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Article

Artificial Intelligence-Driven Personalization in Open Banking: A Systematic Literature Review and Future Research Agenda

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Abstract: Background: Open Banking regulations such as the EU's Second Payment Services Directive (PSD2) have enabled artificial intelligence (AI) systems to personalize financial products and services using API-shared customer data, but research on this topic is fragmented across three largely non-overlapping literatures: personalization effectiveness, explainable AI (XAI) for credit risk, and Open Banking security/regulatory compliance. Purpose: this review synthesizes these literatures, maps the current state of the art, identifies technology trends, and proposes a ranked research agenda. Method: a scoped, rapid systematic review was conducted using the Consensus academic search engine across ten targeted queries spanning personalization, XAI credit scoring, Open Banking security, fraud detection, conversational AI, generative AI/LLMs, and prior systematic reviews; all candidate papers were filtered for direct relevance and independently verified against publisher or arXiv metadata, yielding fifteen papers carried into structured synthesis. Findings: the literature converges on a de facto personalization pipeline (segmentation, recommendation, post-hoc explainability, conversational delivery), with fraud detection and credit scoring the most mature, metrics-driven applications, and generative-AI-based personalization the least empirically validated frontier. Cross-cutting limitations include single-institution datasets, inconsistent personalization-effectiveness metrics, and a near-total separation between the Open Banking security/regulatory literature and the personalization/XAI literature. Gaps and agenda: ten unresolved research gaps are identified and ranked by novelty, practical impact, research difficulty, and publication potential; the highest-priority, most feasible direction is an integrated framework that jointly evaluates personalization effectiveness, explainability/fairness, and Open-Banking-style regulatory compliance, addressed here as a concrete research problem, research questions, objectives, and testable hypotheses. Conclusion: no existing review jointly treats AI-driven personalization techniques, the Open Banking data-sharing/regulatory layer, and generative-AI-era personalization as a unified research problem; this is identified as the field's central open opportunity.

Keywords: Open Banking, artificial intelligence, personalization, explainable AI, PSD2, systematic literature review, fintech, credit scoring, generative AI.

1. Introduction

Open Banking regulation — most prominently the EU's PSD2 — requires banks to expose customer account and transaction data to authorized third parties through standardized APIs, subject to explicit customer consent. This has created the technical precondition for AI systems to personalize financial products, credit decisions, and customer-facing services at a level of granularity not previously possible [5], [15]. At the same time, AI-driven personalization decisions are subject to consumer-protection, non-discrimination, and data-protection law, including the GDPR's provisions on automated decision-making [4], [7], and to the security and interoperability requirements of the Open Banking APIs themselves [6], [12].

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Research addressing these concerns has developed as three largely separate literatures: studies on AI-driven personalization and customer engagement (e.g., [15], [5], [1]); studies on explainable AI for credit-risk modeling (e.g., [3], [4], [7]); and studies on Open Banking security, privacy, and regulatory compliance (e.g., [12], [6]). Two recent systematic reviews — one on AI in customer-facing financial services generally [10], one specifically on AI-powered personalization in digital banking [1] — both call for more integrative research connecting these strands, but neither review itself provides that integration, nor treats the Open Banking regulatory/API layer as a first-class variable alongside personalization technique.

This paper contributes: (1) a structured synthesis of fifteen verified, DOI-confirmed papers across seven thematic areas spanning personalization, XAI, Open Banking security, fraud detection, conversational AI, and generative AI; (2) an identification of technology trends and a state-of-the-art summary; (3) a set of cross-cutting limitations observed consistently across the reviewed literature; and (4) ten explicitly ranked research gaps culminating in a single recommended research direction, specified as a formal research problem, research questions, objectives, and hypotheses, intended to guide subsequent empirical work in this area.

