Impact of Artificial Intelligence on FinTech Innovation and Customer Experience

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Abstract

AI has become an essential tool in financial technology due to its ability to make data-driven decisions, ensure continuous access to services, foresee risks, and now personalize service interactions. But the discussion about efficiency has shifted to a harder question: What will be necessary for AI to lead to real innovation in the FinTech business and also to enhance the customer experience without compromising trust, fairness and transparency? This research will answer that question by conducting an original secondary-data empirical study utilizing a structured content analysis of 30 recent articles published in 2021-2026, mostly peer-reviewed journal articles, along with a few authoritative policy reports. Google Scholar-indexed search was conducted to identify the corpus and then coded in terms of the application domain, the innovation mechanism, outcome of the customer experience, methodological designing, trust and transparency factors, and risk and governance issues. Based on these results, five segments have the highest innovation impact for AI—credit scoring and underwriting, fraud detection and digital onboarding, conversational service and self-service systems, robo-advisory, and regulatory technology. In the coded corpus, AI's transformative advantages were most clearly perceived with respect to speed, convenience, personalisation and increased access, subject to transparency, perceived control, institutional trust and blended human oversight. Best outcomes for customer experience were found in low friction, repetitive, and information-rich transactions, and highest risks were identified in ambiguous credit decisions, intrusive data collection and usage, and over-automated service transactions. The study thus concludes that the effect of artificial intelligence in FinTech is not fully captured by the intensity of adoption, but rather by the algorithmic capability, combined with the governance quality, and the customer-centric design. The results provide a research-informed synthesis that can serve the purpose of doctoral research by transforming the concept of an artificial intelligence from merely a tool for automation to a contingent IA for which the value for the customers depends on its explainability, ethical regulations, and context-sensitive design..

Keywords: *Artificial Intelligence (AI), Financial Technology (FinTech), FinTech Innovation, Customer Experience, Machine Learning, Digital Banking, Customer Satisfaction, Financial Services, Fraud Detection, Personalized Financial Services.*

Introduction

The modern FinTech industry is characterized by the combination of software, data systems, platform business models and financial intermediation. AI has fueled that change by enabling the automation of learning from alternative data, predictive risk in real time, suspicious transaction analysis, personalised touchpoints and financial recommendations at scale. International policy institutions and academic analyses have recently reached a shared view: AI is no longer a side activity within the financial system, but rather affects capital-market activities, lending, customer acquisition, compliance and financial inclusion (Aldasoro et al., 2024; Bahoo et al., 2024; World Economic Forum, 2025).

Artificial Intelligence has a particularly important role in the FinTech space, because digital-native companies do not engage in competition based on the number of branches or the legacy incumbent's organizational framework, but rather on speed, data richness and service redesign. Machine learning models and alternative data sources have enhanced the ability to lend and revolutionized the inference of creditworthiness in lending. For fraud prevention, intelligent systems are now analyzing behavioral clues, event logs and transactional irregularities that are missed by rules-based systems. AI-powered chatbots, self-service platforms, and robo-advisors have revolutionized customer interface management, changing customer expectations for response times, availability, and personalization. Meanwhile, the same literature reveals that the benefit to the customer is not a given. Low trust or reluctance to use the model could result from opaque models, unclear accountability, privacy issues, and perceived unfairness, particularly in high-stakes scenarios like lending or investment counseling (Montagnani et al., 2024; Devlin et al., 2025; Fundira & Mbohwa, 2025; Balaskas, 2026).

This paper adopts the approach of a research paper and rather than a narrative review, it performs a structured empirical analysis of a defined literature corpus. The main research question of the paper is whether artificial intelligence's influence is mostly positive or negative on the innovation and customer experience of the FinTech sector and how or under which conditions. Researched and directed by the following analytical questions. What are some key transformative developments in FinTech innovation where AI has made substantial contributions in scholarship over the last year? Second, what are the outcomes of those innovations that are consistently linked with customer experience? Third, what conditions of governance, trust and transparency enable the positive or negative impact of artificial intelligence on customer outcomes? The study aims to provide a doctoral-level synthesis that transcends technological enthusiasm and delves into how AI reshapes the production process of financial services while simultaneously changing the nature of customer experience (Ameen et al., 2021; Roy & Vasa, 2024; Scherer & Lehner, 2025; Chen et al., 2026).

