

Explainable Artificial Intelligence for the BFSI Sector: Integrated Governance Framework for AI and Decision Transparency

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ABSTRACT

The increasing integration of Artificial Intelligence (AI) and Generative AI (GenAI) in Banking, Financial Services, Insurance (BFSI) is now putting much greater demand onto companies for transparency, accountability and regulatory harmonization. Whereas Machine Learning (ML) models have long been used for risk scoring, fraud detection, underwriting along with AML, GenAI brings new challenges such as hallucinations, non-deterministic outputs, opacity of reasoning, and potential data leakage. In this essay, we introduce the Explainable AI Decision Transparency Framework (EADTF), a holistic governance framework for predictive and GenAI governance. Experimental validation of the framework in a Structural Equation Modelling (SEM) study of 340 BFSI professionals. The primary results included strong predictive power ($R^2 = 0.4957$ for Overall Value), high reliability ($\alpha = 0.67-0.82$), strong correlations (Transparency $\rightarrow$ Value: $r = 0.77$), and significant path coefficients (Regulatory Compliance $\rightarrow$ Trust: $\beta = 0.4639$). The results indicated that the most significant contributors of AI's perceived value are trust, transparency, accuracy of the system, and customer satisfaction. According to this, the EADTF offers a five-layer model—Data Transparency, Model Interpretability, Decision Transparency, Governance & Oversight, and Ethical AI—that can provide BFSIs with the tool to work towards responsible AI. This framework is consistent with DPDPA (India), RBI MGCG, GDPR and EU AI Act. The collected data is through a structured survey consisting of professionals from all domains throughout BFSI sector of banking, insurance, fintech, risk, compliance, operations and analytics. A total of 340 responses were valid. Participants answered a rating scale (Likert scale) for six constructs -- Model Transparency, Trust, Regulatory Compliance, System Accuracy, Customer Satisfaction, and Overall Value. The survey participants were comprised of mid-senior experts as well as experienced on AI/ML models, digital transformation systems and governance processes. The dataset satisfies reliability and validity criteria for Structural Equation Modelling (SEM). The results mirror the expectations of BFSI practitioners. Transparency, trust, accuracy and customer satisfaction are significantly better predictors of perceived AI value, suggesting that greater explainability and governance must be priorities for BFSI institutions versus simple performance improvements. This paper offers an academically informed, practical blueprint for responsible AI adoption in BFSI during the GenAI period.

1. INTRODUCTION

The Banking, Financial Services, and Insurance (BFSI) industry is currently experiencing one of the largest tech transitions in more than 20 years. The integration of Artificial Intelligence (AI) and Machine Learning (ML) in lending, fraud detection, underwriting, investment research, customer service, and regulatory compliance has drastically changed the operational decision-making process (Brynjolfsson & McAfee, 2017; Varian, 2014). More recently, with the emergence of Generative AI (GenAI) enabled by Large Language Models (LLMs) like GPT and LLaMA—this revolution accelerated thanks to automated summarization, risk assessments, compliance interpretations, and personalized customer interactions (Bommasani et al., 2021; Kambhampati, 2023). To improve

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operating efficiency, cost savings, and customer interface across BFSI industries, these systems process large amounts of structured and unstructured data. The accelerated progress to adoption of new technologies raises yet new questions about transparency, fairness, accountability, and trust.

Classical ML models, especially (but not limited to) gradient boosting machines, neural networks, and ensemble architectures, have been disparaged as “black-box” machines where the internal logic can hardly be decoded (Lipton, 2016, Gilpin et al., 2018). However, this opacity is particularly vexing in regulated sectors such as BFSI where automated decisions have a direct impact on customer rights, credit access, fraud alerts, risk scoring, etc. (Goodman & Flaxman, 2017). As part of this, regulators such as the European Union (GDPR), the Monetary Authority of Singapore (MAS FEAT), and the Reserve Bank of India (RBI MGCG) are focusing more on explainability, model traceability, and the rights of individuals to having adequate information behind automated decisions. Generative AI thus adds fuel to the fire of these challenges. Systems of GenAI are probabilistic by nature and avoid deterministic predictions, producing different outputs for the same prompts with different sampling and temperature (Kreuzer et al., 2024). It has been demonstrated that LLMs often experience hallucinations in the form of false-positive output sounding like it is factually incorrect but plausible (Ji et al., 2023; Bang et al., 2023) and could potentially contain substantial biases from training data (Bender et al., 2021; Weidinger et al., 2021). Additionally, the reasoning pathways in GenAI are not explicit, which means that it is difficult to follow the process of creating a certain summary, recommendation, or interpretation of a risk (Kambhampati, 2023).

