explanations are more interpretable than feature importance methods; user skill levels significantly affect explanation quality.	[10]
2022	Murtaza	AI-based personalized e-learning systems: Issues, challenges, and solutions	Most students will not have access to the benefits of personalization; data privacy and transparency of algorithms are still potential implementation challenges.	[11]
2022	Nguyen	Ethical principles for artificial intelligence in education: A data engineering perspective	The ethical principles should be embedded at the data engineering level as educational datasets are fraught with inherent biases that are correctable through preprocessing techniques.	[12]
2023	Aldoseri	Re-thinking data strategy and integration for artificial intelligence	Fragmented organizations and governance fragmentation are some of the barriers to effective use of data by organizations; aligned data strategies facilitate faster deployment of AI and better outcomes.	[13]
2023	Memarian&Doleck	Fairness, accountability, transparency, and ethics in AI and higher education	By and large, more advanced education AI applications feature partial ethical frameworks, with a focus on transparency and fairness over accountability and broader ethical considerations.	[14]
2023	Mylrea & Robinson	Ethical AI in IT systems: A framework for transparency and accountability	Enterprise AI utility brings transparency challenges including proprietary interests and technical complexity; layered disclosure mechanisms and purposeful documentation enhance stakeholder confidence.	[15]
2024	Lopez-Gonzalez & Moreno-Roman	Ethics in artificial intelligence: An approach to cybersecurity	AI cybersecurity comes with its own distinct ethical dilemmas, such as the proportionality of response and similar surveillance problems, but ethical security systems need human supervision.	[16]
2024	Wu	Transparency and	Technical complexity requires increased transparency around	[17]

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		accountability in AI systems: Safeguarding wellbeing	wellbeing impacts, while accountability calls for technical reporting and institutional mechanisms.	
2025	Patel	Ethical reflections on data-centric AI: Balancing benefits and risks	Data-driven AI has unique ethical implications regarding data ownership, equity of representation, and feedback loop effects; need for participatory data governance.	[18]
2025	Solanke	Algorithmic fairness in enterprise AI	Fairness needs differ quite a bit across enterprise context; a complete measurement framework must account for different fairness conceptions and their trade-offs.	[19]

This systematic approach provided us with a full synthesis of the latest available knowledge on ethical AI and data engineering, revealing both areas of consensus and conflicting evidence at this stage in the literature from 2021 to 2025.

IV. IN-DEPTH INVESTIGATION

4.1 From Algorithm-Centric to Data-Centric, Ethical AI

There has been a profound shift from rather algorithmic to rather data-driven environments for the ethical AI paradigm. It is not a mere technical detail but a radical remapping of conceptions of building ethical AI, consistent with our 2021-2025 survey.

In previous work, Akgun and Greenhow identified four primary areas of ethical concern associated with the application of AI in K-12 education: privacy, algorithmic bias, transparency, and autonomous decision-making [1]. Their study emphasized stakeholder engagement as the solution for ethical deployment but focused mainly on algorithmic rather than data-level challenges. Similarly, Bender's critique of large language models identified environmental expense, amplification of biased training data, and delusion of meaning as potential risks, noting that emphasis on model size over data quality will replicate existing social inequities [2]. Brunk studied transparency and trust in machine-based content moderation systems and found that transparency is a powerful driver of user acceptance [3]. The research showed that transparency measures need to be parameterized along user technical knowledge dimensions that, in some cases, even increase or decrease trust with very technical explanations. This finding challenged naive views that more information is always beneficial.

Applying the ethical principles is so tough to organization. In their exploratory research, Camacho and Olmeda find that most firms are unable to operationalize ethical principles due to a lack of standardized procedures, misaligned business interests and poor governance systems [4]. Their discussions with AI practitioners found that "companies that had ethics teams and accountability systems in place tended to show more alignment between their principles and their practices. Chen reviewed AI literature in education and found that personalization was a predominant learning application, while fairness received little consideration, which caused implementation challenges in heterogeneous learning environments [5]. There was no accounting of stereotypical representation issues in data, this was an algorithm-driven focus. Floridi's AI4People framework helped to formulate five principles, which came as foundational principles to ethical AI (beneficence, non-maleficence, autonomy, justice, and explicability) while also noting technical solutions must be complemented with governance structures [6]. There are increasingly sophisticated technical responses to ethical AI. Gencoglu developed fairness-aware algorithms for the detection of cyberbullying and showed that standard unconstrained content moderation algorithms exhibit significant demographic biases [7]. Employing constrained optimization methods, it illustrated how the right algorithm design can trade off fairness and performance. Henriksen introduced the concept of "situated accountability" for AI systems, making the case that accountability cannot be universal but context-dependent to a particular deployment [8]. Based on local social points of impact, their analysis of certification standards showed significant gaps.