Literature Survey

The literature shows that AI brings two general benefits to the FinTech innovation. The first is process innovation, which involves quicker, more precise delivery of current financial processes like scoring, fraud checking, onboarding and monitoring. The second is service innovation - innovation of customer-facing services like conversational banking, robo-advisory, dynamic personalisation and platform-based financial guidance. According to the large literature syntheses, the application families that are still dominant in the field of finance are predictive systems, on the one hand, and classification and detection systems, on the other hand, and the current wave also brings the addition of generative and explainable capabilities to the existing machine-learning pipelines (Bahoo et al., 2024; Roy & Vasa, 2024; Aldasoro et al., 2024).

One of the areas with the most research and development is the issue of credit assessment. Research on FinTech lending indicates that machine learning and alternative data can enhance the predictive power, expand access to thin-file and previously marginalized borrowers, and enable innovative lending business models. According to Tigges et al. (2024), the integration of AI and alternative data into FinTech lending has been linked to enhanced predictive capabilities, reduced default risks, real-time credit evaluation, and increased access to credit. However, the authors also highlight ethical issues concerning consent, bias, traceability, and data misuse. Gambacorta et al. (2024) also find that the non-traditional data machine-learning models are superior to the traditional models, especially in adverse conditions, for a Chinese FinTech firm. In a progressive step, Xia et al. (2025) implement credit risk design with a large language model, revealing that the narrative data extraction approach can enhance the predictive ability of the credit rating model, while interpreting the model using the SHAP method retains the interpretability of the model. In summary, these studies indicate that AI is transforming underwriting practice beyond mere data analysis, impacting the very definition of 'what's credit-worthy information' (Xia et al., 2025; Gambacorta et al., 2024; Tigges et al., 2024).

The second large stream of literature is on fraud prevention and compliance. Digital onboarding and online banking spaces produce a complex event trail, in which adaptive models have a greater capability to capture fraudulent behaviour than static rules. In the context of an actual FinTech event log, Da Silva et al. (2023) show that the use of process-mining techniques can achieve high accuracy for legitimate and fraudulent users classification, and expose the vulnerabilities in the process that can be further exploited by users. Natural-language-processing approaches outperform traditional approaches that rely on features, and can maintain privacy more effectively when used for extracting action sequences from online and mobile banking, according to Boulieris et al. (2024). Teichmann et al. (2023) highlight that technology-driven compliance serves to improve efficiency and reduce costs, whereas Wang and Chen (2024) argue that data analytics, long-term customization, and business-model design with the stakeholders in mind are key to RegTech's success. The results confirm that A.I. is driving innovations at the core of FinTech's operational activities, reducing the "marginal cost" of vigilance, detection and compliance execution (da Silva et al., 2023; Boulieris et al., 2024; Teichmann et al., 2023; Wang & Chen, 2024).

The third stream is concerned with innovations in customer interface. Ameen et al. (2021) demonstrate that perceived convenience, personalization, trust, and relationship commitment are key to better AI experience customer experience. Bhatnagr et al. (2024) reveal that personalisation, anthropomorphism and perceived control enhance the online customer experience and intention to recommend, while perceived risk decreases these. In banking-specific contexts. The levels of understandability, automation, competence, personalization, interaction, and intimacy of chatbots influence the customer satisfaction and continuance intention, with the negative effect of intrusiveness on the intrinsic value of chatbots (Nguyen & Le, 2025). Similarly, Zungu et al. (2025) found that personalization and convenience greatly improve the self-service customer experience with AI, and trust has an impact on subsequent results like brand attachment. Hence, the findings reveal that the benefits of customer experience more relate to the ease, usefulness, responsiveness, and nonobtrusiveness of the AI system than to its novelty itself (Ameen et al., 2021; Bhatnagr et al., 2024; Nguyen & Le, 2025; Zungu et al., 2025).

Research is furthering the trust factor of Customer Experience with Robo-advisories. Luo et al. (2024) conclude that performance efficacy, privacy protection, corporate reputation and ease of use all foster trust and adoption intent, but that experienced investors are more trust-driven, whereas less experienced investors are more value-driven. While commercial robo-advisors emphasize simplicity and customer perceptions, the literature suggests there is a trade-off between technical optimality and mass-market usability, as suggested by Scherer and Lehner (2025). S. Cao et al. (2025) point out that technology trust, firm-specific trust, and system trust are all different types of drivers that influence acceptance of robo-advisory, while S. Chen et al. (2026) find that autonomy, intelligence, interpretability, interactivity, and structural assurance all contribute to trust formation. As shown in this stream, customer experience of AI-based financial advice is inextricably linked with the concept of trust architecture: The service's functionality does not suffice if it is not interpretable, socially legitimate and institutionally anchored (Luo et al., 2024; Scherer & Lehner, 2025; Cao et al., 2025; Chen et al., 2026).

