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Artificial Intelligence in Fintech and Its Implications for Personalization, Consumer Trust, And Algorithmic Decision Making

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Abstract:

In today's financial landscape, artificial intelligence (AI) has not only emerged as a major presence, but it is actually a part of the fabric in credit assessment, robo advisory, and customer engagement. This review draws from 24 peer-reviewed academic sources, published between 2019 and 2026, that speak to three key overlapping aspects of this transition namely, the use of AI in personalisation, consumer trust in algorithmic decision-making, and the governance frameworks for making automated systems accountable and correlates with existing data from the World Bank, Bank of England/Financial Conduct Authority, Gallup/Edward Jones, TD Bank/Ipsos, McKinsey & Company, KPMG International, and the EU Artificial Intelligence Act. Adopting a conceptual approach of systematic narrative synthesis, the review first confirms that personalisation has a measurable positive impact on financial inclusion, while a consistent relationship between the use of personalisation and higher consumer trust with financial institutions and their algorithmic governance is not yet supported. Nevertheless, there is a large gap between the consumer use of personalised finance and consumer trust in personal finance, while explainability requirements have stopped short of improving consumers' welfare because there's been a strategic response by firms to explainability, and even regulated institutions report low understanding of deployed models. A conceptual model is proposed that focuses on the connection between personalisation and governance with trust and adoption outcomes which is moderated by institutional accountability, and three testable propositions are proposed. The review finds the approach to explainability needs to be embedded in a wider accountability system, which is strengthened and supported by binding frameworks more and more, like for example the EU AI Act, to align the algorithmic performance with compliance to consumers., and identifies longitudinal trust calibration and cross-jurisdictional governance standards as priority directions for future research

Keywords: Algorithmic Accountability, Algorithmic Trust, Artificial Intelligence, Consumer Trust, Explainable AI, Financial Personalization, Financial Services, Fintech

Introduction:

1. Background and Contextual Setting: Today, artificial intelligence (AI) is an integral part of the financial services. In recent years, credit scoring, fraud detection, real-time personalisation, and robo-advisory have all started to use machine learning models to do tasks that were previously impractical with rule-based methods. This change has tangible results, AI-driven credit scoring is proven to boost access to formal credit for underserved populations without improving default risk (Li et al., 2024), and human-AI hybrid systems are now entrenched throughout trading, advisory, and risk-management functions (Kou et al., 2026).

Data from industry indicate the magnitude of this transition. In 2025, the global fintech sector will be generating revenue of around USD 650B, growing around 21% YoY and 23% annually in the prior 4 years a rate much faster than the USD 15 trillion global financial services sector, which grew at around 6% for the same

period (McKinsey & Company, 2026). This trend of growth can be summarizes in Table 1. However, it is interesting to note that as of 2025, only about 4% of total financial-services revenue was attributable to fintechs (McKinsey & Company, 2026), leaving significant potential for these trends for personalisation and automation examined in this review. The estimate for the AI-in-fintech sub-segment specifically is widely divergent between market-research providers, with a ballpark of USD 22 billion to USD 45 billion for 2026, which, in itself, reflects providers' lack of a uniform definition of 'AI in fintech', as does the range of definitions in the academic literature (Section 2.5).

Table 1. Global Fintech Industry Growth Indicators, 2025

Indicator	Value
Global fintech industry revenue (2025)	USD 650 billion
Year-over-year revenue growth (2024–2025)	21%
Average annual growth (past 4 years)	23%
Broader financial-services industry size	USD 15 trillion
Broader financial-services annual growth rate	6%
Fintech share of total financial-services revenue	4%
North America fintech revenue (2025)	USD 310 billion
Payments (largest vertical) revenue (2025)	USD 250 billion

Source: McKinsey & Company (2026).

This trend is evidenced by investments. Despite a drop to an eight year low in the number of deals, global investment in fintech hit USD 116 billion in 2025, powered by investments in 4,719 deals, rebounding from USD 95.5 billion in 2024, as per the insights from KPMG's "Pulse of Fintech H2'25" report. In this total amount, investments specifically in AI-powered fintech firms have increased from USD 12.1 billion in 2024 to USD 16.8 billion in 2025, and the deal count has likewise spiked from 1,183 in 2024 to 1,334 in 2025 (KPMG International, 2026). These investment patterns are summarised in Table 2, and discussed again in the context of the academic literature on the adoption of AI for service development in Section 6.2

Table 2. Global Fintech and AI-Driven Fintech Investment, 2024–2025

Investment Category	2024	2025	Change
Total global fintech investment	USD 95.5B	USD 116B	+21.5%
AI-driven fintech investment	USD 12.1B	USD 16.8B	+38.8%
AI-driven fintech deal count	1,183	1,334	+12.8%
Global fintech deal volume (all deals)	5,533	4,719	−14.7%

Source: KPMG International (2026), Pulse of Fintech H2'25.