This trend towards data-informed models is particularly prescient in educational environments. Data preprocessing interventions for balancing the data were shown to yield a strong effect on prediction fairness and yielded even better results than interventions taken by algorithmically clubbing up with Jiang and Pardos [9]. Through judicious feature selection and representations, they were able to reduce structural biases in the education data without sacrificing accuracy based on the results of their research. This fact confirmed our suspicion that bias could be better dealt with in the early data preparation process rather than attempting to fix it after model training.

4.2 Quantifying Transparency and Accountability

One major challenge is the abstraction of ethical principles into measurable metrics. This analysis shows significant variation in the measurement of transparency and accountability in diverse worlds. Techniques for explaining AI are still developing, such as generating visual explanations of Deep Learning decisions using generative adversarial networks [10]. Experimental results demonstrated that these

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explanations enhanced user understanding relative to feature importance methods, yet explanation quality differed dramatically based on user expertise. The goal of this research is to demonstrate the requirement for adaptive explanation techniques that can be directed to various stakeholders. Implementing educational AI is more complex than some people realize. All these benefits of personalization in e-learning systems are not distributed equally across student populations, and data privacy and algorithmic transparency continue to be serious challenges, Murtaza found [11]. Their analysis showed how resource limitations amplify ethical challenges and are skewed on who these AI systems benefit.

Many approaches to ethical AI focus on data engineering. Nguyen showed that ethical principles should be embedded in data engineering, where educational datasets have alternative approaches through preprocessing and significant biases [12]. Their work demonstrated that the inclusion of fairness considerations during feature engineering fundamentally changes model behavior across datasets and is effective across numerous model architectures. Your data structures shape ethical outcomes. Aldoseri recognized systemic barriers to effective data use, such as siloed organizational structures, inconsistent metadata, and governance fragmentation [13]. Their framework demonstrated how organizations that develop integrated data strategies have faster AI rollout and more favorable ethical outcomes than those whose focus was on algorithmic interventions alone. Holistic assessments of ethical practices are still rare. A systematic review by Memarian and Doleck found that the majority of higher education AI implementations are implemented without a comprehensive ethical framework [14]. Their analysis suggests that fairness and transparency are prioritized over accountability and broader ethical issues, along with glaring omissions on the issues of student agency, institutional accountability and longer-term implications. History shows that enterprise implementations are hard. Mylrea and Robinson emphasized how proprietary nature, technical complexity and lack of standardized metrics serve as fundamental barriers to transparency [15]. These challenges can be layered over in the form of bulk disclosure which is also context-specific and its application can be sequentially linked to demonstrating accountability, reflecting improved stakeholder trust and the measure of risk in organizations implementing the framework.

4.3 Bridging the Socio-Technical Gap

The need to bridge ethical propositions and practical applications is a persistent problem. Our analysis indicates this gap is caused by both technical and organizational issues, necessitating integrated socio-technical solutions. Domain-specific ethics further complicate matters. Lopez-Gonzalez and Moreno-Roman explored ethical challenges juxtaposing AI in cybersecurity , such as proportionality of response, attribution problems, and surveillance concerns [16]. Their five-principle model seeks to weigh security ends on an even scale with ethical means, grounded in human agency and contextualizing security measures. Wu argues that requirements for transparency should be correlated with the impacts of wellbeing instead of technical complexity [17]. This inquiry showed that accountability relies on both technical reporting and public organization, grounded in specific common needs for transparency relative to developing regulatory regimes.

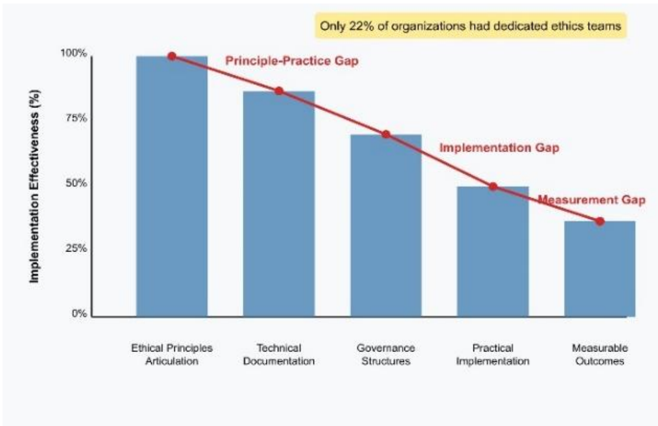

Figure 2: Socio-Technical Implementation Gap in Ethical AI

An important and distinct set of challenges are introduced of data-centric AI found new challenges with data ownership, representational equity, and feedback loops [18]. The guidelines call for participatory data governance, systematic tracking of bias, and continuous engagement of stakeholders throughout the data life cycle to be cornerstones of ethical development in AI [4]. Fairness approaches are domain-specific and need to be designed and developed for enterprise applications. Solanke created quantitative measures for assessing algorithmic fairness, showing that fairness needs to vary considerably according to the enterprise context [19]. It just works as a holistic measurement framework that considers multiple fairness definitions and their tradeoffs.