The last cross-cutting theme is about ethics, explainability and financial inclusion. Devlin et al. (2025) suggest that trust, as a construct, is vital in the context of FinTech but has not been sufficiently theorized, particularly in light of the changes in trustee relationships with the advent of big data and AI. In banking, the ethical concerns of AI have taken shape around data privacy, algorithmic bias, fairness, transparency, and regulatory oversight, as illustrated by Fundira and Mbohwa (2025). By raising the issue of disclosure and explainability, specific to consumer-facing FinTech, Balaskas (2026) refines the argument by considering not only how disclosure and explainability affect uptake, but also how they affect the calibration of trust. The discussion keeps going on inclusion, with Subramaniam et al. (2025) and Kshetri (2021) suggesting that AI can help to broaden inclusion by reducing information frictions, and by enabling digital financial channels, if infrastructure, information literacy, and governance can match up. There is therefore a conditional interpretation that can be drawn from the literature – AI can provide more innovation and inclusion, but this requires transparency and governance to match with predictive capability (Devlin et al., 2025; Fundira & Mbohwa, 2025; Balaskas, 2026; Subramaniam et al., 2025; Kshetri, 2021).

Research Methodology

The research design used in this study is the document-based empirical research design which is based on structured content analysis. The unit of analysis is the published study, which does not refer to the individual respondent or firm. The approach was chosen as the research question is related to the pattern of evidence that emerges over a span of an evolving body of work, not a particular institution. A design like this is suitable when the field is growing quickly, primary data is spread out across countries and platforms, and you are building theory based on finding similar mechanisms across different, and sometimes disparate, empirical contexts (Bahoo et al., 2024; Roy & Vasa, 2024; Fundira & Mbohwa, 2025).

The source corpus was built by searching the Google Scholar repository using the search terms: “artificial intelligence” and “FinTech” and “customer experience” and “credit scoring” and “robo-advisory” and “chatbots” and “fraud detection” and “RegTech” and “financial inclusion” and “trust” and “explainability,” on July 2–3, 2026, under Google Scholars. The sources focused on recent publications (2021 and later), sources that were directly relevant to FinTech or very closely related to digital financial services, and sources that could be obtained from reputable journal publishers or authoritative institutional outlets. A set of 30 sources was the final corpus. Twenty-seven peer-reviewed journal articles and three institutional reports (BIS, World Bank and World Economic Forum) were included to reflect macro-level developments and policy frameworks that are also of important significance to the FinTech environment (Aldasoro et al., 2024; Klapper, 2024; World Economic Forum, 2025).

All sources were manually coded on six variables: main application field of the source, main innovation mechanism, customer experience outcome, methodological design, conditions of trust and transparency, and risk/governance issues. Single or multi labelling was possible. For instance, a robo-advisory study could be classified as a “wealth tech” study, a “trust” study and a “customer experience” study. The material was then coded in initial coding and subsequently clustered into six analytic clusters: credit scoring and underwriting, fraud detection and digital onboarding, conversational AI and self-service, robo-advisory and wealth technologies, ethics/trust/explainability, and inclusion/ecosystem effects. Frequency analysis then produced descriptive tables and figures, and interpretive comparison was then used to discuss the differences in outcomes of innovation and experience depending on the type of application. The original results are generated by the results below—counts, distributions, and integrative judgments—performed on the study's own coding of the defined corpus, as opposed to them being copied from any single review (Tigges et al., 2024; Chen et al., 2026; Balaskas, 2026).

