



Bias and Fairness in Large Language Models for Financial Compliance: Risks and Mitigation

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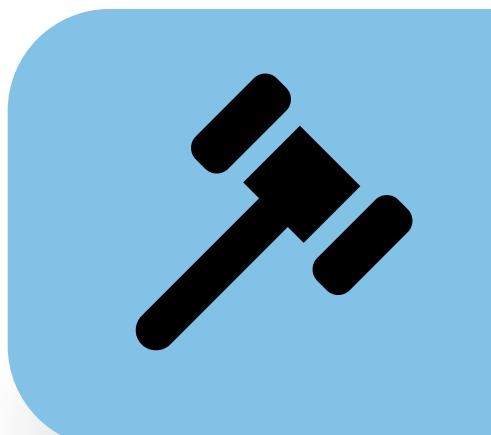
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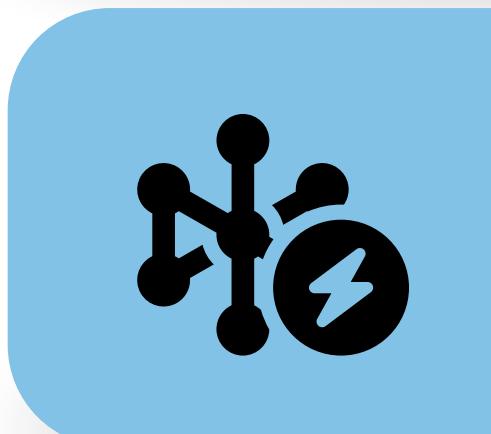




Why this research matters



Finance is highly regulated



LLMs can automate compliance tasks



Bias: risk to fairness, trust and legality

Regulatory Frameworks
Solvency II • IFRS 17 • Basel III • AMLD



LLM Processing
GPT-4 • FinGPT • BloombergGPT



Outputs
Obligations • Risk classification • Summarisation



Bias in compliance remains under-researched

Research Problem

Bias well studied in:

- Healthcare
- Hiring
- Criminal Justice

Gap: Little research in
Financial Compliance
(High stakes, under-studied)



How can bias and fairness be evaluated and mitigated in LLMs for compliance?

Types of bias?

**General vs
domain-specific
models?**

**Effective
mitigation
strategies?**



05

1

Detect bias

2

Compare models

3

Test mitigation

4

Build auditing framework



Literature Review (Bias & Fairness)

“Stochastic parrots” risk
(Bender et al., 2021).

Fairness metrics
(Mehrabi et al., 2021).

Context-dependence
(Blodgett et al., 2020).





Literature Review (Governance)

Right to explanation
(Goodman & Flaxman, 2017).

GDPR/AI Act
Finance = “high risk”
(Veale & Edwards, 2018).

RegTech governance issues
(Zetzsche et al., 2020).





Literature Review (LLMs in Finance)

Model	Type	Training Data	Strengths	Limitations
GPT-4	General-purpose	Broad internet corpus	Strong general NLP, versatile, state-of-the-art reasoning	Not finance-specialised, may hallucinate
FinGPT	Finance-specific (open-source)	Financial texts & datasets	Domain-tuned, open-source, adaptable for fine-tuning	Still emerging, smaller scale vs GPT-4
BloombergGPT	Finance-specific (proprietary)	Large-scale financial data	High accuracy on financial NLP benchmarks, industry-validated	Closed model, limited access

BloombergGPT & FinGPT:
strong performance
(Bloomberg, 2023).

Empirical results
but little fairness
testing.

ESMA & Turing (2025):
call for fairness in
financial AI.



Research Design Overview

Regulatory Data

Solvency II · IFRS 17 · Basel III · AMLD
Public documents (PDF/HTML → text)

Models

GPT-4 (general)
FinGPT (finance)
BloombergGPT (benchmarks)

Tasks

Obligation extraction
Risk classification
Regulatory summarisation

Outputs assessed for Accuracy (P/R/F1, ROUGE) and Fairness (consistency, calibration, parity)