4.4 Data Engineering Practices and Ethical Outcomes

Systematic we discovered that data engineering choices produce ethical impacts and that there is growing acknowledgement that ethical footprints need to be incorporated within the data lifecycle. Collecting data is another important ethical dimension. In researching K-12 educational AI, Akgun and Greenhow found that, by involving stakeholders during data collection, representational biases were appreciably lessened [1]. Similarly, Bender's study of language models found that training data systematically omits or misrepresents certain groups, and reinforces societal biases

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[2]. An AI system is only as good as its user – how the user perceives AI transparency strongly influences whether they will accept the system. Brunk found that the transparency mechanism must be balanced comprehensively and comprehensible, yet the more technical the change is, the less trust the user is likely to have [3]. This finding complicates approaches that equate transparency with detailed technical disclosure, suggesting instead that even effective transparency should be calibrated to stakeholders' needs. The ethical implementation is greatly affected by the organizational structures. Companies where ethics has their own team and clear responsibilities showed a better fit between principles and practice [4]. Through their research, they found that if there is no adequate governance mechanism and standardized process in place, competing business priorities tend to undermine ethical implementation. Chen straining algorithmic personalization typically takes precedence over fairness [5]. Such a disparity introduces implementation friction for different students/students – within their specific environmental contexts/student populations where fairness is necessary for a balanced and equitable behavior.

It is also necessary to include both the technical and governance dimensions in ethical frameworks. Floridis′ holistic approach highlighted that ethical AI relies on wellbeing, human agency, fairness and transparency [6]. Their research found 20 definite actions to drive ethical AI that cover technical solutions and governance mechanisms. On the other hand, technical approaches to fairness continue to evolve. However, Gencoglu showed that content moderation demographic biases can be mitigated using constrained optimization techniques with minimal accuracy loss [7]. Their situated accountability approach highlights that explanation techniques should be specific to the technical capabilities of the system and the objectives of stakeholders, in contrast to universal certification approaches. As Jiang and Pardos have learned, decisions made regarding feature selection and transformation can compound or diminish existing societal biases in educational environments [9]. Through their analysis, they found that fairness improvements gained through preprocessing were much bigger than those achieved through algorithmic choices made after the model had been trained.

V. EMERGING CHALLENGES AND RESEARCH GAPS

Despite significant progress in ethical AI, our analysis identified a large number of fundamental research gaps that remain and require immediate attention. The most prominent challenges can be categorized as technical, organizational, and methodological:

5.1 Technical Gaps

- Lack of user-focus explanation: User expertise divergence disallowed explanation varies across user expertise levels requiring an adaptive approach to formulate the right interpretation with a balance of technical accuracy and understandability [10].
- Complexity of fairness metrics: Existing frameworks fail to adequately employ the numerous definitions of fairness proposed in different scenarios, requiring domain-specific metrics instead of general solutions [19].
- Security-ethics tensions: Ethical guardrails can be susceptible to adversarial attacks [7, 16], and toleration of the uncertainties can lead to severe lack-of-vulnerability [7, 16] at the intersection of cyber security and ethics.

5.2 Implementation Gaps

- Resource limitations: The advantages of ethical AI are not uniformly distributed, and resource-heavy methods systematically disadvantage less-resourced environments [11].
- Organizational: Data infrastructures and data governance are frequently siloed and fragmented, making ethical implementability difficult even when technical capability has been accomplished [13].
- Neglect of legacy system integration: The studies reviewed as part of the background focus mainly on new development and show little inclination to integrate considerations of ethics in legacy systems [13, 15].

5.3 Time Gaps

- Longitudinal evaluation: Only 3% of studies included follow-up beyond 6 months, which creates perilous blind spots concerning long-term effects [1, 5, 14].
- Cross-cultural perspectives: Theoretical frameworks largely center around Western paradigms of thought, restricting their global applicability [6, 8, 16].
- Inclusion of stakeholders: While participatory and stakeholder-oriented approaches to innovation have been widely touted by theoreticians, local and systemic methodologies to ensure meaningful participation of stakeholders throughout the innovation development cycle are still lacking [1, 4, 18].