Three safeguards were employed to enhance the analytical validity. First, the focus was on the recency aspect, so as to ensure that the present and recent developments on generative, explainable and regulatory aspects are covered. Second, the innovation studies were all kept, including the customer-facing ones as well as the back-end ones because the customer experience of FinTech products is also driven by invisible operational systems, as well as visible interfaces. Third, adverse findings were given equal weight to beneficial findings, to keep issues of trust erosion, privacy concerns and bias risks analytically salient but not lost amidst efficiency stories. The design is also not causal measurement per se in the econometrics sense but rather generates evidence as pattern detection and interpretation throughout the current research arena. While this is recognised, it does not diminish the value of the study for theory development and doctoral synthesis as the study has a purpose of identifying conditions under which AI is more likely to create a lasting value for customers within the FinTech space (Montagnani et al., 2024; Devlin et al., 2025; Fundira & Mbohwa, 2025).

Results and Discussion

Research activity has indeed picked up considerably after 2023, reflecting in the coded corpus. The majority of the analyzed material dates back to 2024 and 2025, reflecting a growing engagement with the topic as AI tools like generative AI, explainable AI, and policies came under increased policy review. Significantly, the massing of studies in those years was not restricted to technical research. It also featured legal analysis, adoption-focused trust building, as well as research into the customer experience, indicating a shift of focus from the narrower question of “can AI optimize finance?” to “how can AI change the nature of financial service relationships?” (Bahoo et al., 2024; Devlin et al., 2025; Balaskas, 2026).

Table 1 presents the descriptive profile of the analyzed corpus.

Profile of the analyzed source corpus	Number of studies
Survey, SEM, or adoption modeling	7
Qualitative interview or mixed-method design	3
Modeling, classification, or transactional analytics	5
Systematic review, bibliometric review, or structured synthesis	9
Legal, policy, or governance analysis	6
Total	30

Table 1 reveals that the field is methodologically plural and does not seem to be dominated by one design. The studies are predominantly survey-based for customer-experience studies, but transactional or model-based for underwriting and fraud studies. The governance and trust questions are overrepresented in the review and legal-analysis format, as it is hard to get standardized real-world data on explainability, harm to customers, and accountability of institutions. Substantively, the evidence base for efficiency gains is more robust than the evidence base for long-horizon customer welfare, which is a research gap that can be pursued in the future for doctoral studies (Ameen et al., 2021; Gambacorta et al., 2024; Fundira & Mbohwa, 2025).

Figure 1 visualizes the publication distribution in the coded corpus.

Figure 1. Studies in the coded corpus by publication year

The debate itself is influenced by a second generation AI-in-finance agenda, as this is the theme of the concentration for 2024-2026. Previous research has concentrated on accuracy and automation, whereas more recent research has given more weight to the notions of trust transfer, explainability, governance, and customer perception. This change is especially apparent in the areas of research on robo-advisory, customer-interface, and AI-ethics, where barriers to adoption cannot be reduced to mere functionality (Cao et al., 2025; Chen et al., 2026; Fundira & Mbohwa, 2025; Balaskas, 2026).

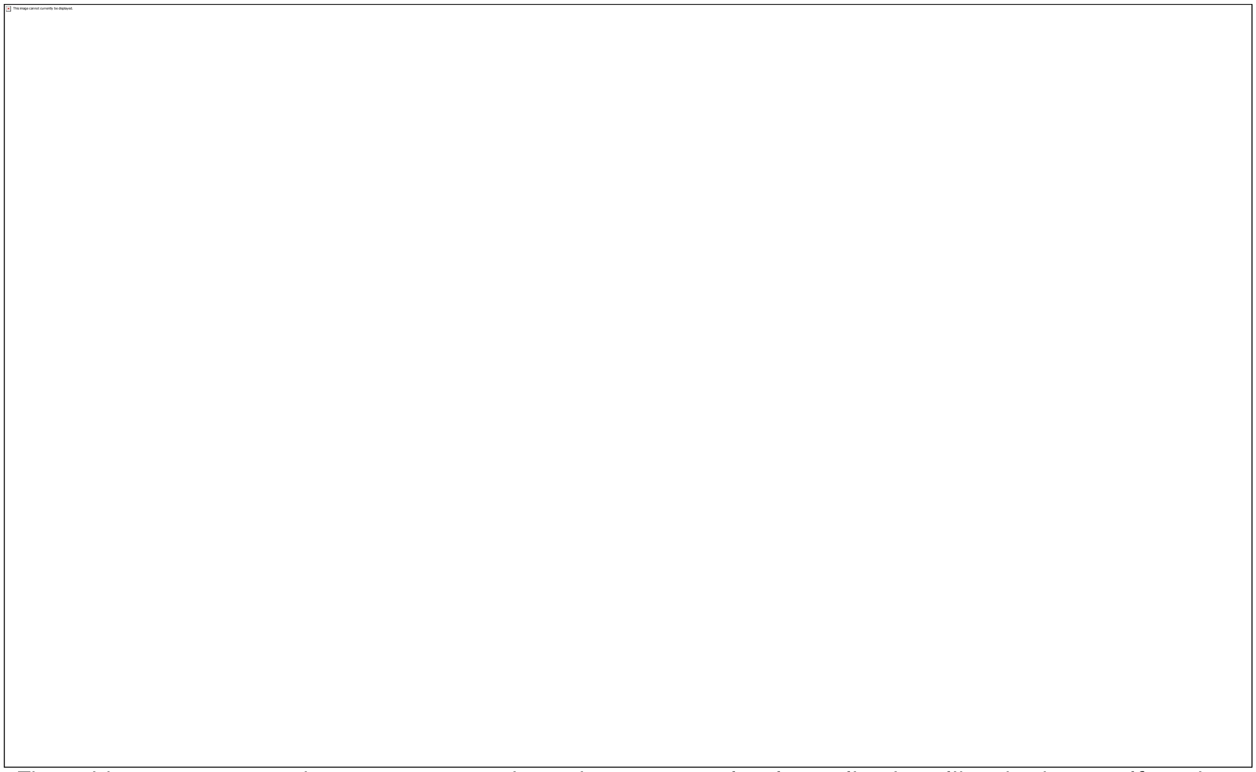
Table 2 summarizes the primary application domains and coded innovation effects.