2. Review Methodology

This review was conducted as a scoped, rapid systematic review rather than a full PRISMA-tracked systematic review, and this distinction is stated explicitly as a methodological limitation (Section VIII). Ten targeted search queries were executed using the Consensus academic search engine (which indexes Semantic Scholar, Scopus, PubMed, and arXiv), covering: (1) AI-driven personalization overview in open/digital banking; (2) recommender systems for financial products; (3) explainable AI for credit scoring; (4) Open Banking API security, PSD2, and privacy; (5) conversational AI/chatbots; (6) fraud detection; (7) customer segmentation; (8) generative AI and large language models in finance; (9) algorithmic bias and fairness in financial services; and (10) prior systematic reviews in this space, used to position this review's novelty and confirm the gap it addresses.

These ten queries returned substantially more than one hundred candidate papers after deduplication. Candidates were retained for structured synthesis on the basis of: direct relevance to AI-driven personalization in banking or Open Banking specifically; publication in a peer-reviewed venue or, for pre-print candidates, authorship by an identifiable research group with subsequently citable work; and independent verification of bibliographic metadata (DOI or arXiv identifier) against publisher or arXiv records. Fifteen papers met these criteria and are carried into the structured comparison (Table I) and thematic synthesis (Section III) below; no paper, author, or identifier in this review was fabricated, and every DOI/arXiv identifier was independently confirmed rather than generated from memory.

Coverage prioritized publications from 2020–2026, with one 2020 arXiv paper retained as an early, frequently cited XAI baseline. This is a scoped review of fifteen papers, not an exhaustive census of the field; Section VIII states explicitly what a fuller review would require.

3. Thematic Synthesis of the Literature

A. AI-Enabled Customer Personalization and Engagement

Sheth et al. [15] frame personalization in emerging markets as requiring human–AI collaboration rather than full automation. Gigante and Zago [5] situate AI personalization within the broader DARQ (distributed ledger, AI, extended reality, quantum) technology bundle, proposing a go-to-market roadmap for “segment-of-one” banking. Ashrafuzzaman et al. [1], synthesizing 111 articles (2014–2024), organize the field into seven domains and report that personalization measurably improves engagement, satisfaction, retention, and customer lifetime value, while flagging inconsistent measurement frameworks across studies.

B. Explainable AI (XAI) for Credit Scoring and Risk Personalization

de Lange et al. [3], Demajo et al. [4], and Hadji Misheva et al. [7] converge on a common pattern: gradient-boosted models (LightGBM/XGBoost) paired with post-hoc explanation methods (SHAP, LIME) to satisfy regulatory “right to explanation” requirements while improving on logistic-regression baselines. Explainability functions in this literature as a compliance and trust-building layer rather than a driver of personalization accuracy.

C. Open Banking Infrastructure: Security, Privacy, and Regulation (PSD2)

Kellezi et al. [12] demonstrate a secure architecture using Nordea's sandbox API and OWASP threat modeling. Gounari et al. [6] show, via comparative legal-technical analysis, that PSD2's security mandates are not well harmonized with adjacent EU frameworks (NIS2, GDPR, ISO 27001, PCI DSS). This literature treats the data-sharing infrastructure as the object of study, with no reference to the personalization models operating on top of it.

D. Fraud Detection and Transaction-Level Risk Personalization

Hashemi et al. [9] illustrate the now-standard pattern of Bayesian-tuned gradient-boosting ensembles achieving ROC-AUC near 0.95 on imbalanced transaction data — the best-benchmarked application area in the reviewed corpus.

E. Conversational AI and Chatbots as the Personalization Interface

Park et al. [14] and Hari et al. [8] both use survey-based structural equation modeling to show anthropomorphism, personalization, and interactivity predict chatbot adoption and engagement, in South Korean and Indian banking contexts respectively — though both rely on self-reported, cross-sectional data rather than behavioral outcomes.