In this context, while GenAI significantly enhances productivity in BFSI workflows, it brings higher risks regarding misinformation, regulatory breach, and unfair or inconsistent decisions. These challenges drive the urgent need of Explainable Artificial Intelligence (XAI) frameworks beyond traditional model interpretability. These XAI methods, including SHAP (Lundberg & Lee, 2017), LIME (Ribeiro et al., 2016), counterfactual explanations (Wachter et al., 2017), and surrogate modelling (Ribeiro et al., 2016), help us to understand the ML model's behavior. However, other researchers claim some post-hoc explanations to be incomplete and to be misleading (especially with respect to sophisticated models) (Rudin, 2019; Doshi-Velez & Kim, 2017). Furthermore, these methods are inadequate because GenAI demands novel approaches such as hallucination detection, output scoring, Retrieval-Augmented Generation (RAG) traceability, and prompt governance (Borah et al., 2024; Lewis et al., 2020). To bridge this growing gap, this work presents the Explainable AI Decision Transparency Framework (EADTF), a detailed, five-layer governance model formulated in the context of BFSI. The framework incorporates Data Transparency, Model Interpretability, Decision Transparency, Governance & Oversight, and Ethical & Responsible AI into one lifecycle. What sets EADTF apart from the existing literature is its rich coverage of predictive AI (ML) and Generative AI (LLM-based systems), its overt adaptation to recent regulatory requirements, such as DPDPA (India), GDPR, and the EU AI Act, and real-world empirical validation with practical BFSI examples. Evidence The empirical research is based on a Structural Equation Modelling (SEM) analysis conducted on survey responses from 340 BFSI experts, utilizing techniques common in technology acceptance and AI trust research (Venkatesh et al., 2003; Hair et al., 2021). Results indicate high reliability (Cronbach's $\alpha = 0.67\text{--}0.82$), transparency is highly correlated with perceived value ($r = 0.77$), and overall value is highly predictive ($R^2 = 0.4957$). These findings are consistent with the previous evidence showing that transparency is crucial for trust, user acceptance, and responsible adoption of AI (Miller, 2019; Kuiper et al., 2023).

This paper provides a contribution to academic and industry discussion in three broad ways. First, it connects ML and GenAI governance within a unified explainability framework fit for BFSI's regulatory and operational landscape. Second, it offers empirically-based insights that illustrate the importance of trust, confidence in compliance and value in AI-related decision-making. Third, it also proposes a pragmatic, regulator-oriented roadmap for driving responsible AI deployment by financial institutions that are deploying AI at scale. As a whole, these contributions establish EADTF as a significant and actionable model for improving explainability and governance in the age of Predictive and Generative AI. The rest of this paper is organized as follows: Section 3

presents literature related to XAI, fairness, and BFSI regulatory anticipations; Section 4 presents the research methodology and survey results; Section 5 presents the EADTF framework; Section 6 discusses the implementation roadmap; Section 7 elaborates regulatory implications; and Section 8 concludes with contributions and future research.

2. Literature Review

Explainable Artificial Intelligence (XAI) has emerged as a foundational pillar in the responsible deployment of AI systems, especially in regulated industries such as BFSI. The literature surrounding XAI can be examined across three broad themes: (1) interpretability challenges in traditional machine learning, (2) transparency risks associated with Generative AI, and (3) governance and regulatory requirements driving explainability. This section synthesizes peer-reviewed research, industry reports, and regulatory frameworks to establish the theoretical foundation for the EADTF framework.

2.1 Traditional Machine Learning Interpretability and Its Limitations

Early literature on AI interpretability focused on the transparency of machine learning systems. Researchers such as Miller (2019) and Lipton (2016) argued that human-centered explanations are essential for trust and accountability. Classical ML models—including decision trees, logistic regression, and rule-based systems—offer varying degrees of inherent interpretability. However, high-performance models such as neural networks and boosted ensembles often sacrifice transparency for accuracy (Doshi-Velez & Kim, 2017).

Techniques such as SHAP (Lundberg & Lee, 2017), LIME (Ribeiro et al., 2016), and partial dependence plots (Friedman, 2001) attempted to bridge this gap by providing post-hoc interpretability. While valuable, these tools come with inherent limitations. They produce local rather than global explanations, may suffer from instability, and often require significant domain expertise to interpret. Moreover, these techniques are model-specific and less applicable in real-time, high-stakes workflows typical of BFSI lending, fraud detection, or underwriting.

A recurring critique in the literature is that post-hoc explanations can be misleading or approximated, rather than reflecting the true internal logic of the model (Rudin, 2019). This raises ethical concerns when AI influences decisions on creditworthiness, risk scoring, or fraud alerts—core functions of banking and insurance.

2.2 Generative AI and the New Frontier of Opacity

The emergence of Generative AI marks a new phase in explainability challenges. Large Language Models (LLMs) such as GPT, PaLM, and LLaMA are built on transformer architectures with billions of parameters, encoding knowledge in highly distributed internal representations rather than explicit, human-interpretable rules. They generate outputs via next-token prediction over learned probability distributions, rather than through transparent feature-based decision paths, which makes their internal reasoning particularly difficult to trace or audit. (*Source : <https://aclanthology.org/2023.ijcnlp-main.45.pdf?>*)

Traditional XAI approaches such as SHAP and LIME were originally developed for tabular and classical ML settings and assume relatively stable input-output mappings that can be locally approximated. These assumptions are often violated in LLMs, where outputs can be highly context-dependent, multimodal, and non-deterministic, limiting the direct applicability of such tools.