Primary AI application domains and dominant innovation effects	Number of studies	Dominant innovation effect
Credit scoring and underwriting	6	Faster decisions, broader data use, improved risk prediction
Fraud detection, digital onboarding, and AML-adjacent monitoring	6	Better anomaly detection, real-time vigilance, lower fraud exposure
Conversational AI, chatbots, and self-service banking	5	Always-on service, lower response friction, personalization
Robo-advisory and AI-enabled investment support	5	Scalable advice, lower advisory cost, portfolio guidance
Trust, explainability, ethics, and governance	5	Trust calibration, disclosure, accountability, fairness framing
Inclusion and digital finance ecosystem effects	3	Access expansion, lower information frictions, outreach to underserved users

Innovation activity is most pronounced in credit scoring and fraud management, perhaps not surprisingly, as these are data-intensive, repeatable, high volume financial activities. Where the focus is on pattern recognition at speed, as opposed to relational nuance, AI has proven most effective, the evidence shows. Gambacorta et al. (2024) demonstrate improved prediction when stressed and Xia et al. (2025) demonstrate that new language-model workflows can augment lending data and keep it interpretable. At the same time, da Silva et al. (2023) show how process mining and natural-language-processing techniques can have a tangible impact on fraud-related detection and on the manual workload. Boulieris et al. (2024) confirm the same. For this reason, these regions are the most advanced areas of AI-driven FinTech innovation at present, in the corpus analyzed (Gambacorta et al., 2024; Xia et al., 2025; da Silva et al., 2023; Boulieris et al., 2024).

Figure 2 shows the distribution of application domains across the corpus.

Figure 2. Distribution of coded AI application domains



The evidence to support the customer experience is more complex. In applications like chatbots, self-service, and robo-advisory, it is not enough that the job is completed, but that customers feel intelligible, in control, personalized, and assured by the institutional aspect. Bhatnagr et al. (2024) demonstrate that intention to recommend is significantly related to online customer experience, and Nguyen and Le (2025) found that even with high functional competence, intrusiveness decreases chatbot value. While personalization and convenience will continue to play an important role in the experience of AI-enabled self-service, aesthetics alone will not be enough, state Zungu et al. (2025). The study findings from robo-advisory are that trust is not only a first-order adoption condition but also appears as a first-order adoption condition for more experienced investors, or for services that involve uncertainty or value commitments in the long term (Bhatnagr et al., 2024; Nguyen & Le, 2025; Zungu et al., 2025; Luo et al., 2024).

Table 3 consolidates the coded customer-experience outcomes.

