

**Making Monetary Transactions Feel Like Natural Conversations:
A Conversation Design Framework for Banking UX**

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Abstract

Retail banking depends on digital channels to serve customers, yet many current interfaces remain complex, especially among users with limited technical proficiency. Most conversational assistants are limited to simple, one-off commands rather than the multi-step workflows a financial transaction already involves. This paper presents a Conversational Banking Interaction Framework (CBIF) that organizes financial tasks as structured conversations including clarification, confirmation, and context awareness, and that combines voice, text, touch, and biometric authentication to balance ease of use with privacy and security. A prototype instantiation was evaluated through expert heuristic inspection and a comparative usability study. The evaluation supports the framework's specific interaction mechanisms without establishing a general advantage for the conversational paradigm, and it yields implementation recommendations relevant to financial inclusion.

Keywords: Conversational AI, Retail Banking, Multi-Modal Interaction, Self-Service Banking, Financial Technology (FinTech), Human-Computer Interaction (HCI)

Introduction

Over the last 20 years, retail banking has undergone a radical transformation as providers transition service delivery from physical branches to digital channels (Felipe et al., 2025). Mobile applications, online banking portals, and call center automation via self-service channels have become the touchpoints for customers to access financial services. In 2023, 48.3% of U.S. households that have current bank accounts accessed their accounts primarily using mobile banking, and a total of 70.5% of those households used off-site channels (e.g., mobile, online, or telephone banking) as their primary access method (Federal Deposit Insurance Corporation, 2024). On the other hand, just 28.9% of all households indicated that in-person banking was their primary method of banking. These trends are also witnessed globally as financial institutions increasingly roll out digital platforms to cut operating costs and enhance the scalability of services.

The digital banking infrastructure has much investment, but a lot of that investment is rarely applied to tackling user experience issues related to these digital platforms. Bueno et al. (2024) revealed that many of today's interfaces are challenging for users to navigate successfully. Traditional mobile banking applications are entirely menu-driven and require the user to navigate through multiple pages before identifying the feature they want to use for a financial task. Most of these platforms are designed with the assumption that users have an adequate familiarity with banking language and system architecture, which is not true for many individuals (Zhu & Wang, 2022). This typically results in a high level of cognitive load for users trying to perform simple activities such as finding transactions, processing payments, or fixing account issues (Bueno et al., 2024).

These design issues have inspired the need to make digital banking feel more relatable and conversational. This is why today, large banks are beginning to add conversational assistants, and most are already running at scale. By 2024, Bank of America's virtual assistant Erica had already supported over 42 million clients and handled more than 2 billion customer interactions and over 1.2 billion personalized insights and guidance messages, as highlighted in Figure 1 (Bank of America, 2024). These assistants can help to find a transaction, check their balance, lock or unlock a card, and support digital payment systems. However, as much as this data shows progress, Vuković et al. (2025) asserted that the current generation of conversational banking

systems is somewhat constrained in its scope. As of now, conversational assistants work as automated customer service agents instead of complete financial integrations, which is clearly missing the point. Their abilities are usually limited to simple commands or predefined intents, like “check balance” or “find transaction” (Oyeniya et al., 2024), which, for the most part, is not a complicated feature on the digital banking platforms. Systems often fail to handle the complex multi-turn dialogue required for secure financial transactions when users try to execute more sophisticated financial operations (Hasan et al., 2023). As a result, conversational banking has yet to realize its full potential as a first-choice interface for digital financial services.

Figure 1

Erica in Numbers



Note. From Bank of America (2024).

Research Aim and Contributions

This research focuses on the relationship between conversational AI and improving economic interactions in customer relations while strengthening trust in financial relationships through the adoption of conversational design principles within the digital banking environment.

A proposed conversational design framework utilizes multi-turn dialogue structures, sequence-aware trust interaction patterns, and multi-modal interface mechanisms, which will be used to support the retail banking user experience. Additionally, this framework provides guidelines for developing an improved inclusive, transparent, and usable conversational banking system. Finally, based upon an evaluation of a prototype instantiation of the framework, these results were turned into actionable implementation recommendations.