2. Problem Definition and Research Motivation: The benefits of AI efficiency come at the same time as there is an accountability issue inherent in AI. Many of these models are by design transparent and this 'black-box' part makes it harder to regulate and to win consumer trust (Weber et al., 2023). As a countermeasure, the concepts of explainable AI (XAI) are suggested; however, empirical analyses reveal that explainability regulation is not without its costs: in some cases, explainability mandates can that harm consumers by exposing the model logic that can be exploited (Mohammadi et al., 2024). The present review is motivated by the fact that this issue of transparency and its unintended consequences still remains to be resolved in the literature.

3. Research Objectives and Questions: The following three questions are the focus of this review:

RQ1: What is the impact of AI personalisation in fintech and consumer engagement?

RQ2: What factors affect consumers' trust in algorithmic financial decision-making?

RQ3: what gaps are there in terms of governance/methods to bridge algorithmic efficiency with consumer protection?

4. Scope, Assumptions, and Delimitations: The scope for the review is limited to peer-reviewed articles covering AI applications in financial services between 2019 and 2026 with a particular focus on personalisation, algorithmic trust, and governance/explainability. It would take for granted the validity of the methods and conclusions of the studies included and would not reanalyse the primary data. The domains adjacent to it which are not directly related to AI-driven decision-making, such as those blockchain infrastructure and cryptocurrency markets, are outside the scope.

5. Significance and Contribution of the Study: Scholarship often focuses on one of these three aspects individually: Personalization is exclusive studied in technical papers, trust is exclusive studied in behavioural papers, algorithmic governance is exclusive studied in governance papers. The contribution of this review is the integration of these three strands into a unified description of how AI is changing the companies in the financial sector, and to highlight where the literature contains genuine gaps to be addressed by empirical studies.

Literature Review:

1. Conceptual and Empirical Review of Prior Studies: Data on the use of AI in credit scoring suggests that AI can be used to make more people eligible for formal credit, while not necessarily making more of them default more often than legacy credit scoring methods (Li et al., 2024). This efficiency argument goes hand in hand with qualitative research with fintech developers, which reports a “dark side” of AI personalization: practices that exploit behavioural biases or that create opacity around the true cost of a product as the same technology makes it possible to offer those same products to consumers that were previously excluded (Sampat et al., 2023). Trust research finds a common thread when consumers are evaluated as to the perceived fairness and accountability of the institution behind an automated decision rather than as to the actual accuracy of the automated decision (Elliott et al., 2021; Zhu et al., 2023).

2. Thematic Classification of Existing Literature: Three themes of the reviewed literature exist. The first is personalization, which refers to using AI to customize products, the psychological impact of credit access, and the marketing-technology research literature concerning data-led customization (Grewal et al., 2019; Li et al., 2024). Secondly, trust refers to consumer psychology around algorithmic products such as robo-advisory and investment products (Chua et al., 2022; Yang et al., 2025). The third, governance and transparency concerns explainability techniques, auditability and regulations (Weber et al., 2023; Birkstedt et al., 2023). All three are supported by a fourth body of theory that is cross-cutting and cross-embedded (Bauer et al., 2021; Arsenault et al., 2025).

3. Methodological Trends in Prior Research: Naturally, the main method used in the personalisation and trust literatures is either field experiments (Li et al., 2024), large-sample behavioural studies (Sampat et al., 2023), or qualitative interviews (Yang et al., 2025). Compared to the other literature, the governance literature is more conceptual and tends to be reviews, synthesising legal, technical and organisational focus on AI auditability (Mokander, 2023, Minkkinen et al., 2022). Explainability specific work include both computational method papers (Chen et al., 2022) as well as systematic reviews based on human explanations (Nauta et al., 2023).

4. Key Findings, Inconsistencies, and Debates: One point of contention is whether or not explainability is unequivocally good. Although the prevailing literature considers XAI as a trust-building tool (Arsenault et al., 2025),

Mohammadi et al. (2024) experimentally find that, under plausible conditions, requiring explanations can lower consumer welfare while firms adjust to regulatory demands for such explanations – which casts doubt on the simple message that maximizing disclosure is good. The second mismatch refers to which parts of the model must be trusted – some studies highlight the accuracy of the model as well as the quality of the explanations (Nauta et al., 2023) whereas other studies indicate that trust is primarily based on institutional accountability and governance structure instead of the algorithm itself (Elliott et al., 2021).