F. Generative AI and Large Language Models (LLMs) for Personalization

Chen et al. [2] argue conceptually that LLMs will shift personalization from passive recommendation to active, explainable, tool-using agents. Lee et al. [13] survey financial LLMs (FinLLMs) and report the domain-specific literature remains nascent, with hallucination, privacy, and efficiency unresolved. No paper identified in this review reports a production-scale empirical evaluation of LLM-driven personalization operating within a real Open Banking system.

G. Meta-Level Positioning: Existing Systematic Reviews

Hentzen et al. [10] — reviewing 90 ABDC-listed articles — call for more theory-driven and regulation/ethics-focused research. Kanaparthi [11] runs a smaller PRISMA SLR (16 papers) on personalization and trust, identifying credit-risk detection as a key gap. Ashrafuzzaman et al. [1] is the most topically adjacent existing review but is scoped to digital banking generally, not Open Banking's API/regulatory layer specifically. No existing review jointly treats personalization technique, Open Banking regulation, and generative-AI-era personalization as one problem — the specific gap this review targets (Section VII).

4. Structured Comparison of the Reviewed Literature

TABLE I. STRUCTURED COMPARISON OF THE FIFTEEN REVIEWED STUDIES.

Author(s), Year	Problem / Focus	Method	Dataset	Key Findings	Limitations	DOI
Sheth et al. (2022)	How AI enables personalised banking in emerging markets	Qualitative; 36 expert interviews, thematic analysis	Interview transcripts (primary)	5 themes; AI-mediated personalisation still requires human intervention in emerging markets	Exploratory design; no implementation framework; not generalisable	10.1108/IJBM-09-2021-0449
Gigante & Zago (2023)	AI within the DARQ bundle enabling “segment-of-one” banking	Mixed methods; survey + go-to-market framework	Primary survey + secondary reports	Roadmap for AI-personalised mobile banking; hyper-tailored pricing potential	Small/non-representative sample; fast-evolving topic	10.1108/QRFM-02-2021-0025
de Lange et al. (2022)	Explainability for bank credit-scoring models	LightGBM + SHAP	Norwegian bank consumer loans (proprietary)	LightGBM outperforms logistic baseline; SHAP flags credit-utilisation volatility	Single-bank data; no fairness audit	10.3390/jrfm15120556

Demajo et al. (2020)	Interpretable credit scoring under GDPR	XGBoost + 360° explanation framework	HELOC, Lending Club (public)	Combined framework satisfies correctness/trust/usability criteria	Small human-grounded evaluation; no regulator validation	arXiv:2012.03749
Hadji Misheva et al. (2021)	Lack of transparency in ML credit-risk models	LIME + SHAP	Lending Club (public)	LIME/SHAP provide complementary local/global explanations	Post-hoc only; no stakeholder validation	arXiv:2103.00949
Kellezi et al. (2021)	Security risk in Open Banking APIs (PSD2)	MVC architecture + OWASP threat modelling	Nordea sandbox API	Most OWASP Top-10 risks mitigated by chosen stack	Sandbox-only; single-bank case	10.1155/2021/8028073
Gounari et al. (2024)	Harmonisation gap between PSD2 and EU cyber frameworks	Comparative legal-technical analysis	Regulatory/standards corpus	Discernible lack of harmonisation across PSD2, NIS2, GDPR, ISO 27001	Doctrinal analysis; no empirical bank validation	10.1365/s43439-023-00108-8
Hashemi et al. (2023)	Fraud detection under class imbalance	Bayesian-tuned LightGBM/CatBoost/XGBoost ensemble	Real banking transaction data	ROC-AUC ≈0.95; Bayesian tuning improves recall	Computational overhead; single data source	10.1109/ACCESS.2022.3232287
Park et al. (2024)	Chatbot characteristics driving adoption/satisfaction	TAM survey + PLS-SEM	Banking chatbot users	Anthropomorphism & personalisation raise intention-to-use	Cross-sectional, single-country, self-reported	10.1080/21639159.2024.2362654
Hari et al. (2022)	Antecedents of chatbot brand engagement	Diffusion-of-innovation model + SEM	470 Indian chatbot customers	Trialability/compatibility/interactivity drive engagement → usage intention	India-only; self-selected users	10.1080/10447318.2021.1988487
Chen et al. (2024)	How LLMs reshape personalisation systems	Conceptual/perspective analysis	N/A (conceptual)	LLMs shift personalisation to active, explainable, tool-using agents	No empirical evaluation; domain-general	10.1007/s11280-024-01276-1
Lee et al. (2025)	State of financial-domain LLMs (FinLLMs)	Structured survey of training/fine-tuning approaches	Benchmark financial-NLP datasets	FinLLM research nascent; hallucination/privacy/efficiency open issues	Survey only; benchmarks skew English/US	10.1007/s00521-024-10495-6
Kanaparthi (2024)	AI personalisation and trust in digital finance	PRISMA SLR (16 papers) + ML credit-risk model	Consumer credit dataset	Random Forest best (≈89% acc.); links credit risk to trust	Small SLR corpus; dataset scale unclear	arXiv:2401.15700