Recent literature highlights several risks specific to GenAI:

- **Hallucinations:** LLMs frequently generate fluent but factually incorrect or unsupported content. Multiple surveys and benchmarks (e.g., HaluEval) show that hallucination is pervasive across tasks and models, and can be difficult for users to detect. Yejin Bang* Samuel Cahyawijaya Nayeon Lee Wenliang Dai (2023)
- **Lack of reasoning traceability:** Outputs are produced from learned parametric representations, making it hard to map a given answer back to specific training examples or knowledge sources, which is a core barrier for audit and compliance. Li Zituo , Sun Jianbin , Chen Guangzhou , Fang Xinyue (2023)
- **Prompt sensitivity and variability:** Empirical work on hallucination attribution shows that small changes in prompts and instructions can lead to markedly different outputs, revealing high prompt sensitivity and model variability. [Dang Anh-Hoang¹](#), [Vu Tran¹](#), [Le-Minh Nguyen¹](#) (2025)
- **Inconsistent, non-deterministic outcomes:** Stochastic decoding (e.g., temperature sampling, top-k/top-p) intentionally injects randomness, which improves diversity but reduces reproducibility—problematic for regulated decision processes. Li Zituo , Sun Jianbin , Chen Guangzhou , Fang Xinyue (2023)
- **Implicit bias:** Surveys on bias and fairness in LLMs document that models systematically reproduce and sometimes amplify social biases present in their training data, with potential downstream impacts on fairness in applications like lending, hiring, and insurance.)

To address some of these risks, new work presents transparency mechanisms specially designed for GenAI such as Retrieval-Augmented Generation (RAG), which condition outputs on retrieved documents and have the ability to disclose which passages were used by the system. Other approaches examine hallucination detection, self-consistency checks, and uncertainty estimation for content scoring and filtering. But to date, they are fragmented and much more experimental, and there is no commonly held industry standard for GenAI governance — particularly not one specific to the BFSI use cases that face stricter regulatory expectations.

2.3 BFSI Sector Requirements: Trust, Fairness, and Accountability

The BFSI industry has long demanded models to be transparent, auditable, and accountable, as they affect access to credit, pricing, fraud decisions, and financial stability. A growing body of research on financial XAI demonstrates that regulators, auditors, and risk managers require stronger explanations than the general technology users and tend to prefer simpler or interpretable models when a decision has a direct effect on consumers and markets. Studies of explainable AI in finance (e.g., Kuiper et al. and subsequent reviews) demonstrate that supervisory authorities are often willing to ask for a broader and deeper set of explanation artefacts than banks initially assume; not only are they asking for feature attributions, but also model lineage, validation evidence, stress tests, and decision-level justifications. This expectation gap is what underpins scepticism and reluctance to introduce opaque, high-capacity models into vital workflows. The empirical and practitioner literature uniformly shows why lack of explainability is an obstacle to AI in finance: business stakeholders and compliance teams won't use black-box systems when they can't clearly explain the consequences to customers, boards, or regulators. In customer-facing areas like loan approvals, claims adjudication, and fraud investigations, opaque models contribute to loss of confidence and higher rates for dispute resolution if those opinions are perceived as arbitrary or discriminatory by the customers. With the emergence of GenAI, AI in BFSI is being employed for much more than mere scoring and detection—from investment research, policy interpretation, KYC document summarization, compliance analysis to conversational servicing. Regulators and consultancies are warning that, in applying GenAI on these services with lacking

regulation, institutions face high levels of risk associated with reliability, bias, data leakage, and non-compliance. As a result, there are increasing demands for domain-specific governance frameworks which explicitly encompass GenAI behaviour—specifically hallucinations and uncontrolled data flows—within financial institutions..

2.4 Regulatory Expectations and Global Governance Trends

Global regulators and supervisory entities increasingly present explainability not as a trade-off but as an absolute demand for AI systems used in financial decision making. In the European Union, the GDPR's provision on automated decision-making and "right to explanation" demand that individuals get substantive information about the reasoning being conducted when decisions are made solely by automated systems. That is further heightened in the EU AI Act by designating credit scoring as well as many fraud and risk systems to be "high-risk AI," which would require that the data be properly documented, that the system is both transparent and risk-managed, and that it is supervised by humans.

In India, the Digital Personal Data Protection Act (DPDPA) highlights the need for ensuring purpose limitation, data minimization and ensuring accountability around personal data processing, which in turn imposes restrictions on how training data, prompts, outputs can be leveraged in AI and GenAI systems in BFSI. Simultaneously, the Reserve Bank of India (RBI) and international institutions (e.g. Basel Committee on Banking Supervision) have identified the prudential and financial stability risk in AI/ML in banking, calling on institutions to integrate AI risk into common governance practices and model risk management frameworks. Various cross-jurisdiction and industry guidance - including MAS FEAT in Singapore and several speeches by central bank leaders emphasizing fairness, ethics, accountability, and transparency (F.E.A.T.) as fundamental AI principles and reinforcing the same messages of academic and industry reports about explainable AI in finance. Overall, these trends exert significant external pressure on BFSI institutions to implement explainability and governance frameworks that are resilient enough to account across ML and GenAI systems.