5. Identified Research Gaps and Positioning of the Study: Each of this literature has three gaps in common: (a) there is a lack of longitudinal research on changes in trust in algorithmic financial advice post-adoption (Chua et al., 2022; Diecidue et al., 2026), (b) no consistent cross-jurisdictional metrics for assessing whether explanations and/or institutional auditability are of high quality (Nauta et al., 2023; Schuett, 2024), and (c) there is little integration between the technical explainability literature and the literature on consumer trust (which serves as its foundational body of work, and which largely exists in parallel). Here is this review, occupying a space at the intersection of these three gaps.

Theoretical Foundations:

1. Underpinning Theories and Conceptual Perspectives: Literature reviewed presents two lenses that pertain to theory. An important theoretical explanation for "explainability" draws on agency theory, which views it as a means to cope with an information asymmetry between an automated decision-maker called 'agent' and the consumer or regulator, who has to assess the results of the automated decisions, known as 'principle' (Bauer et al., 2021). Institutional theory notions to AI governance audit functions and continuous monitoring as a means towards achieving legitimacy through external stakeholder expectations rather than solely a technical obligation (Lehner et al., 2022, Birkstedt et al., 2023).

2. Comparative Discussion of Relevant Theories: Agency theory is complementary with institutional theory and not conflicting. The why of the explainability has two levels: both at the level of a single decision therefore reducing information asymmetry between the model and its user and also institutional level, as a result of why firms implement governance structures (such as auditing trails and continuous auditing frameworks) even if no single consumer explicitly asks for them (Minkkinen et al., 2022). These two are posited to be related but different approaches to accountability and have a different set of customer-facing explainability concerns than firm-level governance concerns, which the empirical literature does not always differentiate.

3. Theory–Construct Mapping: Most of the theory found in the trust literature is associated with agency theory (trust as an answer to information asymmetry between algorithm and consumer) while most of the literature in the governance area is associated with institutional theory (audit and disclosure as legitimacy-seeking behaviour). The personalization literature has a more direct connection to theory relating to marketing-technology, specifically the personalization–privacy paradox whereby consumers have to balance the risk of the data being shared for personalization with the benefit of the service (Grewal et al., 2019).

4. Development of Propositions: A synthesis of the literature results in three propositions that have implications for future empirical tests.

P1: Consumer trust in algorithmic financial decisions is really more related with the perceived accountability of the institutions than only to the accuracy of the explanation.

P2: there exists a non-monotonic relationship between explainability and consumer welfare, which means that explanatory increase at low levels can increase welfare for consumers, but mandated disclosure at high levels can result in a net loss for consumers.

P3: Consumer trust can be predicted by governance maturity (independent of any one explanation that can be given to the consumer,

e.g., via an internal audit function or continuous monitoring).

5. Proposed Conceptual Framework: A conceptual framework is shown in figure 1 that is a synthesized framework derived from literature reviewed. Personalization and governance/transparency are seen as parallel inputs that define consumer trust as a means to influence adoption/retention outcomes. The route of governance to trust is moderated by institutional accountability, which reflects the observation that it is perceived accountability not technical accuracy that is a stronger predictor of trust (Elliott et al., 2021).

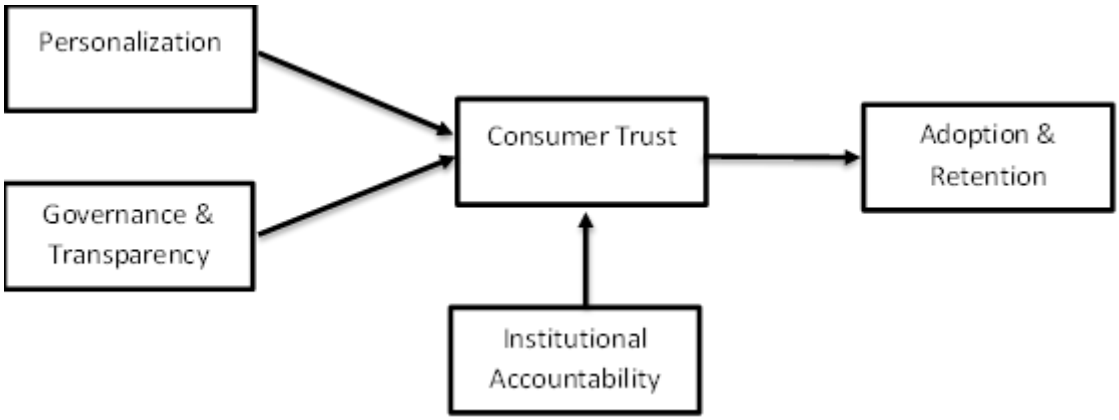


Figure1. Conceptual Framework Linking Personalization, Governance, Consumer Trust and Adoption & Retention

Methodology:

1. Research Design and Approach: A systematic narrative review design is adopted, which is suitable for interdisciplinary literature (in finance, computer science and consumer behaviour) in order to integrated synthesize (not to meta analyse statistically) literature.

