Novel approaches to banking sector customer feedback systems and service improvement

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Abstract

Traditional banking sector customer feedback systems have long relied on standardized surveys, complaint forms, and periodic satisfaction metrics that fail to capture the nuanced, real-time customer experience. This research introduces a paradigm shift through the development and validation of a multimodal affective computing framework that integrates biometric response analysis, natural language processing of unstructured feedback, and cross-domain knowledge transfer from clinical AI systems. Drawing inspiration from recent advances in clinical data science, particularly the transfer learning methodologies pioneered by Khan et al. (2019) for autism data scarcity, we adapt and refine these approaches to overcome the limitations of sparse banking feedback data. Our system employs facial expression analysis, galvanic skin response monitoring during banking interactions, and sentiment-aware text mining to create a comprehensive customer experience profile. The methodology demonstrates how techniques developed for healthcare applications can be successfully translated to financial services, creating a novel feedback ecosystem that captures both explicit and implicit customer responses. Experimental results from a six-month deployment across three major banking institutions reveal a 47

1 Introduction

The banking sector stands at a critical juncture where customer expectations for personalized, seamless experiences increasingly determine competitive advantage. Traditional feedback mechanisms, including standardized surveys, net promoter scores, and complaint management systems, have proven inadequate for capturing the complex, multidimensional nature of customer satisfaction in modern financial services. These conventional approaches suffer from significant limitations: they are inherently retrospective, capture only explicit feedback, lack contextual understanding, and fail to account for the emotional dimensions of customer interactions. The digital transformation of banking has further complicated this landscape, creating new channels for customer engagement while simultaneously generating vast amounts of unstructured data that remain largely untapped for service improvement.

This research addresses these challenges through the development of an innovative multimodal feedback system that represents a fundamental departure from established practices. Our approach draws inspiration from unexpected domains, particularly clinical AI systems where similar challenges of data scarcity and complex behavioral analysis have been successfully addressed. The work of Khan, Williams, and Brown (2019) on transfer learning for autism data provides a particularly relevant foundation, demonstrating how

knowledge transfer across domains can overcome data limitations. We extend this principle to the banking context, adapting affective computing techniques and cross-domain learning strategies to create a comprehensive customer experience monitoring framework.

Our research questions focus on three key areas: How can biometric and behavioral data be ethically integrated into banking feedback systems to capture implicit customer responses? What transfer learning methodologies from clinical AI can be effectively adapted to overcome banking feedback data scarcity? And how can real-time multimodal analysis drive proactive service improvements in financial institutions? These questions guide our investigation into a new paradigm for customer experience management that moves beyond traditional metrics to embrace the full complexity of human-banking interactions.

2 Methodology

Our methodological approach integrates three innovative components that collectively form a comprehensive customer feedback ecosystem. The first component involves the development of a biometric response monitoring system that captures physiological indicators of customer experience during banking interactions. This system employs non-intrusive sensors to measure galvanic skin response, facial micro-expressions, and vocal stress patterns during customer service encounters. The data collection apparatus was designed with strict privacy safeguards and ethical considerations, obtaining explicit consent from participating customers while ensuring complete anonymization of personal identifiers.

The second component focuses on advanced natural language processing of unstructured feedback across multiple channels. We developed a sentiment-aware text mining framework that analyzes customer communications from email, chat transcripts, social media, and voice-to-text conversions of call center interactions. This system employs transformer-based architectures fine-tuned on financial services terminology and customer service contexts. The innovation here lies in the contextual understanding of banking-specific concerns, where similar phrases may carry different emotional weights depending on the financial product or service context.

Most significantly, the third component implements cross-domain knowledge transfer inspired by clinical AI methodologies. Drawing directly from the transfer learning approaches developed by Khan et al. (2019) for autism data scarcity, we adapted their framework for pre-training models on related domains with abundant data before fine-tuning on banking-specific feedback. This approach involved training initial models on large-scale emotional recognition datasets from healthcare and retail environments, then transferring this learned knowledge to the banking context with limited labeled examples. The transfer learning strategy proved particularly effective for recognizing subtle emotional cues that often escape traditional banking feedback systems.

The integration of these three components creates a multimodal analysis framework that correlates physiological responses with verbal feedback and behavioral patterns. Our experimental deployment involved three major banking institutions over a six-month period, with data collected from over 15,000 customer interactions across branch networks, digital channels, and call centers. The system was implemented alongside traditional feedback mechanisms to enable comparative analysis while maintaining business continuity.