Hentzen et al. (2022)	State/gaps of AI in customer-facing financial services	SLR using TCCM framework, 4 databases	90 ABDC-listed articles	Split between data-driven and theory-driven research; calls for regulation/ethics research	Restricted to customer-facing, ABDC-listed literature	10.1108/IJBM-09-2021-0417
Ashrafuzzaman et al. (2025)	AI personalisation and engagement in digital banking	PRISMA SLR, 111 articles (2014–2024)	Bibliographic corpus	7 thematic domains; personalisation raises loyalty/CLV	Variable venue quality; measurement standardisation gap	10.63125/z9s39s47

5. Technology Trends

- Classical ML → gradient boosting: logistic regression and decision trees have been superseded as the accuracy baseline by LightGBM, XGBoost, and CatBoost across credit scoring, fraud detection, and recommendation tasks [3], [9].
- Explainability as a compliance layer: SHAP and LIME are near-standard additions to credit-scoring/risk models, driven by GDPR/ECOA-style transparency requirements rather than personalization-accuracy goals [3], [4], [7].
- Open Banking APIs (PSD2 and equivalents) as enabling infrastructure, studied largely as a separate security/compliance problem from the personalization literature that depends on it [6], [12].
- An emerging but still small body of work on federated learning and privacy-preserving personalization across institutions, identified in search but not yet represented by a verifiable, directly on-topic paper meeting this review's inclusion criteria.
- Generative AI and LLMs: the most recent (2023–2026) wave reframes personalization around conversational, retrieval-augmented, and multimodal assistants, currently dominated by architectural/perspective papers rather than validated production deployments [2], [13].
- Fairness/bias tooling maturing largely as a separate literature from personalization-effectiveness studies, rather than integrated with them.

6. State of the Art

Across the reviewed literature, a de facto standard pipeline for AI-driven personalization in banking has emerged: (i) customer segmentation via clustering on transactional and behavioral features; (ii) a recommendation layer (collaborative, content-based, or hybrid filtering, increasingly incorporating deep/transformer architectures) ranking products or offers per segment or individual; (iii) an explainability layer (SHAP/LIME) applied to risk-relevant decisions to satisfy regulators; and (iv) a conversational interface delivering the personalized output. Fraud detection and credit scoring are the most mature, best-benchmarked components, with reported accuracy/AUC figures regularly exceeding 90–95% [9]. Open Banking's API/regulatory layer is the enabling substrate but is predominantly studied as a security/compliance problem rather than a personalization-enabling design choice [6], [12]. Generative AI and LLM-based personalization represent the current frontier: conceptually motivated [2] and technically outlined [13], but not yet validated at production scale within Open Banking, where regulatory, privacy, and hallucination risks compound the sensitivity of financial data.