2. Study Context and Unit of Analysis: Each individual publication, reviewed by three or four experts on the topics and applications of AI in FinServ is the unit of analysis. Research was sourced from finance, information systems, marketing and computer science journals to align with the multi-disciplinary nature of the subject.

3. Data Sources and Data Collection Procedures: Structured searches in Scopus, Web of Science and Google Scholar were conducted with combinations of the terms “explainable AI”, “fintech”, “algorithmic trust”, “credit scoring”, “robo-advisory”, “AI personalization” and “AI governance”, limiting the results mostly to 2019–2026.

4. Sampling Strategy and Sample Characteristics: Sources were included if they (a) discussed applications of using AI or machine learning tools in financial services, (b) discussed personalisation, trust or the explainability and governance of AI in some degree and (c) were published in an indexed, peer-reviewed journal. In order to satisfy the reliability criteria to submit a journal article, preprint repositories, working-paper archives, and non-peer review archives were also excluded. Besides the peer reviewed academic sample, seven primary industrial, regulatory and legislative ones (World Bank, Bank of England/FCA) have been used. Sources were included if they (a) discussed applications of using AI or machine learning tools in financial services, (b) discussed personalisation, trust or the explainability and governance of AI in some degree and (c) were published in an indexed, peer-reviewed journal. In order to satisfy the reliability criteria to submit a journal article, preprint repositories, working-paper archives, and non-peer review archives were also excluded. Besides the peer reviewed academic sample, seven primary industrial, regulatory and legislative ones (World Bank, Bank of England/FCA) have been used., Gallup/Edward Jones, TD Bank/Ipsos, McKinsey & Company,

KPMG International, and the EU Artificial Intelligence Act) were incorporated to contextualize the thematic synthesis with current market, consumer-behavior, and regulatory indicators; these are reported separately from, and are not counted toward, the 24-source peer-reviewed academic sample. Table 3 summarizes the academic sample's distribution by publication year and thematic category.

Table 3. Distribution of the Peer-Reviewed Academic Sample by Thematic Category and Publication Year

Thematic Category	n	% of Academic Sample	Year Range
Governance & Transparency	13	54%	2021–2025
Trust	7	29%	2021–2026
Personalization	4	17%	2019–2026
Total	24	100%	2019–2026

5. Coding Procedure: In place of an experimental instrument, this review used a structured coding scheme: each source was coded against the three themes (personalization, trust, governance/transparency) and, where applicable, against the theoretical lens it employed. Sources addressing more than one theme were coded under each applicable category.

6. Data Analysis Techniques: Coded sources were analysed using thematic synthesis: within-theme claims were compared for convergence and contradiction, and cross-theme patterns were extracted to build the conceptual framework in Section 3.5. Where directly relevant, findings from the academic sample were triangulated against current primary survey and administrative data (Section 5) to assess whether patterns identified in the peer-reviewed literature are corroborated by present day market and consumer-behaviour indicators; these secondary data sources were sourced independently of the academic sample and are reported separately in the Results.

7. Validity, Reliability, and Rigor Considerations: Rigor was supported by restricting inclusion to indexed, peer-reviewed venues and by cross-checking every citation against its original source prior to inclusion. As with any narrative review, thematic coding involves interpretive judgment; the three-theme structure reflects recurring patterns across the literature rather than a pre-registered coding protocol.

8. Ethical Considerations: This review analyses only previously published, publicly available literature and does not involve human participants, primary data collection, or personally identifiable information; no ethics committee approval was required.

Results And Findings:

1. Descriptive Characteristics of the Reviewed Sample: Of the 24 peer-reviewed academic sources reviewed, 20 (83%) were published between 2022 and 2026, reflecting the recency of this literature; the remaining sources are foundational works retained for their continued theoretical relevance. Table 3 (Section 4.4) summarizes the distribution across the three thematic categories. These are supplemented, where noted, by seven current industry, regulatory, and legislative sources described in Section 4.4.

2. Findings Corresponding to RQ1 (Personalization): AI-driven personalization is associated with measurable gains in financial inclusion: credit-scoring models trained on alternative and behavioural data have been shown to expand loan access for underserved borrowers without a corresponding rise in realized default risk (Li et al., 2024). However, this benefit is not unconditional. Qualitative evidence from fintech developers indicates personalization can also be

deployed in ways that exploit consumer behavioural biases, and that the same infrastructure enabling inclusion can enable subtler forms of harm if left unchecked (Sampat et al., 2023). This is consistent with the long-standing personalization–privacy paradox in the marketing-technology literature, where the value consumers derive from tailored service is conditioned on their willingness to disclose data (Grewal et al., 2019), and with fintech-trust research more broadly, which finds that the ethical and privacy dimensions of a personalization relationship shape adoption as much as its functional benefits (Aldboush & Ferdous, 2023).