Literature Review

Theoretical Framework

The study uses a combination of three theoretical lenses, namely the Technology Acceptance Model (TAM), Cognitive Load Theory (CLT), and Human-Computer Interaction (HCI). TAM suggests that users adopt digital systems based primarily on perceived usefulness and perceived ease of use (Schorr, 2023). Systems that make it easier to perform financial tasks and require less interaction effort are therefore more likely to be adopted over time in the field of digital banking. The ability of users' working memory to engage with complex information contexts is limited, according to Cognitive Load Theory (Clark & Kimmons, 2023). Cognitive stress and reduced usability result from interfaces that require users to understand unfamiliar vocabulary, navigate through multiple options, or remember which step of the process they are on. In HCI research, usability, feedback, and error prevention are essential design elements for single interactive systems (Norman, 2013). When taken as a whole, these lenses provide a theoretical framework for evaluating conversational interfaces as ways to reduce interaction complexity in digital financial systems and enhance user experience.

Conversational Interfaces in Service Systems

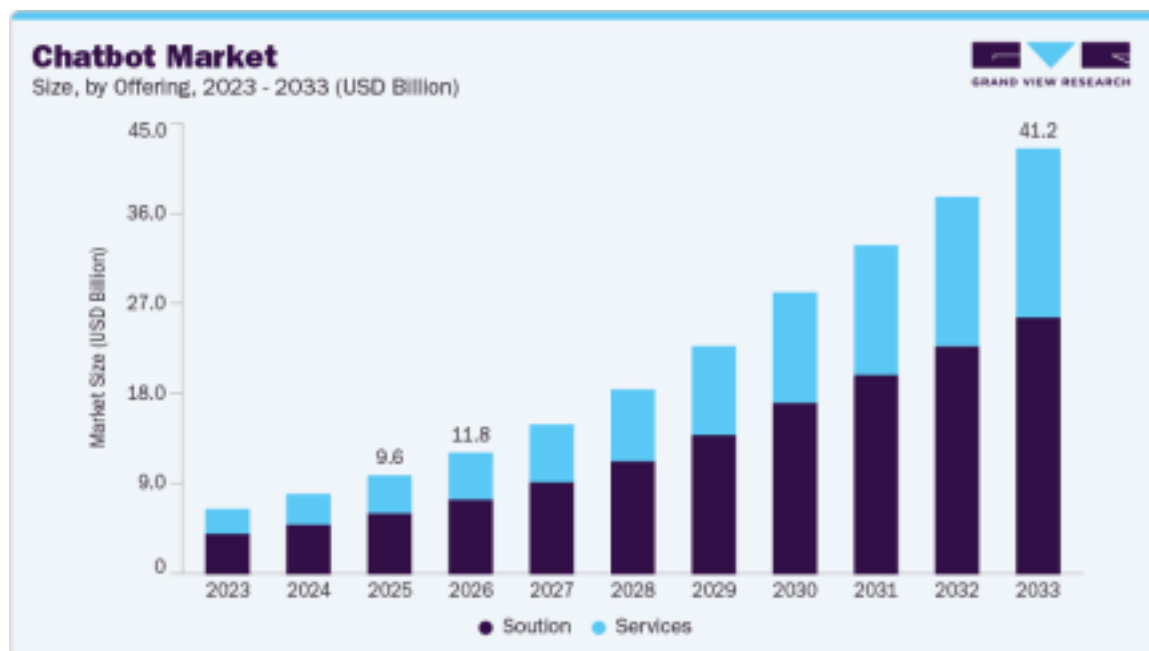
In the span of a few years, Conversational AI has evolved from what was known to be simple rule-based programs into increasingly sophisticated AI-enabled systems capable of supporting complex interactions across service environments (Hua et al., 2025). Earlier conversational agents like ELIZA ran on simple pattern-matching algorithms that faked interaction without any understanding of the language (Rajaraman, 2023). Although such