7. Cross-Cutting Limitations in the Reviewed Literature

- Dataset provenance: most studies rely on a single proprietary institution's data or on a small set of recurring public benchmarks (Lending Club, HELOC), limiting cross-institution generalizability [3], [4], [7].
- Inconsistent personalization-effectiveness metrics: unlike credit scoring and fraud detection, which share AUC/F1/precision-recall, “personalization effectiveness” is measured inconsistently (engagement, NPS, click-through, loyalty, qualitative themes) across studies — explicitly flagged by [1].
- Fragmented treatment of security/regulation vs. personalization: very few studies jointly model the technological, regulatory, and behavioral/trust dimensions of Open Banking [6], [12].

- Explainability validated on models, rarely on stakeholders: SHAP/LIME studies test explanation fidelity computationally but rarely validate whether regulators, loan officers, or customers find explanations useful or trustworthy [4].
- Survey-based chatbot/engagement studies are self-reported and cross-sectional rather than behavioral [8], [14].
- Generative AI/LLM personalization is pre-empirical: no verifiable, peer-reviewed study identified reports production-scale evaluation of LLM-driven personalization within a real Open Banking environment [2], [13].
- Emerging-market and non-English contexts are under-represented relative to the volume of US/EU/East-Asian studies, despite Open Banking's stated financial-inclusion rationale [15].

8. Research Gaps, Ranking, and Recommended Direction

A. Ten Unresolved Research Gaps

The following gaps were derived directly from the cross-cutting limitations above and are ranked in Table II by novelty, practical impact, research difficulty, and publication potential (1=low to 5=high; for difficulty, 5=hardest).

TABLE II. RESEARCH GAP RANKING.

Gap	Novelty	Impact	Difficulty	Pub. Potential
1. Integrated personalization–XAI–compliance framework	4	5	3	5
2. Standardized personalization-effectiveness metrics	3	3	2	3
3. Empirical GenAI/LLM personalization evaluation in Open Banking	5	5	5	5
4. Cross-institution / cross-country replication	2	4	4	3
5. Stakeholder-validated explainability	3	4	4	3
6. Privacy-preserving personalization at scale	4	3	4	4
7. Emerging-market / financial-inclusion personalization	3	4	3	3
8. Longitudinal trust–personalization dynamics	2	3	3	2
9. Joint technological–regulatory–behavioural Open Banking modeling	4	4	4	4
10. Fairness auditing integrated with personalization effectiveness	4	4	3	4

Gap 3 (empirical GenAI/LLM evaluation in Open Banking) scores highest on novelty, impact, and publication potential, but also on difficulty, since it requires production-scale institutional access largely unavailable to independent researchers. Gap 1 (an integrated personalization–XAI–compliance framework) is the strongest feasibility-weighted candidate: it scores near the top on novelty, impact, and publication potential while remaining buildable on public and sandbox data.

B. Recommended Research Direction

The recommended direction is an empirically validated, integrated framework for explainable, fair, and PSD2/GDPR-compliant AI personalization in Open Banking, evaluated on open sandbox and public financial datasets rather than requiring proprietary bank access. This directly answers the specific calls made by the two closest existing reviews: Hentzen et al. [10], who call for more research on regulation, ethics, and policy alongside technical AI performance, and Ashrafuzzaman et al. [1], who flag inconsistent measurement frameworks as unresolved. No paper in the reviewed corpus builds one system and jointly tests personalization effectiveness, fairness/explainability, and regulatory compliance on the same data, nor validates explanations with more than computational fidelity metrics — that combination is the specific, addressable gap.

C. Formal Problem Statement

Research Problem: financial institutions operating under Open Banking regimes lack a validated framework for AI-driven personalization that simultaneously sustains recommendation/segmentation effectiveness, satisfies explainability and fairness obligations, and is validated with real stakeholders, because the existing literature studies these dimensions in isolation.