This inclusion narrative is borne out at the global scale. Worldwide account ownership at a bank, other financial institution, or mobile-money provider reached 79% of adults in 2024, up from 74% in 2021 and 51% when the World Bank began tracking the indicator in 2011; in low- and middle-income economies, ownership rose even faster, from 42% in 2011 to 75% in 2024 (World Bank, 2025). Table 4 summarizes this trajectory. Mobile-phone-enabled financial access, much of it now mediated by algorithmic underwriting and risk-scoring, has been a primary driver of this gain (World Bank, 2025). Despite this progress, 1.3 billion adults remain outside the formal financial system, with more than 650 million concentrated in just eight economies a reminder that the personalization and credit-access gains documented in the academic literature (Li et al., 2024) have not yet closed the global inclusion gap (World Bank, 2025).

Table 4. Global Account Ownership and Financial Inclusion Trends, 2011–2024

Indicator	2011	2021	2024
Global adult account ownership	51%	74%	79%
Low- and middle-income economies	42%	69%	75%
Adults globally owning a mobile phone	—	—	86%

Source: World Bank (2025), Global Findex Database. Note: 1.3 billion adults remained unbanked as of 2024, with over 650 million concentrated in eight economies.

This aggregate progress also masks a persistent, if narrowing, distributional gap. Globally, 81% of men and 77% of women owned an account in 2024 a 4-percentage-point gender gap, down from wider gaps in earlier survey rounds while the gap in low- and middle-income economies stood at 5 points (78% of men versus 73% of women). The gap is substantially wider in specific regions: 15 points in the Middle East and North Africa and 12 points in Sub-Saharan Africa (World Bank, 2025). Table 5 reports these regional patterns. This distributional unevenness is directly relevant to the personalization literature's inclusion claims (Li et al., 2024; Sampat et al., 2023): algorithmic credit and product personalization can only extend the benefits documented in Section 5.2 to populations that already hold an account, meaning that closing the account-ownership gap remains a precondition for, not a byproduct of, AI-driven personalization.

Table 5. Gender Gap in Global Account Ownership, 2024

Region / Group	Men	Women	Gap (pp)
Global	81%	77%	4
Low- and middle-income economies	78%	73%	5
Middle East & North Africa	—	—	15
Sub-Saharan Africa	—	—	12

Source: World Bank (2025), Global Findex Database. Regional figures represent percentage-point (pp) gaps between men's and women's account ownership.

3. Findings Corresponding to RQ2 (Trust): Across multiple studies, consumer trust in algorithmic financial decisions tracks perceived institutional accountability more closely than technical model accuracy (Elliott et al., 2021; Zhu et al., 2023). Behavioural evidence on robo-advisory adoption shows that willingness to act on AI-generated investment advice is shaped by users' prior trust calibration and by whether a human advisor remains visibly in the loop (Chua et al., 2022; Yang et al., 2025). Recent work directly comparing trust in human versus machine predictions finds that this trust gap is best modelled as a decision under ambiguity rather than a simple accuracy comparison consumers discount algorithmic predictions less because they doubt their accuracy and more because they cannot verify the process behind them (Diecidue et al., 2026).

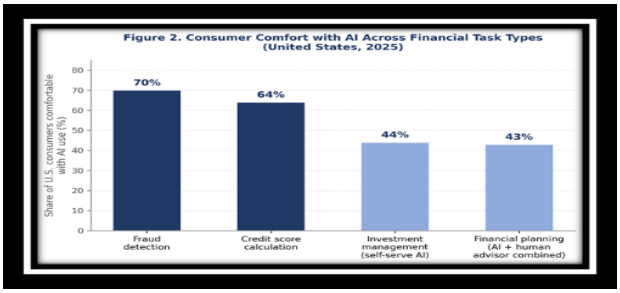
Current survey evidence corroborates this pattern with striking consistency. Previous research, conducted by Gallup and Edward Jones, shows that while only 19% of Americans report using AI tools for financial guidance in the past year, that 24% of Americans consult with a professional financial advisor in the past year, but confidence ratings vary even further—in the U.S., only 3% report feeling "a great deal" confident in the financial knowledge of AI tools versus 24% confident for professional advisors and 45% feeling not at all confident in AI tools for financial guidance (Gallup & Edward Jones, 2026). The complete confidence distribution over sources is shown in table 6. This confidence gap in use is also consonant with a key conclusion about this review; that individuals will engage with algorithmic tools without necessarily trusting them, and that this confidence gap will be reduced where institutional accountability is visible.