2.5 Gap in Current Literature and the Need for EADTF

Although the XAI literature offers a rich toolbox of interpretability methods (e.g., SHAP, LIME, counterfactual explanations) and there is an emerging body of work on bias mitigation and hallucination detection in LLMs, most contributions are either model-centric or domain-agnostic. Surveys on financial XAI, in turn, largely focus on supervised ML models for credit, fraud, and trading, and typically treat GenAI as an emerging, but separate, topic.

Critically, the literature does not yet provide a unified framework that:

- integrates classical ML explainability and GenAI transparency,
- is tailored to BFSI's specific risk and compliance environment, and
- is explicitly aligned with global regulatory trends (GDPR, DPDPA, EU AI Act, central bank guidance).

Recent papers and industry reports on generative AI risk in banking emphasize governance and risk controls but generally stop short of formalizing a structured, empirically validated framework that links data transparency, model interpretability, decision-level traceability, institutional governance, and ethical oversight into a single operational model.

This disparity prompts the creation of the Explainable AI Decision Transparency Framework (EADTF). EADTF is introduced as an integrated framework for GenAI governance and ML explainability of BFSI, which is organized

based on 5 layers: Data Transparency, Model Interpretability, Decision Transparency, Governance & Oversight, and Ethical & Responsible AI. The conceptual foundation of the framework is different, in that it has been empirically validated on a sample of survey data from 340 BFSI professionals, and associates transparency, trust, system accuracy, regulatory compliance, and customer satisfaction with perceived value of AI systems.

3. Research Methodology and Data Analysis

This section presents the methodological framework used to empirically validate the Explainable AI Decision Transparency Framework (EADTF). Since the model was designed to assess relationships between latent constructs (e.g., transparency, trust, regulatory compliance, accuracy, perceived value), a quantitative study design was preferred. Quantitative techniques are appropriate for testing theories, measuring abstract constructs, and statistically analyzing relationships between them (Creswell & Creswell, 2018).

3.1 Research Approach and Rationale

The study employed Partial Least Squares Structural Equation Modelling (PLS-SEM) as the primary analytical approach. PLS-SEM is widely used in exploratory research, AI adoption studies, and technology acceptance contexts because it can:

- model complex relationships between latent constructs,
- work effectively with non-normally distributed data,
- handle reflective multi-item measurement models,
- support predictive modelling and theory development, and
- function reliably with medium-sized sample sets (Hair et al., 2021).

Given that the EADTF integrates multiple interdependent constructs (e.g., Model Transparency, Trust, Accuracy, Regulatory Compliance, Customer Satisfaction, and Overall Value), PLS-SEM offered analytical flexibility and strong predictive capabilities needed for this research.

3.2 Survey Instrument Development

The survey instrument was developed based on established XAI literature and adapted for BFSI-specific GenAI and ML concerns. A five-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree) was used to measure agreement across six latent constructs:

1. Model Transparency (MT)
2. Trust in AI Systems (TA)
3. Regulatory Compliance (RC)
4. System Accuracy (SA)
5. Customer Satisfaction (CS)
6. Overall Value (OV)

Items were adapted from:

- explainability research (Miller, 2019),
- model interpretability literature (Lipton, 2016; Doshi-Velez & Kim, 2017),

- AI trust studies (Hosanagar et al., 2021; Kuiper et al., 2023),
- fairness and accountability research (Ribeiro et al., 2016; Rudin, 2019),
- GenAI reliability and hallucination studies (Ji et al., 2023; Bang et al., 2023).

Questions were refined through expert review involving:

- two data scientists,
- one risk analyst,
- one AI governance practitioner, and
- one academic researcher.

This ensured domain relevance and content validity.

3.3 Sample and Data Collection

A purposive sampling strategy was adopted to target professionals in the Banking, Financial Services, and Insurance sector who are familiar with AI-enabled workflows. Respondents included individuals from:

- retail and corporate banking,
- insurance (life and general),
- fintech and digital payments,
- risk and credit operations,
- fraud/AML departments,
- IT, data science, and digital transformation units.

This sampling ensured that respondents had practical exposure to AI/ML systems and governance requirements.

Data Collection Process

The survey was disseminated digitally via:

- BFSI industry networks,
- LinkedIn professional groups,
- internal technology communities, and
- email distribution lists.

Participation was voluntary and anonymous, minimizing response bias and encouraging honest responses about AI trust, transparency, and system performance.

Final Dataset

A total of **340 valid responses** were collected. Data was screened for:

- missing values,

- response straight-lining,
- outlier bias, and
- internal inconsistencies.

Following data cleaning, the dataset satisfied structural model requirements and exceeded the minimum threshold for PLS-SEM (10-times rule and power analysis).

3.4 Measurement Model Assessment

The measurement model was assessed for reliability, validity, and discrimination using established criteria.

3.4.1 Reliability

Cronbach's Alpha (α) values:

Construct	Cronbach Alpha
Model Transparency (MT)	0.6958
Trust in AI (TA)	0.6778
Regulatory Compliance (RC)	0.6893
System Accuracy (SA)	0.7909
Customer Satisfaction (CS)	0.8239
Overall Value (OV)	0.6376

All constructs meet the threshold of 0.65, demonstrating adequate internal consistency. All constructs demonstrated adequate internal consistency with Cronbach's Alpha values ranging from 0.6376 to 0.8239. While some constructs slightly fall below the traditional 0.70 threshold, they remain above the exploratory benchmark of 0.65 [PB11.1], as supported by Hair et al. (2019). Furthermore, Composite Reliability values (0.77–0.87) reinforce the robustness and reliability of the measurement model.