Coded customer-experience outcomes across the source corpus	Positive evidence	Cautionary evidence
Speed and convenience	18	2
Personalization and relevance	14	3
Trust and assurance	12	10
Inclusion and accessibility	9	3
Privacy, fairness, and non-intrusiveness	2	15

Table 3 is analytically revealing in that the strongest positive outcomes are in different dimensions as are the strongest cautionary outcomes. AI-driven FinTech systems offer a range of benefits, including speed, convenience, and personalization. In contrast, the issues of privacy, fairness and overreach are the most recurring issues. In between is trust, which can grow if transparency is high, structural assurance is high, and the institutions are reputable, but can erode when decisions are opaque or when people feel like they're being replaced by automation. This pattern helps in a mediated interpretation of impact. The most reliable applications of AI to enhance the customer experience are in situations where there is little risk and little friction. It becomes more competitive in higher stakes decisions, like lending, pricing credit and investment recommendations, and identity sensitive decisions (Ameen et al., 2021; Cao et al., 2025; Chen et al., 2026; Devlin et al., 2025; Balaskas, 2026)..

Figure 3 illustrates the balance between positive and cautionary customer-experience evidence.

Figure 3. Positive versus cautionary evidence by customer-experience dimension

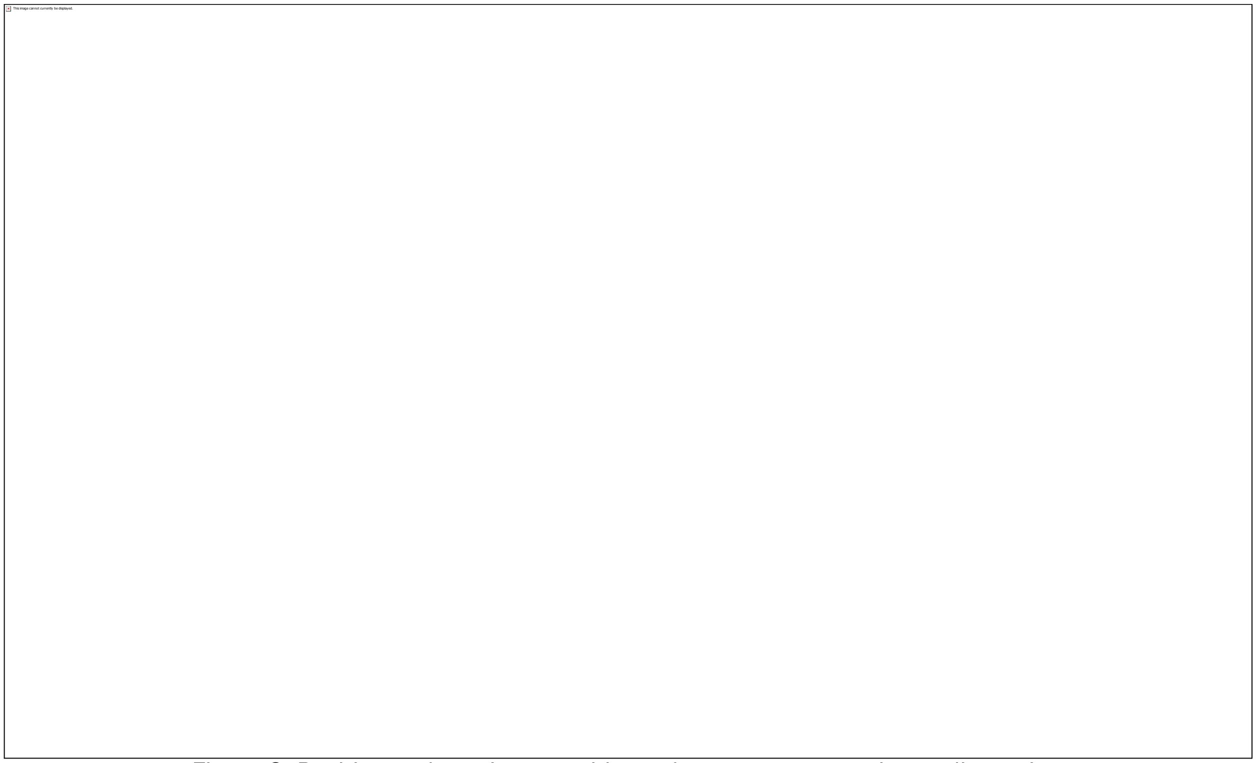


Figure 3. Positive and cautionary evidence by customer-experience dimension

The next discussion that follows from figure 3 is at the heart of the contribution of this paper. It is important to note that the impact of AI in FinTech can't be gauged as being either good or bad. Rather, the evidence suggests a complex multiple impact cratering event. The impact of AI at the operational level is consistently enhanced by improvements in speed, scale, and pattern recognition. It can help to minimize friction and increase relevance at the service layer. But at the relational level, performance is not enough: it is trust that requires interpretability, fairness, disclosure, governance and perceived control. This is why in the Chatbot context, the same technology obtains high recommendation intent, in the Robo-advisory context, it gets great adoption gains when it is presented in a trusted context, and in the Banking-governance context, it gets high ethical concerns (Bhatnagr et al., 2024; Chen et al., 2026; Montagnani et al., 2024; Fundira & Mbohwa, 2025).

The corpus also indicates that the hybridization is approaching a balance. However, Bhatnagr et al. (2024) mention that humans are still preferred in more complex banking situations. Cao et al. (2025) find that even when digitally capable, hybrid robo-advice models with assisted human advice are preferred. Scherer and Lehner (2025) found that commercial robo-advisors give advice in a way that makes it easy to understand and appealing to a wide audience. The findings suggest that successful innovations in FinTech do not necessarily render human intermediation obsolete, but shift it to the exception handling, reassurance, explanation and relationship repair. In this regard, customer experience is improved not by eliminating humans at any cost, but by shifting the use of human expertise to the most mistrusted or least readable places for AI (Bhatnagr et al., 2024; Cao et al., 2025; Scherer & Lehner, 2025).