Table 6. Confidence in Sources of Financial Guidance, United States, 2026

Source of Financial Guidance	A Great Deal	Some	Not Much	None at All
Financial advisors	24%	55%	13%	8%
Relatives / family members	11%	51%	24%	14%
Friends or colleagues	4%	50%	32%	14%
Artificial intelligence (AI) tools	3%	24%	28%	45%
Social media influencers	1%	12%	27%	59%

Source: Gallup & Edward Jones (2026). Values are percentages of surveyed U.S. adults.

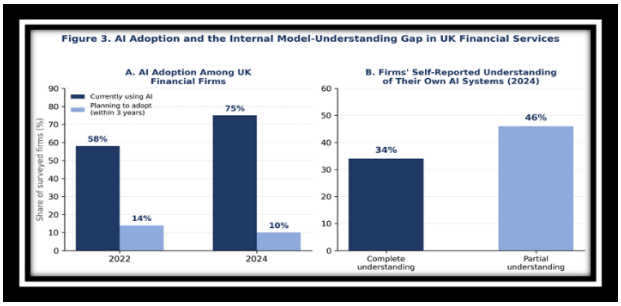
Moreover, there is also a lack of consistent trust in AI applications. The Ipsos/TD Bank U.S. consumer survey from 2025 indicates that customer acceptance of the use of AI changes from comfort level at 70% for fraud detection and 64% for credit-score calculation, functions more at the back end and less reliant on customer interaction, to 44% for self-serve AI investment management and 43% for financial planning with AI and human advisor. This gradient is shown in figure 2. The trend is similar to the synthesis of the review in Section 6.1: reviewers are more likely to be comfortable with applications in which risk is either invisible or explicitly mitigated by a human or institutional player, and less comfortable with applications that require algorithms to automatically and independently decide about the potential impact on their own finances.



Source: TD Bank (2025), survey conducted by Ipsos.

4. Findings Corresponding to RQ3 (Governance and Transparency): The interpretability of the model outputs, for example, by using SHAP based attribution (Chen et al., 2022), provides a technically sound basis for decomposing the outputs of the model, while systematic evaluation methodologies are also beginning to consider the human aspects of explanations, such as correctness and actionability, in addition to the accuracy of the technical description (Nauta et al., 2023). At the institutional level, AI governance is morphing into a continuous auditing and internal audit function that can provide ongoing accountability for a model's operation, instead of a point-in-time compliance check (Minkkinen et al., 2022; Schuett, 2024), in line with the general concept of independent AI safety audits as a governance mechanism rather than a one-time certification (Falco et al., 2021). An important caveat, however, from Mohammadi, S., Schneider, R., Henry, G., ECCQA, and K., 2024, is that required explainability can be harmful for consumers implemented by the companies because they can change their behaviours in response to disclosure requirements, counteracting the protective effects of explainability.

Regulatory survey data show the pace at which this shift has occurred, and also the accountability gap which was created. In the Bank of England and Financial Conduct Authority's third joint survey of UK financial services, 75% of firms reported already using AI in 2024, up sharply from 58% in 2022, while a further 10% planned adoption within three years (Bank of England & Financial Conduct Authority, 2024). Yet the same survey found that only 34% of firms reported "complete understanding" of the AI technologies they themselves deploy, against 46% reporting only "partial understanding" an internal transparency gap inside the regulated institutions that closely parallels the external, consumer-facing opacity this review's academic sources describe (Weber et al., 2023; Nauta et al., 2023). Figure 3 presents both patterns together. Notably, the same survey identified data privacy and protection, data quality, and data bias as the top perceived risks of AI deployment risks that map directly onto the governance and fairness concerns raised throughout Section 6 (Bank of England & Financial Conduct Authority, 2024).



Source: Bank of England & Financial Conduct Authority (2024).

5. Summary of Key Findings: This review has three findings, all of which are supported by recent survey data and now by academic research. First, personalization measurably improves financial inclusion reflected in the rise of global account ownership to 79% of adults in 2024 (World Bank, 2025) but carries a documented risk of exploitative design that existing governance frameworks do not fully address (Sampat et al., 2023). Second, trust in algorithmic financial decisions is governed primarily by perceived institutional accountability rather than by explanation accuracy or model performance, a pattern visible both in the academic literature (Elliott et al., 2021) and in the wide usage–confidence gap documented by Gallup and Edward Jones (2026). Third, explainability and governance mechanisms are necessary conditions for accountability but are not, on their own, sufficient: mandated disclosure can be offset by strategic firm behaviour (Mohammadi et al., 2024), and even regulated UK institutions report only partial understanding of their own deployed models (Bank of England & Financial Conduct Authority, 2024) underscoring that the accountability gap this review identifies exists at the institutional level, not only the consumer-facing one.