systems showed the possibility of what conversational interaction could be, Singh and Namin (2025) noted that they were still limited in that their responses were fixed and could not adapt to changes in context. The next generations of conversational systems pioneered rule-based dialogue architectures whose purpose was to drive users through clearly defined task flows, like booking a service or retrieving information (McTear et al., 2016). These systems were more efficient when conducting tasks in structured environments, but struggled when users made requests in unanticipated ways. Feine et al. (2019) emphasized that the rigidity of these systems constrained their effectiveness in actual service contexts, where users' requests often require interpretation and contextualization. In order to improve conversational technologies, natural language processing and machine learning have undergone many changes. Modern assistants like Siri, Alexa, and Google Assistant have shown the increasing potential for more natural conversational interaction as an alternative interface paradigm (Mariani et al., 2023).

According to Grand View Research (2025), the global chatbot market could reach **\$41.2 billion by 2033**, highlighting the growing organizational dependence on conversational systems for delivering digital services and engaging customers Figure 2.

Figure 2

Chatbot Market



Note. From Grand View Research (2025).

Conversational AI in Digital Banking

The adoption of conversational AI in the banking industry has accelerated rapidly. According to a study conducted by Juniper Research, banks could save up to \$7.3 billion by automating most of their routine enquiries with conversational AI technology (Juniper Research, 2019). This mode of banking is already being adopted today. Most big financial institutions have already launched conversational assistants as part of their digital ecosystems (Vuković et al., 2025). However, conversational banking systems today are still very much limited. Chau et al. (2025) pointed out that the majority of banking chatbots are centered on support and customer tiers instead of financing processes. Users are mostly interested in the completion of tedious tasks that would typically require them to call customer service or visit in person. However, these chatbots tend to be built on intent classification models that consider input from the user and map it to a specific command, like “check balance” or “transfer money.” This works well for simple requests, but the approach struggles when financial tasks involve multiple steps (Chau et al., 2025).

Summary

While many of these companies are growing quickly through the adoption of digital banking, financial access remains a big barrier. Globally, an estimated 1.4 billion adults do not have access to bank accounts (Basnayake et al., 2024). They are not the only ones who face challenges with access. For those who do have bank accounts, purposeful use of digital financial services varies considerably based on factors such as financial literacy levels, technological familiarity, and language proficiency (Basnayake et al., 2024). The United States faces language barriers that are a significant accessibility concern due to its diversity. Over 26 million residents in the United States are Limited English Proficient (LEP) (more than 1 in every 10 residents), and over 67 million speak a language other than English at home (Ramirez et al., 2023). Since financial terminology can be complex and tricky to translate correctly, digital banking interfaces can be especially challenging to design for newcomer or multilingual populations (Ramirez et al., 2023). Yet, existing research on conversational banking systems concentrates mainly on

automating customer services rather than conceptualizing the design of conversational frameworks that enable holistic financial workflows (Allouch et al., 2021; Chau et al., 2025). Thus, there is little research on how conversational interaction can be framed to support multi-turn financial transactions with trust, privacy, and inclusivity considerations (Luger & Sellen, 2016; Ntoa, 2024). Addressing this gap requires the design of frameworks that integrate conversational dialog managers with trust-aware financial interaction mechanisms.

Methodology

Research Philosophy and Design Approach

This paper employs a human-centered design approach to investigate different ways in which conversational interfaces can enhance the quality of interaction users have with digital banking environments. Human-centered design prioritizes the design of technological systems, putting the users' needs, behaviors, and cognitive limitations at the core, rather than solely technical system architecture (Norman, 2013). This approach is crucial in the context of digital banking because financial tasks are typically complex and require ample decision-making steps, sensitive information handling, and different levels of user expertise. To put this perspective into practice, a Design Science Research (DSR) approach is used. Design science research emphasizes the development and assessment of artifacts designed to solve practical information systems problems (Geerts, 2011). Unlike other purely empirical approaches, the DSR approach focuses on designing innovative artifacts such as models, frameworks, and prototypes (Peppers et al., 2018).