Last but not least, the inclusion literature moderates the notion that AI-powered FinTech equates to finance democratization. Subramaniam et al. (2025) report positive cross-country effects of AI on financial inclusion, while Kshetri (2021) visualizes AI as a means to increase access in developing settings. However, these gains will rely on digital infrastructure, consumer awareness, data rights, and institutional confidence. Klapper's World Bank paper backs this up, finding that digital finance has the potential to increase the number of accounts and payments, but also that it comes with risk of fraud, over-indebtedness and disclosure issues. Thus, the role of AI in customer experience in inclusive FinTech is not to only be access-only but also an access-plus-protection issue (Subramaniam et al., 2025; Kshetri, 2021; Klapper, 2024).

Conclusion

This study aimed to analyze the relevance of AI in Fintech innovation and customer experience by analyzing 30 recent sources in a structured empirical way. The findings lead to three generalizations. In the first place, AI is already a key innovation driver in the FinTech industry and has been most influential in credit scoring, fraud detection, digital onboarding, customer self-service, robo-advisory and regulatory-tech solutions. Secondly, there are real but mixed effects on the customer experience. Improved speed, convenience, personalisation and access to scalable services are the benefits that are most consistent. Third, because the benefits of such technologies are dependent on social and institutional, rather than just technical, mediation—explainability, transparency, and protection of privacy, structural assurance, fairness safeguards, and continued availability of human support in complex or high-risk moments (Gambacorta et al., 2024; Xia et al., 2025; Bhatnagr et al., 2024; Chen et al., 2026; Balaskas, 2026)—are matters that must be considered.

The conceptualization of AI in FinTech is theoretically not the same as a standalone technology variable. It has a relational and configurational impact. AI innovates when it becomes part of a data-rich process that incentivises adaptive learning, and it contributes to better customer experience only if the customers can understand, trust and challenge the results in an accountable service processes. The future viability of FinTech competitions will hinge more on creating trustworthy AI-service assemblages that both are predictive and intelligible and also ethically compliant. Considered in terms of practice, it is pertinent to highlight the importance of explainable underwriting, privacy-enhancing personalization, human-in-the-loop escalation for sensitive cases, and transparent disclosure strategies that balance trust and not simply maximize trust (Devlin et al., 2025; Fundira & Mbohwa, 2025; World Economic Forum, 2025).

There are some limitations of the study. Since the design is coded on published sources, it is not possible to measure the actual causal magnitudes or compare firms based on a harmonized data set. There is also a geographically uneven evidence base, with a large number of studies falling within particular national settings and/or types of service. However, these constraints do not detract from the main contribution. The authors prove that artificial intelligence can affect the innovation process and the customer experience in FinTech in terms of conditional, domain-specific, and governance-dependent. That finding is sound, useful and well-grounded in the state of the research literature.

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