Evaluation & Fairness Metrics

Accuracy Metrics

Precision

Recall

F1



ROUGE/BERTScore

Fairness Metrics

Consistency

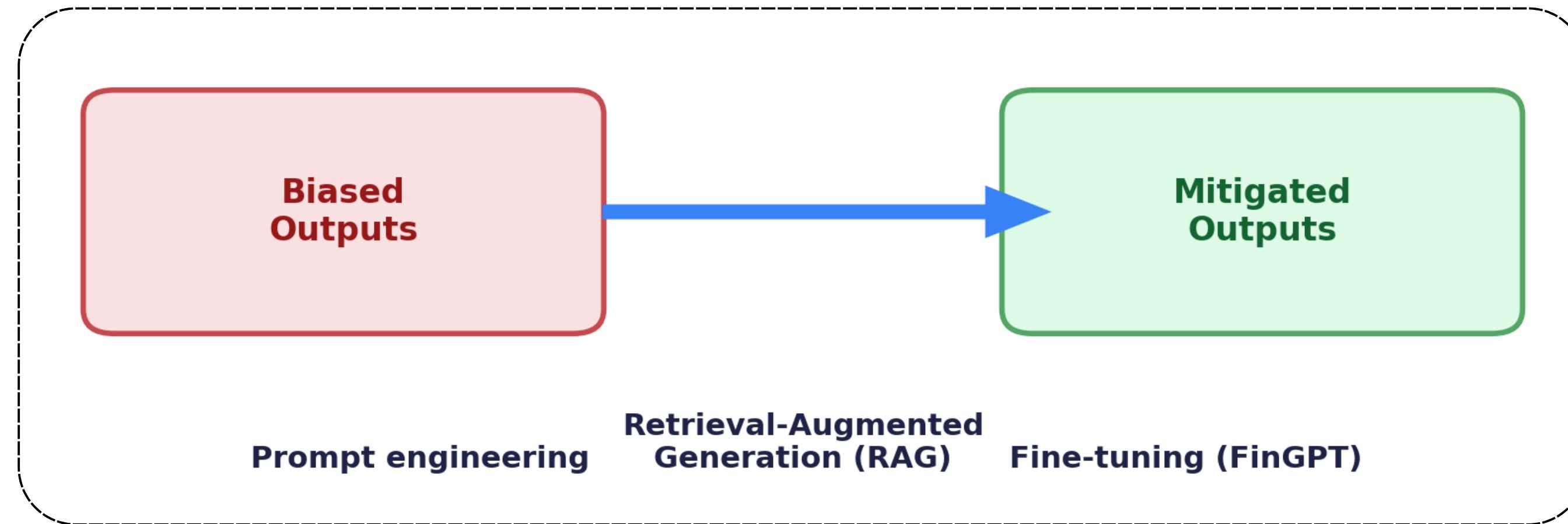
Calibration



Parity Skew Review
(Mehrabi et al., 2021)

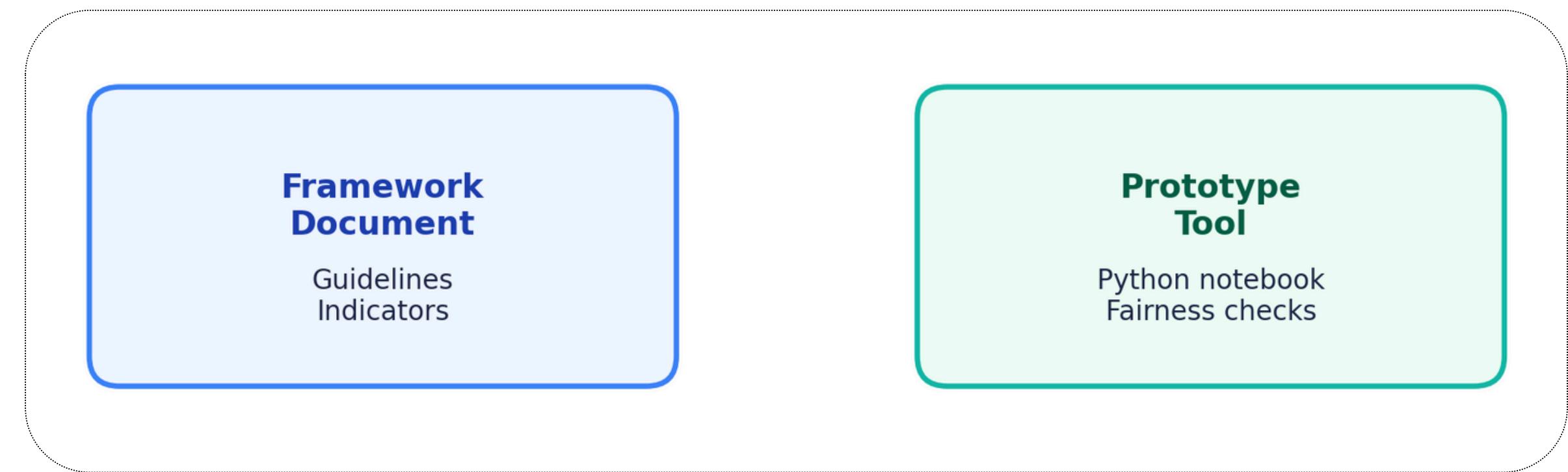
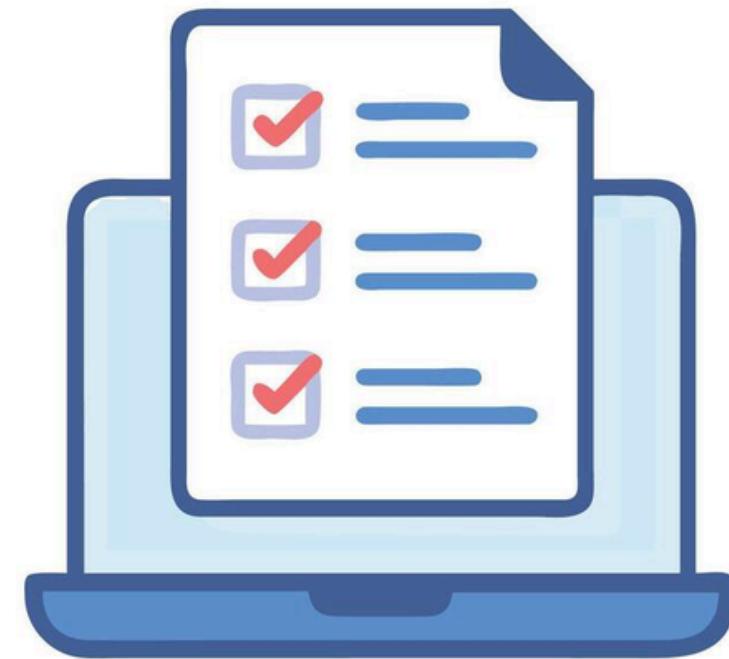