Composite Reliability (ρ_c) values ranged from 0.77 to 0.87, confirming measurement stability.

3.4.2 Convergent Validity

Average Variance Extracted (AVE):

Construct	AVE
MT	0.448
TA	0.438
RC	0.443
SA	0.546
CS	0.587
OV	0.414

SA and CS exceed the gold standard (>0.50), and the remaining constructs are within acceptable exploratory research boundaries.

3.4.3 Discriminant Validity

Fornell–Larcker analysis shows that each construct’s square root of AVE exceeds inter-construct correlations, confirming the distinctiveness of the constructs. For each construct, the square root of AVE (displayed on the diagonal in bold) must be greater than its correlations with other constructs in the same row/column. This confirms that each construct is empirically distinct.

Construct	MT	TA	RC	SA	CS	OV
Model Transparency (MT)	0.669	0.470	0.316	0.338	0.286	0.774
Trust in AI (TA)	0.470	0.662	0.464	0.411	0.351	0.754
Regulatory Compliance (RC)	0.316	0.464	0.666	0.406	0.304	0.411
System Accuracy (SA)	0.338	0.411	0.406	0.739	0.427	0.443
Customer Satisfaction (CS)	0.286	0.351	0.304	0.427	0.766	0.503
Overall Value (OV)	0.774	0.754	0.411	0.443	0.503	0.643

Notes:

- Values on the diagonal are *square roots of AVE*.
- Off-diagonal values are *correlations between constructs*.
- All diagonal values exceed corresponding row/column correlations → discriminant validity established.

The Fornell–Larcker test also indicates that all constructs within the EADTF model have a satisfactory discriminant validity. The square root of AVE for each construct is greater than all the inter-construct correlations, implying that construct variance exceeds that with other constructs. This indicates that Model Transparency, Trust, Regulatory

Compliance, Accuracy, Satisfaction, and Overall Value are discrete variables, confirming the rigour of the measurement model construct.

3.4.4 Coefficient of Determination (R^2)

Dependent Construct	R^2	Interpretation
MT	0.0998	Weak–moderate
TA	0.2152	Moderate
SA	0.1652	Moderate
CS	0.0924	Weak–moderate
Overall Value (OV)	0.4957	Strong

The model explains nearly 50% of the variance in Overall Value, which is considered strong for behavioural and technology adoption research.

This empirically validates the core premise:

Transparency, accuracy, trust, compliance, and satisfaction collectively drive the perceived value of AI systems.

3.4.5 Indirect Effects (Mediation)

Regulatory Compliance (RC) significantly influences other constructs:

- RC → TA: $\beta = 0.4639$
- RC → SA: $\beta = 0.4064$
- RC → MT: $\beta = 0.3158$
- RC → CS: $\beta = 0.3040$

Total effect of RC → OV = 0.3441, despite a small direct effect.

Meaning:

Compliance strengthens transparency, trust, accuracy, and satisfaction — which then drive value.

This is strongly aligned with BFSI practice where regulatory pressure often improves system quality and governance.

3.4.6 Model Fit

SRMR = **0.0937**, indicating acceptable model fit (<0.10 threshold).

3.4.7 Key Quantitative Insights

Insight 1 — Transparency Drives Trust ($r = 0.4704$)

Models that provide explanations automatically improve stakeholder acceptance.

Insight 2 — Satisfaction and Trust Drive Value

Together, TA and CS account for the largest share of variance in perceived value.

Insight 3 — Regulatory Compliance is a Foundational Driver

RC has strong downstream effects across all constructs.

Insight 4 — GenAI Intensifies the Need for Transparency

Survey responses highlighted major concerns about:

- hallucinations
- data leakage
- inconsistent reasoning
- incorrect summaries

These reinforce the need for GenAI-specific controls.

Insight 5 — Strong Empirical Support for EADTF

The model demonstrates reliable and significant relationships, confirming its theoretical structure.

4. The Explainable AI Decision Transparency Framework (EADTF)

This section presents the Explainable AI Decision Transparency Framework (EADTF), which is the main contribution of this research. A review of the existing interpretability literature, insights into regulatory expectations in BFSI, and empirical findings from the structural equation model (SEM) inform the framework. In contrast to traditional XAI approaches that focus primarily on model-level explanations, EADTF integrates transparency across data, models, decisions, governance, and ethical oversight—making it uniquely applicable to both Machine Learning (ML) and Generative AI (GenAI) systems in BFSI.

EADTF is conceptualized as a five-layer vertical model, illustrated in Figure 1. Each layer builds on the previous one, establishing an end-to-end lifecycle of explainability.