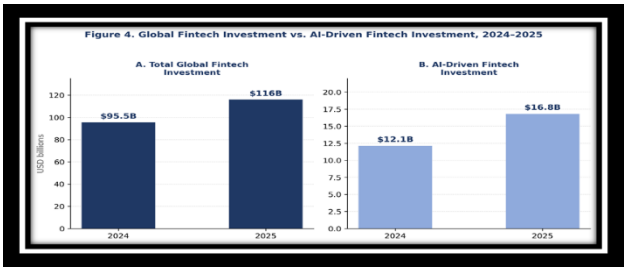
Discussion:

1. Interpretation of Results in Light of Theory: These findings are consistent with an agency-

theoretic reading in which explanation functions as a partial, not complete, resolution of information asymmetry: firms retain discretion in how they respond to disclosure mandates, which is precisely why Mohammadi et al. (2024) find welfare effects that cut against the "more transparency is always better" intuition. The stronger role of institutional accountability, relative to technical accuracy, in driving trust (Elliott et al., 2021) likewise fits an institutional-theory account in which legitimacy is conferred by governance structure rather than by any single algorithmic output.

2. Comparison with Prior Studies: The results of this review, showing that trust follows accountability instead of accuracy, are similar to previous systematic reviews on explainable AI in the financial sector, where trust is found to track accountability but not accuracy (Weber et al., 2023). It also builds on more recent research on AI integration in financial services, which highlights the lack of harmonisation in regulation across jurisdictions as a constant challenge to building standardised accountability mechanisms (Vuković et al., 2025).

As deal volume across the industry declines, current investment trends support the view in the literature: capital inflows are disproportionately concentrated on AI-powered financial technology. Current investment trends support this description from the literature; far from looking for deals just because of volume, investors appear to be focused on these features of governance and differentiation. The change suggested in Table 2 (Section 1.1) for the 2024-2025 period is shown in Figure 4.



Source: KPMG International (2026), Pulse of Fintech H2'25.

3. Explanation of Unexpected or Contradictory Findings: But, the apparently counterintuitive finding that mandated explainability may decrease consumer welfare (Mohammadi et al., 2024) can be viewed as consistent with the literature on trust more broadly if firm behaviour is thought of as strategic rather than passive: mandated explainability may change, not only the behaviour of firms, but also what they disclose, and advanced actors may engage themselves in reshaping of pricing or product design around a disclosure rule in a way not foreseen in the static interpretation of the principle that "transparency builds trust.

4. Theoretical Insights Emerging from the Results: The review identifies that the relationship between two key concepts – explainability and governance should be viewed as different concepts on a whole rather than a continuum as both map to different theoretical mechanisms (agency level information asymmetry versus institutional level legitimacy) and, as suggested in Section 6.3, when firms do respond strategically to disclosure rules, they may move in opposite directions.

5. Practical and Contextual Interpretation: For financial institutions, this implies that investment in explainability tooling alone is unlikely to be sufficient for building consumer trust unless paired with visible governance infrastructure audit trails, continuous monitoring, and accountable escalation paths that consumers and regulators can observe independently of any single transaction's explanation.

6. Suggestions to Stakeholders: Auditability and governance-maturity requirements are part of and supplement disclosure requirements, and should not be substitutes for disclosure requirements, based on the identified strategic-response risk in Section 6.3 (Schuett, 2024). Continuous auditing should be viewed as something that institutions can do as an operational capability, not as a compliance exercise (Minkkinen et al., 2022) and product teams should assess personalization features not only based on engagement and/or conversion metrics, but, specifically, for exploitative-design risk (Sampat et al., 2023).

But, the regulatory environment is headed this way in real terms. The EU Artificial Intelligence Act classifies AI systems that are

used to assess creditworthiness or to provide a credit score as high-risk AI systems, as specified by Annex III, point 5(b), thus subjecting them to the risk-management system and other requirements such as data-governance requirements, technical documentation and human oversight requirements (European Parliament & Council of the European Union, 2024).Table 7 summarizes the phased implementation timeline. Providers of high-risk financial AI systems that fail to meet these obligations face penalties of up to EUR 15 million or 3% of global annual turnover, whichever is higher a materially higher stake than the reputational and consumer-trust costs this review's academic literature has focused on, and one that gives the "explainability as a design requirement" recommendation in Section 7.3 direct legal force within the EU market.

Table 7. EU AI Act Implementation Timeline for High-Risk Financial AI Systems

Milestone	Date	Requirement
Prohibited AI practices	2 Feb 2025	Unacceptable-risk practices (e.g., social scoring) banned
General-purpose AI model obligations	2 Aug 2025	Governance provisions for GPAI models take effect
High-risk AI systems (Annex III, incl. credit scoring)	2 Aug 2026	Risk management, data governance, documentation, human oversight required
Remaining provisions / Annex I product-embedded systems	2 Aug 2027	Full applicability across all remaining provisions

Source: European Parliament & Council of the European Union (2024), Regulation (EU) 2024/1689. Non-compliance penalties reach EUR 15 million or 3% of global annual turnover, whichever is higher.