Mitigation Strategies



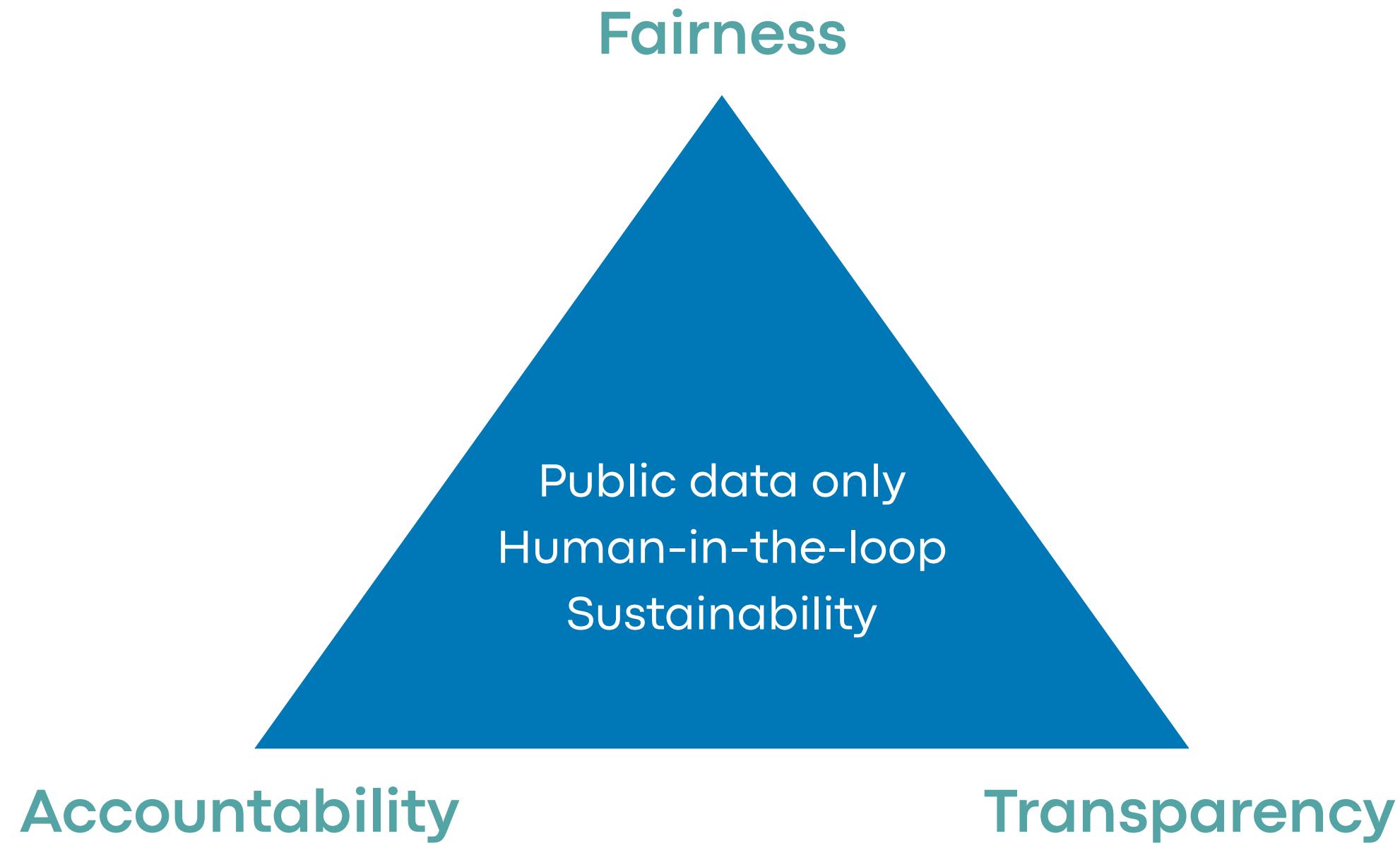


Artefact & Framework



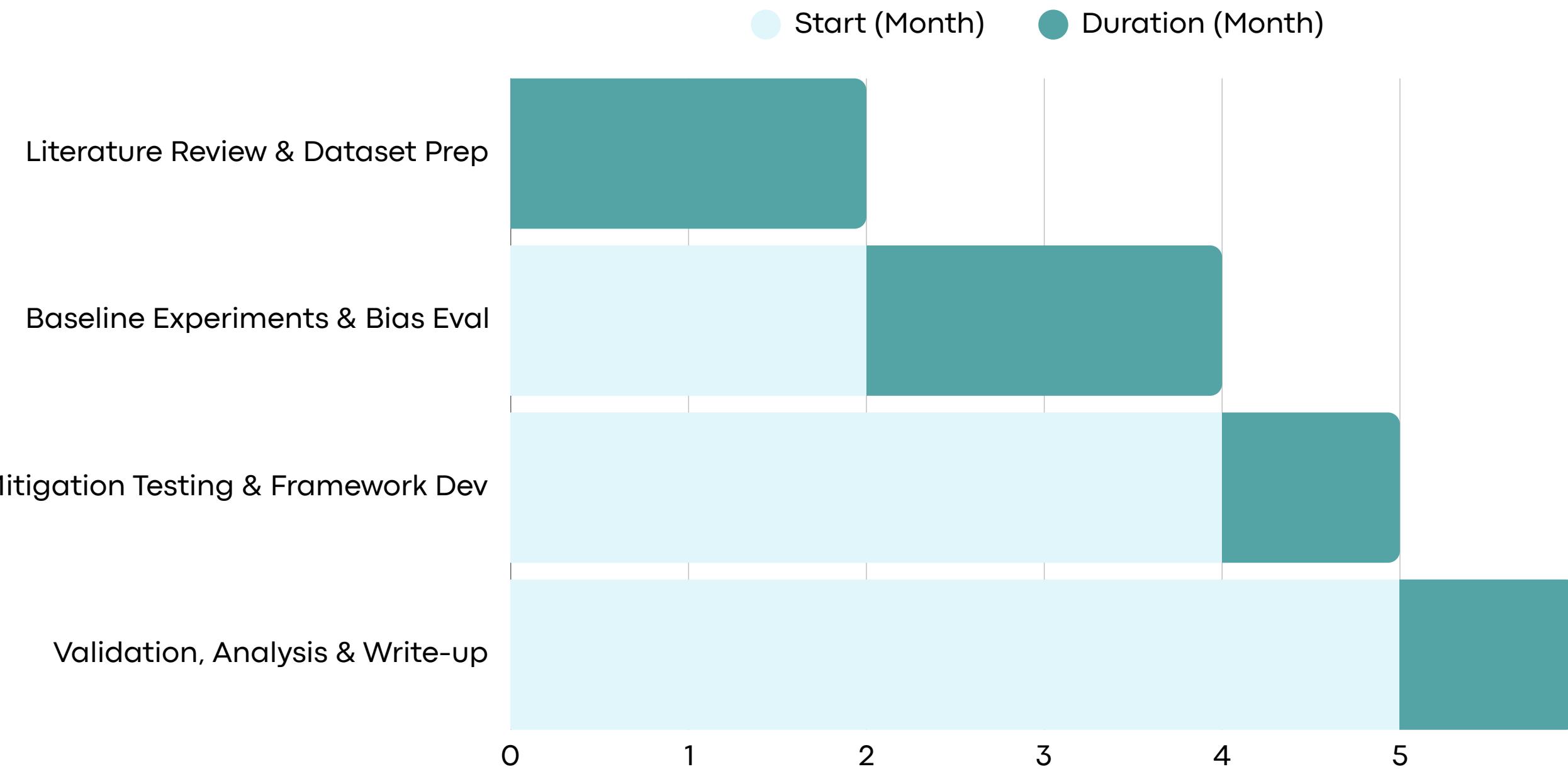