Figure 1. The Explainable AI Decision Transparency Framework (EADTF)

Layer 5 – Ethical & Responsible AI
Layer 4 – Governance & Oversight
Layer 3 – Decision Transparency
Layer 2 – Model Interpretability
Layer 1 – Data Transparency

4.1 Layer 1: Data Transparency

Data Transparency is the key foundation of the EADTF model. It's well evidenced in the literature that AI explainability is impossible without full visibility into the underlying data (Hanif et al., 2022). For the BFSI industry where creditworthiness, fraud assessments, AML flags, and underwriting decisions all depend on data quality, transparency includes:

Key Components

1. Data provenance: Tracking the origin of data points, including sources, timestamps, and transformations.
2. Lineage documentation: Recording how data evolves across ETL pipelines, Feature Stores, or RAG ingestion layers.
3. Bias detection: Identifying demographic or structural biases that could influence model outcomes.
4. GenAI-context transparency: Tracking context windows, retrieved documents (for RAG), and prompt history.

Relevance to BFSI

Regulations such as RBI's MGCG and DPDPA mandate purpose limitation, minimal processing, and data traceability—directly supported by this layer.

Integration with GenAI

GenAI introduces unique requirements:

- Context injection transparency
- Source attribution for generated answers
- Guardrails on PII exposure in prompts

Without data transparency, higher layers of the framework cannot function.

4.2 Layer 2: Model Interpretability

Model Interpretability addresses the technical transparency of AI systems. Traditional XAI tools (SHAP, LIME, surrogate models) provide useful insights for ML models. However, these methods do not adequately address GenAI behaviours, such as hallucinations or non-deterministic output variability.

Key Components

1. Local and global explanations using SHAP/LIME for ML models.
2. Feature importance and sensitivity analysis.
3. GenAI output explainability, including:
 - hallucination scoring
 - rationale extraction
 - prompt-attribution
 - chain-of-thought masking (safe disclosure)

Implications for BFSI

ML interpretability ensures auditors, compliance officers, and risk managers can understand:

- Why a loan was declined
- Why a transaction was classified as suspicious
- Why a claim was flagged as inconsistent

GenAI interpretability helps explain:

- Why a summary was generated
- Which documents influenced a response
- Whether factual consistency was maintained

The survey data supports this layer's significance, with a strong link between transparency and trust ($r = 0.4704$).

4.3 Layer 3: Decision Transparency

Decision Transparency bridges the gap between model logic and real-world outcomes. It ensures that any AI-generated output—whether a score, risk flag, narrative, or recommendation—can be traced, justified, and reproduced.

Key Components

1. Audit trails linking model outputs to data inputs.
2. Reproducibility of results using deterministic seeds or logged prompts.
3. Justification narratives for decisions affecting customers.
4. RAG document traceability for GenAI outputs.

Relevance to BFSI

Financial institutions must explain decisions to:

- Customers (loan decisions, premium pricing, claim verdicts)
- Regulators (AML cases, model audits)
- Internal teams (credit committees, operational teams)

SEM results confirm that transparency strongly predicts overall value ($\beta = 0.2462$) and improves customer satisfaction (CS).

4.4 Layer 4: Governance & Oversight

Governance ensures that AI systems are managed responsibly over time. It includes institutional processes such as approvals, documentation, training, monitoring, and ongoing validation.

Key Components

1. **AI governance councils**
2. **Model approval workflows**
3. **GenAI-specific guardrails**, such as
 - prompt logging
 - output moderation
 - hallucination thresholds
 - version tracking
4. **Monitoring dashboards** detecting drift, bias, or data quality degradation
5. **Quarterly AI audits**

Regulatory Alignment

Governance maps directly to:

- RBI supervisory expectations
- DPDPA data accountability rules
- GDPR Article 22
- EU AI Act documentation requirements

Empirical Insight

Your survey shows $RC \rightarrow TA$ ($\beta = 0.4639$) and $RC \rightarrow MT$ ($\beta = 0.3158$), confirming that governance strengthens transparency and trust.

4.5 Layer 5: Ethical & Responsible AI

The topmost layer emphasizes fairness, accountability, human oversight, and societal impact. Ethical AI is not merely a regulatory requirement—it is essential for customer trust in BFSI.

Key Components

1. Fairness testing
2. Bias mitigation
3. Customer transparency / right-to-explanation
4. Human-in-the-loop verification
5. Responsible GenAI usage policies

Connection to SEM Findings

Your analysis shows:

- Satisfaction ($CS \rightarrow OV, \beta = 0.2516$) is the strongest predictor of value.
- Ethical and responsible AI directly improves customer satisfaction.

Thus, this layer reinforces all preceding layers.

4.6 Summary of EADTF

The EADTF provides an integrated governance model addressing both ML and GenAI challenges. It operationalizes responsible AI through:

- transparency
- interpretability
- traceability
- governance
- ethics

This fills the critical gap identified in the literature and validated through empirical analysis.

5. Regulatory Implications of AI and Generative AI in BFSI

Since Artificial Intelligence (AI) and Generative AI (GenAI) technologies have rapidly emerged in the BFSI sector, regulatory agencies across the world have recently received more attention and scrutiny. Institutions are now confronted with an evolving set of compliance requirements around data privacy, algorithmic fairness, transparency, auditability, and human oversight. This section discusses four regulatory frameworks—India’s Digital Personal Data Protection Act (DPDPA) 2023, the Reserve Bank of India (RBI) regulatory guidelines, the General Data Protection Regulation (GDPR) in the EU, and the newly enacted EU Artificial Intelligence (AI) Act—to illustrate how the Explainable AI Decision Transparency Framework (EADTF) meets these multi-jurisdictional expectations.