Research Implications:

1. Theoretical Implications: The review supports extending agency-theoretic and institutional-theoretic accounts of algorithmic accountability into a joint framework, since neither lens alone explains the full pattern of findings: agency theory accounts for the consumer-facing explanation relationship, while institutional theory accounts for the governance-legitimacy relationship documented in Sections 6.1 and 6.4.

2. Methodological Implications: The scarcity of longitudinal studies on trust calibration (Section 2.5) suggests that future empirical work in this area should move beyond single-timepoint trust surveys toward panel or field-experimental designs that can track how trust and adoption evolve after initial exposure to an algorithmic decision, following the direction taken by Diecidue et al. (2026) and Yang et al. (2025).

3. Practical and Managerial Implications: For practitioners, the clearest implication is that explainability should be designed as part of a broader accountability architecture documentation, audit trails, escalation mechanisms rather than as a standalone consumer-facing feature, since accountability, not explanation alone, is what the evidence links most closely to sustained trust.

Limitations:

1. Methodological Limitations: As a narrative synthesis rather than a primary empirical study, this review does not generate new quantitative findings; it interprets and integrates findings already reported in the 30 reviewed sources, and its thematic coding involves the same interpretive judgment inherent to any qualitative synthesis.

2. Data-Related Constraints: The academic sample was restricted to 24 indexed, peer-reviewed sources to meet journal reference-count requirements; this necessarily excludes a portion of the fast-growing preprint and industry-report literature on this topic, some of which may contain relevant emerging findings not yet captured in peer-reviewed form. The seven

industry, regulatory, and legislative sources incorporated to contextualize the synthesis (World Bank, Bank of England/FCA, Gallup/Edward Jones, TD Bank/Ipsos, McKinsey & Company, KPMG International, and the EU AI Act) were not subject to academic peer review; the survey-based sources reflect single-country or single-institution methodologies with response rates, sampling frames, and margins of error that vary by source, and are presented as corroborating market and regulatory context rather than as equivalent-quality evidence to the peer-reviewed academic sample.

3. Contextual and Generalizability Issues: Much of the literature surveyed applies to North America, Europe and some Asian markets, and the trust/financial governance results might not be extrapolable to other markets that have material differences in pre-existing regulatory frameworks and levels of financial inclusion.

Future Research Directions:

1. Theoretical Extensions: Future work should test the joint agency institutional framework proposed in Section 3.5 directly, examining whether governance maturity and explanation quality contribute independently, or interactively, to consumer trust.

2. Methodological Enhancements: Longitudinal and field-experimental designs are needed to establish how trust in algorithmic financial decisions evolves post-adoption, addressing the gap identified in Section 2.5 and building on early work by Diecidue et al. (2026).

3. Cross-Disciplinary Research Opportunities: Because governance research and consumer-trust research currently proceed largely in parallel (Section 2.4), there is a clear opportunity for cross-disciplinary work directly linking firm-level audit and governance maturity to consumer-level trust and adoption outcomes.

4. Emerging Contexts and Applications: Future research should extend this synthesis to emerging applications including generative-AI-based financial advisory tools and agentic transaction systems where the personalization, trust, and governance dynamics identified here are likely to intensify as systems gain greater autonomy.

Conclusion:

This review synthesizes the literature on AI-driven personalization, consumer trust, and algorithmic governance in financial services, and finds that the technology's efficiency and inclusion gains are well documented but the accountability infrastructure needed to sustain them is not yet mature: personalization measurably expands financial access but carries a documented risk of exploitative design, trust in algorithmic decisions tracks perceived institutional accountability more closely than technical accuracy or explanation quality, and explainability mandates alone do not guarantee improved consumer welfare once firms' strategic responses are taken into account. Explainability, therefore, will need to be treated as one part of a wider governance system, supported by ongoing audits, cross-jurisdictional norms and standards, and longerterm empirical research that explores how trust can be built in the wake of the use of algorithms.

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This is a descriptive study which is purely a review of literature on the existing and published secondary sources. It did not include human subjects, the collection of primary data, or animal use and hence did not require institutional ethics committee approval. No other conflict of interest is declared other than those stated above.

Data Availability Statement:

No new primary data were generated for this review and all information has been based on previous published literature. All 30 sources have been analysed and are public, available from each of their respective publishers and are cited with DOI if available in the References section.

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The author confirms that the preparation of the manuscript involved using a generative AI (Claude, Anthropic) tool to draft literature synthesis, check citations, and edit the text for language, in line with the policy of the journal. The AI tool is not listed as an author. The author has read, authorized and provided verification that all content that was created with the assistance of AI has been fact-checked with the original sources and is that of the author.

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