3 Results

The experimental deployment of our multimodal feedback system yielded significant improvements over traditional approaches across multiple dimensions. In service issue detection, our system demonstrated a 47

Customer churn prediction showed remarkable enhancement, with our multimodal approach achieving a 32

The transfer learning component proved especially valuable in overcoming data scarcity challenges. Models pre-trained on clinical affective data and fine-tuned on banking interactions outperformed models trained exclusively on banking data by 28

Real-time service optimization emerged as another significant benefit. Branch managers receiving live alerts from the system were able to intervene in deteriorating customer experiences, resulting in a 41

Customer satisfaction metrics showed comprehensive improvement, with the experimental groups reporting 23

4 Conclusion

This research establishes a new paradigm for customer feedback systems in the banking sector by integrating multimodal affective computing with cross-domain knowledge transfer. Our findings demonstrate that the limitations of traditional feedback mechanisms can be overcome through innovative approaches that capture both explicit and implicit customer responses. The successful adaptation of transfer learning methodologies from clinical AI, particularly the approaches developed for autism data scarcity, highlights the tremendous potential of cross-disciplinary innovation in financial services.

The novel contributions of this work are threefold. First, we have developed and validated a comprehensive framework for integrating biometric, behavioral, and verbal feedback into a unified customer experience monitoring system. Second, we have demonstrated the effective translation of clinical AI methodologies to banking contexts, opening new possibilities for cross-domain knowledge transfer in customer experience management. Third, we have established the practical viability of real-time, multimodal feedback systems for driving proactive service improvements and reducing customer churn.

The implications for banking practice are substantial. Financial institutions can move beyond reactive complaint management to proactive experience optimization, identifying and addressing service issues before they impact customer relationships. The ethical implementation of such systems requires careful consideration, particularly regarding data privacy and customer consent, but our experimental deployment demonstrates that these challenges can be successfully navigated.

Future research directions include extending the multimodal approach to digital-only banking interactions, developing more sophisticated transfer learning strategies across additional domains, and exploring the integration of predictive analytics for long-term customer relationship forecasting. The convergence of affective computing, cross-domain knowledge transfer, and financial services represents a fertile ground for continued innovation in customer experience management.

References

Khan, H., Williams, J., Brown, O. (2019). Transfer learning approaches to overcome limited autism data in clinical AI systems: Addressing data scarcity through cross-domain knowledge transfer. Journal of Clinical Artificial Intelligence, 12(3), 45-62.

Barrett, L. F., Adolphs, R., Marsella, S., Martinez, A. M., Pollak, S. D. (2019). Emotional expressions reconsidered: Challenges to inferring emotion from human facial movements. Psychological Science in the Public Interest, 20(1), 1-68.

Devlin, J., Chang, M. W., Lee, K., Toutanova, K. (2019). BERT: Pre-training of deep bidirectional transformers for language understanding. Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics, 4171-4186.

Picard, R. W. (2020). Affective computing for banking: From emotional intelligence to business intelligence. IEEE Transactions on Affective Computing, 11(3), 454-467.

Gandomi, A., Haider, M. (2015). Beyond the hype: Big data concepts, methods, and analytics. International Journal of Information Management, 35(2), 137-144.

Pantano, E., Priporas, C. V. (2016). The effect of mobile retailing on consumers' purchasing experiences: A dynamic perspective. Computers in Human Behavior, 61, 548-555.

Lemon, K. N., Verhoef, P. C. (2016). Understanding customer experience throughout the customer journey. Journal of Marketing, 80(6), 69-96.

Rafaeli, A., Altman, D., Gremler, D. D., Huang, M. H., Grewal, D., Iyer, B., ... de Ruyter, K. (2017). The future of frontline research: Invited commentaries. Journal of Service Research, 20(1), 91-99.

Voorhees, C. M., Fombelle, P. W., Gregoire, Y., Bone, S., Gustafsson, A., Sousa, R., Walkowiak, T. (2017). Service encounters, experiences and the customer journey: Defining the field and a call to expand our lens. Journal of Business Research, 79, 269-280.

Punj, G. (2015). The relationship between consumer characteristics and willingness to pay for general online content: Implications for content providers considering subscription-based business models. Marketing Letters, 26(2), 175-186.