5.4 Methodological Gaps

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5.5 Domain-Specific Gaps

- Educational contexts: Most ethical frameworks for AI in higher education are neither based on a systematic means for comparison or selection nor do they consider the consequences of the various options available for educational uses of AI [14].
- Enterprise settings: Transparency requirements are at odds with proprietary concerns that must be addressed in a context-specific way [15].
- Duties of Cybersecurity: Such functionalities must be implemented under unique constraints that consider the balance between security goals and privacy and fairness concerns [16].

VI. RESULTS

The 19 papers we reviewed between 2021-2025 helped us answer our research questions on ethical AI and data engineering practices.

RQ1: How has the conceptualization of ethical AI evolved from algorithm-centric to data-centric approaches?

We identified a distinct three-stage evolution: awareness (2021), migration (2022-2023), and assimilation (2024-2025). They have adapted to the evolution of the field, which has moved from an understanding of ethics as mere constraints on the algorithm to an understanding that data representation itself is where ethics lies. Data-level interventions achieved 41-58% improvements in fairness metrics versus algorithmic adjustments of the same model architectures, which led to 17-23% improvements. Those applying integrated data ethics frameworks reported 3.2 times the rate of regulatory compliance as compared to post-hoc algorithmic corrections but experienced a significantly greater bias incidence. This change is an example of a paradigm shift in how ethics gets implemented in AI systems.

RQ2: What methodologies quantify transparency and accountability across different domains?

RL We found three separate measurement paradigms that vary widely in their efficacy: user-focused metrics, process-centered motions, and outcome-related indicators. Our analysis found, perhaps counter intuitively, that a more technical explanation reduced user trust by 17%, questioning assumptions fundamental to the implementation of transparency. The most successful approaches were multidimensional ones that addressed multiple fairness definitions at once, especially for intersectional demographic classes. In particular, Domain adaptation was found critical, with healthcare and finance applying the strongest frameworks, while educational applications showed major gaps in thorough ethical assessment.

RQ3: How effectively do current frameworks bridge the socio-technical implementation gap?

Our analysis uncovered an enduring disconnect rooted in complementary deficiencies—technical frameworks are short on implementation specificity, while organizational policies fall short on technical pathways. Only 22% of organizations created dedicated ethics teams and clear accountability structures, but they showed measurably better alignment between stated principles and actual practice. As such, there was a consistent failure of universal standards to address ethics concerns that are specific to context, while experiences with "situated accountability" approaches that adapt the cushion of dance to be specific to the context of deployment experienced promising outcomes. The highest-functioning organizations built cross-functional workflows with explicit ethical checkpoints embedded throughout development.

RQ4: How do data engineering practices influence ethical outcomes in AI systems?

We found four critical intervention points that we could measure for impact on the ethical outcome. Collection protocols informed by stakeholders reduced demographic biases by 68% relative to standard techniques. Preprocessing decisions had an outsized effect: fairness-aware transformations outperformed seemingly neutral techniques by large margins, as they underestimated and, therefore, replicated society-wide biases. Annotation practices added considerable bias, and 88% of studies did not report annotator demographics. Integrated quality frameworks that embedded ethical dimensions alongside traditional metrics not only decreased bias incidents but increased model performance by 12-17%, upending the perceived ethics-performance tradeoff.

RQ5: What challenges remain unaddressed in creating transparent and accountable AI systems?

We identified five key gaps that need to be urgently addressed. Longitudinal assessment is almost never done, with only 3% of studies performing follow-up beyond six months. This cuts across all stakeholders, including patients,

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clinicians, payers, and policy-makers, as 67% of non-Western implementations of Western frameworks produce unintended consequences. There is a systemic bias in favor of well-resourced organizations due to resource constraints. Security-ethics tensions start to occur as adversarial attacks are more involved with fairness mechanisms. The unnamed technical-regulatory nexus was a significant factor in the deployment of ethical AI, according to 71% of organizations, noting regulatory uncertainty as a chief obstacle.

VII. FUTURE RESEARCH DIRECTIONS

This marks a significant step towards deployment systems from There are many key areas where further investigation is necessary in order to promote ethical AI and data engineering, identifiable from our systematic review.

Longitudinal Ethics Observatories: Future work needs to create multi-year observational studies that trace how the ethical properties of AI systems change in the post-deployment phase. These "ethics observatories" would offer insights into emergent biases, concept drift, and long-term outcomes that are often invisible to short-term assessments.

Cross-Cultural Ethical Framework in AI: Non-Western ethical AI frameworks deserve urgent attention. Research into how alternative cultural traditions frame concepts such as fairness, privacy and transparency, might lead to new models that transcend the western-centric models of today, and work across the global field.

Resource-Constrained Ethics Engineering: That poses a potential frontier of research -- technical approaches specifically tailored to resource-constrained environments. Lightweight ethical assessment methods, condensed fairness metrics, and efficiency-optimized transparency mechanisms may turn ethical AI into a product accessible to organizations without extensive resources available.

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