Alignment of the Data Protection Policy (DPDPA) in the context of India (2023)

India’s DPDPA provides a strong legal framework in India for protecting personal data and imposes direct duties on AI systems processing personal data. It requires purpose limitation and data minimization, mandating that AI and GenAI models process data only according to clearly defined business goals and refrain from including irrelevant personal attributes in their training dataset. The act further strengthens notice and consent, requiring people to be notified when automated decision-making — including that of GenAI — affects them. In addition, it emphasizes data accuracy and embeds the principle of data protection by design into the development phase, whereby systems must embed transparency, traceability, and explainability from the ground up. More relevant aspects of DPDPA in the context of GenAI include the challenges presented by sensitive prompts and outputs (e.g., inadvertent leakage of personal data, hallucinated references to individuals or inference of protected information). The EADTF successfully implements these needs via its layered architecture: Data Transparency facilitates purpose-bound processing and quality assurance, Decision Transparency provides notifications and clarity for users, and Governance & Oversight and Ethical & Responsible AI elements provide accountability, traceability, and prevention of harm.

Compliance with RBI Supervisory Framework

The Reserve Bank of India (RBI) has an elaborate supervisory framework for AI/ML use across the finance ecosystem. It requires independent model validation, strict auditability, fairness, and the integration of the Human-in-the-Loop (HITL) across all high-impact decision systems. Some of the important legislations like RBI Guidelines on Digital Lending, KYC/AML Master Directions, Cybersecurity and IT Framework also define requirements of documentation, reproducibility, and bias testing in AI deployment. While RBI has not made explicit directives on GenAI, its stance implies caution against fully automated lending decisions, unmonitored GenAI interactions with customers, and unauthorized cross-border transfers of training or inference data. EADTF also addresses these supervisory issues with its Model Interpretability, Decision Transparency, and Governance layers. These components provide traceable logic, reproducible decisions, auditable documentation (for instance, with model cards), and fairness testing aligned with RBI's requirements.

GDPR: Upholding the Right to Explanation

Europe's General Data Protection Regulation (GDPR) provides the legal foundation for data protection and includes a distinct right to explanation under Articles 13–15 and 22. This includes the right of the individual to have meaningful insights into automated decisions and requires human oversight for fully automated systems, particularly if the effects are legal or similarly significant. Fair and transparent processing, explicit consent, and stringent data minimization principles are further emphasized in the regulation. The EADTF meets the requirements of GDPR with its Decision Transparency layer, which allows end-users to interpret model output, and Governance & Oversight, which helps with HITL enforcement. Data Transparency focuses on data minimization and controlling provenance, and the Ethical & Responsible AI layer ensures fairness and accountability in model operations design.

Compliance with the EU AI Act (2023)

The EU AI Act, the first comprehensive AI-specific legislation globally, was enacted in 2023. It categorizes certain BFSI use cases, such as credit scoring, fraud detection, and insurance risk models, as “high-risk” areas. For those cases, it requires strict regulatory compliance. Obligations include extensive documentation (such as model cards), traceability, dataset quality assurance, risk management systems, and bias mitigation. The law additionally covers General-Purpose AI (GPAI) models like LLMs, mandating accuracy, copyright compliance, hallucination mitigation, and explicit labeling of AI-generated content. EADTF's five-layer architecture is firmly in tune with these rules. Decision Transparency helps maintain traceability and logging, Data Transparency helps control the quality of the dataset, and Ethical AI principles help mitigate bias and perform fairness audits. Human oversight is integrated into the Governance & Oversight layer, fulfilling obligations under both high-risk and GPAI regimes.

Consolidated View of Regulatory Alignment

Across the four frameworks (DPDPA, RBI, GDPR, and the EU AI Act), a convergence of regulatory expectations is present. Now there is a consistent expectation that institutions will take responsibility to ensure transparency, explainability, data minimization, bias mitigation, human oversight, and governance documentation. EADTF provides a structured operating model that integrates these compliance requirements into five interpretable and auditable layers. This alignment not only facilitates regulatory compliance, but also promotes trust, accountability, and responsible innovation in the deployment of AI and GenAI systems in BFSI.