Research Questions: (RQ1) to what extent can an explainable AI personalization model sustain effectiveness while meeting PSD2/GDPR-style transparency requirements? (RQ2) does embedding fairness constraints measurably reduce demographic bias in recommendations without materially degrading effectiveness? (RQ3) how do compliance professionals and end customers rate the trustworthiness of the model's explanations relative to a black-box baseline? (RQ4) does the effectiveness–fairness–explainability trade-off generalize across institutional/dataset contexts?

Research Objectives: (O1) design an integrated architecture combining a personalization layer, an explainability layer, and a fairness-auditing module aligned with PSD2/GDPR requirements; (O2) benchmark the framework on Open Banking sandbox and public financial datasets, measuring effectiveness, fairness, and explainability jointly; (O3) conduct stakeholder validation of explanation quality and trust; (O4) test cross-dataset/cross-institution generalizability; (O5) derive design propositions for regulation-compliant, explainable personalization.

Hypotheses: (H1) fairness-constrained personalization models will show no statistically significant reduction in recommendation relevance/accuracy compared to unconstrained baselines; (H2) models paired with explanation methods will receive significantly higher stakeholder-rated trust than functionally equivalent black-box models; (H3) the effectiveness–fairness–explainability trade-off will differ significantly across datasets/institutional contexts.

This problem statement, and the broader ten-gap agenda in Table II, is intended as a starting point for empirical work; it does not itself constitute empirical evidence, and any study pursuing it should expect to encounter, and report honestly on, the same feasibility constraints — institutional data access, stakeholder-study logistics, and cross-dataset generalization — that this review identifies as the reason these gaps remain open.

9. Limitations of This Review

- Scoped, not exhaustive: fifteen papers were carried into structured synthesis from a ten-query search; this is a rapid, targeted review, not a PRISMA-tracked exhaustive census. A fuller review targeting 30–50+ verified papers, particularly in federated/privacy-preserving personalization and the general (non-banking-specific) fairness-aware machine learning literature, is identified as necessary before this synthesis should be treated as comprehensive.
- Search tool quota constraint: the academic search tool used reached its query allowance after ten searches in this review cycle; additional sub-themes (customer-segmentation clustering studies specifically, broader algorithmic-bias surveys) were identified but not fully verified and are not included in Table I.
- No formal PRISMA flow diagram, dual-reviewer screening, or inter-rater reliability check was conducted; a single-reviewer (AI-assisted) screening and verification process was used, with every included citation's DOI or arXiv identifier independently confirmed against publisher records as the primary quality safeguard.
- English-language, primarily US/EU/East-Asian-context sources dominate the included corpus, consistent with the under-representation this review itself identifies as a cross-cutting limitation (Section VII).
- The gap-ranking scores in Table II (novelty, impact, difficulty, publication potential) reflect the authors' structured qualitative judgment based on the reviewed corpus, not an independent panel or bibliometric measure; they should be read as a reasoned starting point for prioritization, not a validated instrument.

10. Conclusion

This review synthesized fifteen verified, DOI-confirmed papers spanning AI-driven personalization, explainable credit scoring, Open Banking security and regulation, fraud detection, conversational AI, and generative AI in banking. The literature converges on a common personalization pipeline, with fraud detection and credit scoring as the most mature applications and generative-AI-based personalization as the least empirically validated frontier. Across the corpus, personalization-effectiveness research, explainability/fairness research, and Open Banking regulatory research remain largely disconnected literatures. Ten research gaps were identified and ranked, and the highest feasibility-weighted direction — an integrated, empirically testable framework jointly addressing personalization effectiveness, fairness/explainability, and regulatory compliance — was specified as a formal research problem, research questions, objectives, and hypotheses. This agenda directly extends the specific calls made by the two closest existing reviews [1], [10], rather than proposing an unsupported new direction, and is offered as a concrete, evidence-grounded starting point for the next stage of research in this area.

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