Ethical Considerations



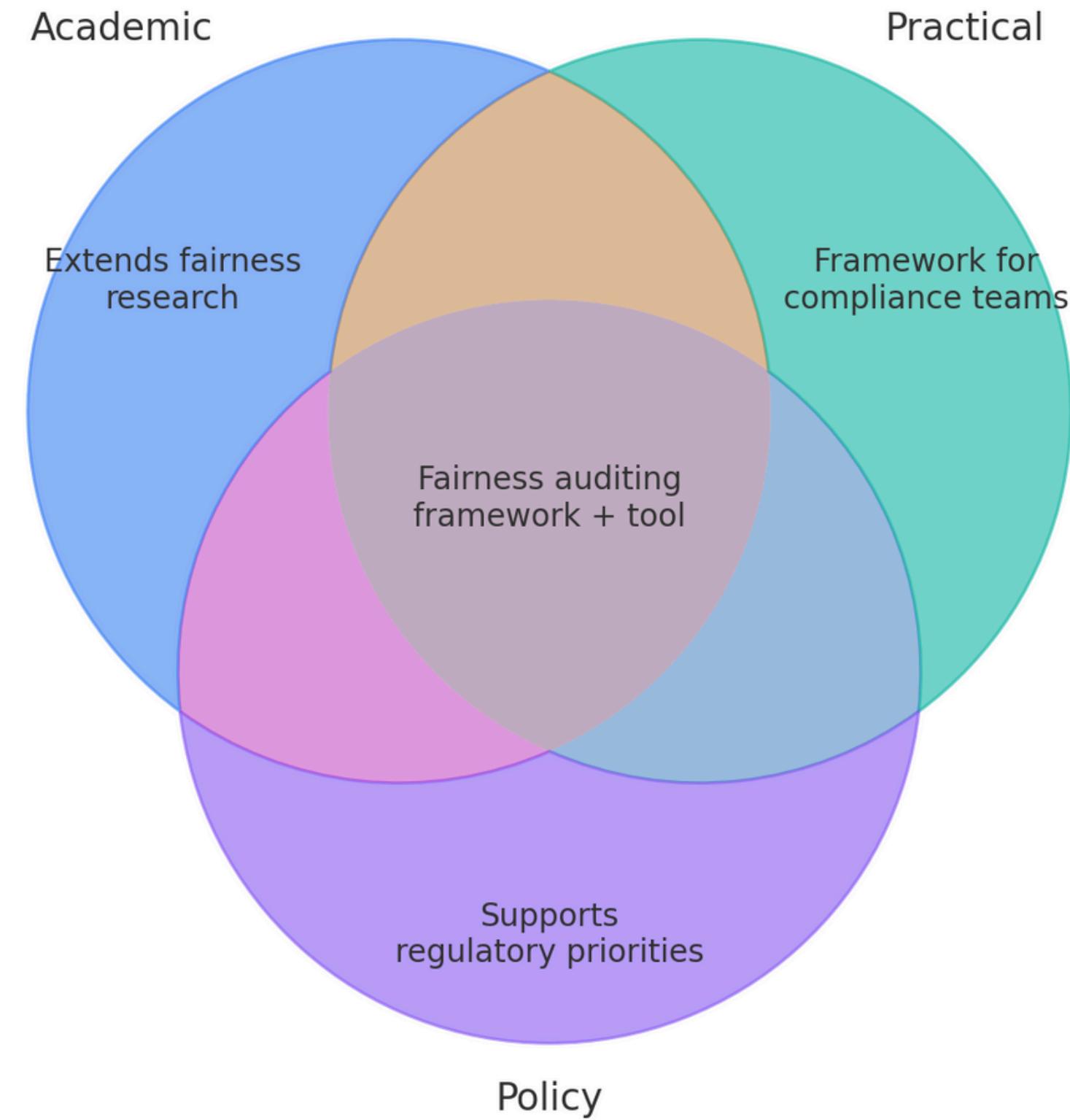


Timeline





Contribution





Conclusion



Bridging Data Science, Finance, and Regulation



Key References

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