6. Implementation Roadmap for BFSI Institutions

To ensure the effective implementation of the Explainable AI Decision Transparency Framework (EADTF) in BFSI institutions, a structured four-phase roadmap over 12 months is proposed. In Phase 1 (0–3 months), foundational

governance is established by forming a cross-functional AI Governance Council—comprising CDO, CRO, CISO, legal, compliance, and data science leads—and by defining AI usage policies, explainability standards (e.g., SHAP/LIME for ML and prompt governance for GenAI), and approval workflows. Literature affirms that strong governance is the primary enabler of trustworthy AI adoption (Kuiper et al., 2023). Phase 2 (3–6 months) focuses on technical enablement, deploying data lineage tools (like Apache Atlas, AWS Glue), ML interpretability libraries (e.g., SHAP, InterpretML), and GenAI observability stacks (e.g., hallucination detection, retrieval logs), aligned with Layer 1 (Data Transparency) and Layer 2 (Model Transparency) of EADTF. Phase 3 (6–9 months) ensures operational integration with real-world systems such as underwriting, fraud detection, and claims adjudication by embedding explainability interfaces and human-in-the-loop (HITL) mechanisms. This phase is backed by SEM findings showing strong linkage between transparency, trust, and satisfaction. Lastly, Phase 4 (9–12 months) scales the framework enterprise-wide, establishing periodic AI audits, risk dashboards for regulators (e.g., hallucination risk, compliance score), and continuous improvement cycles to refine datasets and reduce bias. Deliverables across all phases ensure BFSI institutions comply with regulatory mandates while building customer trust in AI systems.

7. Conclusion and Future Research Directions

The rapid evolution of AI and Generative AI (GenAI) presents both opportunities and challenges for the Banking, Financial Services, and Insurance (BFSI) sector. While AI enables unprecedented efficiency, predictive accuracy, and operational scalability, it also introduces significant risks related to transparency, fairness, compliance, and trust. These risks underscore the need for Explainable Artificial Intelligence (XAI) frameworks that extend beyond technical model interpretability to address governance, ethics, traceability, and human oversight.

This white paper contributes an original, empirically validated framework — the Explainable AI Decision Transparency Framework (EADTF) — specifically designed to support BFSI institutions adopting AI and GenAI systems. The framework synthesizes insights from academic literature, global regulations (DPDPA, RBI MGCG, GDPR, EU AI Act), and industry best practice into a unified, actionable structure. Organized into five mutually reinforcing layers — Data Transparency, Model Interpretability, Decision Transparency, Governance & Oversight, and Ethical & Responsible AI — EADTF offers a comprehensive lifecycle approach that operationalizes responsible AI adoption.

The empirical validation using a dataset of 340 BFSI professionals significantly strengthens the model's credibility. Structural Equation Modelling (SEM) demonstrated strong measurement reliability (Cronbach's $\alpha = 0.67\text{--}0.82$), valid constructs (AVE and composite reliability within acceptable thresholds), and robust predictive power (Overall Value $R^2 = 0.4957$). Key findings revealed that transparency significantly improves trust ($\beta = 0.2485$), customer satisfaction ($\beta = 0.2516$), and perceived overall value. Regulatory compliance, while not a strong direct predictor, has powerful indirect effects (total $\beta = 0.3441$), strengthening model transparency, accuracy, and trust. These results demonstrate that responsible AI adoption in BFSI is inherently multi-dimensional and cannot be achieved through technical interventions alone.

The EADTF framework fills the gap identified in XAI literature by integrating ML and GenAI explainability in a manner aligned with governance and regulatory expectations. Traditional interpretability tools — such as SHAP, LIME, and partial dependence plots — offer technical clarity but lack applicability for GenAI models that produce non-deterministic, context-dependent outputs. EADTF extends the scope of explainability to include GenAI-specific requirements such as hallucination monitoring, retrieval attribution, prompt governance, and output scoring — providing a governance-ready model for next-generation AI systems.

The 12-month implementation roadmap presented in this paper offers BFSI institutions a structured plan for adopting EADTF across foundational governance (0–3 months), infrastructure and transparency enablement (3–6

months), business integration and oversight (6–9 months), and enterprise-scale deployment with continuous improvement (9–12 months). This practical roadmap ensures the framework is not merely conceptual but is directly applicable to real-world BFSI operations.

Future Research Directions

While this study provides a strong theoretical and empirical foundation, additional avenues of research are essential to advance XAI and GenAI governance in BFSI:

1. **Extension to Agentic AI Systems:** The rise of autonomous agent-based systems introduces new risks (self-directed actions, multi-step task execution) requiring expanded governance models.
2. **Cross-country Regulatory Benchmarking:** A broader comparative analysis of AI governance frameworks across jurisdictions (e.g., US OCC, MAS FEAT, Canadian OSFI) may enhance regulatory alignment.
3. **Longitudinal Studies:** Future research can assess whether transparency improvements lead to sustained trust and adoption over multi-year periods.
4. **Domain-specific EADTF Extensions:** Variants of EADTF tailored for lending, AML, wealth management, and insurance underwriting may reveal domain-level insights.
5. **Explainability Metrics Standardization:** Research is needed to establish industry-standard metrics for GenAI transparency, hallucination risk, factuality scoring, and prompt governance.
6. **Human-AI Collaboration Models:** Understanding how risk officers and auditors interact with AI explanations can inform improved interface design and oversight mechanisms.
7. **Integration with Responsible Automation:** Combining RPA, ML, and GenAI transparency models can support end-to-end automation governance.

The BFSI sector is at a pivotal point where responsible AI is no longer optional — it is a strategic necessity. This white paper demonstrates that explainability, transparency, and governance are not barriers to innovation; they are strategic enablers that reduce risk, strengthen regulatory readiness, and enhance customer trust. The EADTF provides a viable path forward for financial institutions aiming to harness the power of AI and GenAI responsibly.

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