Framework Development Process

The framework for conversational banking was developed using a structured design process guided by the principles of Design Science research. The process consisted of three primary stages: problem identification, requirement derivation, and iterative framework development. In the first step, the key usability limitations of existing digital banking systems were identified. This is essential, as it identified the problem through a careful review of scholarly works on conversational interfaces, user experience in digital banking, and

Human-Computer Interaction. Existing research suggests that the vast majority of banking chatbots are still, to some extent, simple command-response interfaces and do not perform well at aiding complex financial interaction flows requiring clarification, confirmation, and context awareness (Bansal, 2024; Chau et al., 2025). These results indicate that multi-step financial tasks require a more formal conversational interaction model. The second step was to identify design requirements based on theoretical findings and limitations of the state-of-the-art systems. These requirements for the system include support for multi-turn dialogue interactions, clarification and ambiguity resolution, explicit confirmations of financial transactions, as well as multi-modal interaction elements (e.g., voice advertisements from the bank). Finally, the last step was the gradual development of the conversational framework. This involved gradual improvements to the design features by implementing the proposed interaction model that was systematically aligned with established principles from HCI and conversational UX design to progressively refine design elements. Through an iterative series of modifications and updates to the tested prototypes, the framework focused on structured dialog management, trust-aware interaction patterns, and support for contextual generation of prompts and cues during financial task completion.

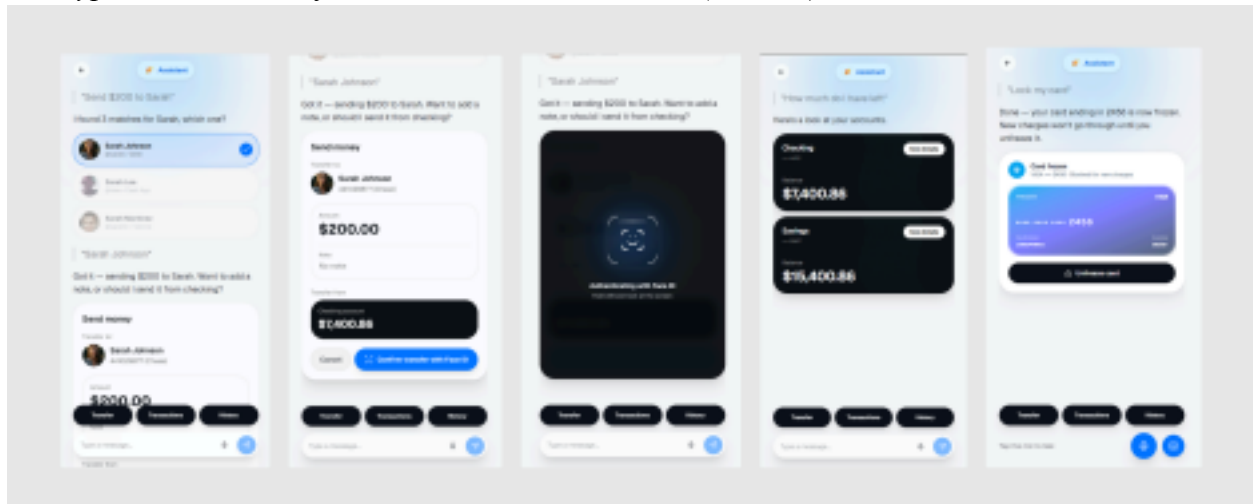
Framework Evaluation

The study was approved by the Morgan State University Institutional Review Board, and informed consent was obtained from all participants. The framework was evaluated through a prototype instantiation of the CBIF interaction model, in two stages. Two evaluators, one from Human-Computer Interaction and one from Computer Science, independently inspected eight conversational states against Nielsen's ten usability heuristics (Nielsen, 1994) and reconciled their ratings. Deficiencies falling within the scope of the design were addressed, and a study was conducted with four participants. Each of the subjects performed all three tasks using both the conversational version of the prototype and a menu-based version of the task. After each condition, participants completed the System Usability Scale (Brooke, 1996), a modified NASA Task Load Index (Hart, 2006) recorded on a 0 to 10 scale with the Physical Demand subscale omitted, and a seven-item instrument based on the Technology Acceptance Model (Davis, 1989). The prototype implements the framework's task flows within a single conversational canvas,

rendering each operation as an inline response card. Figure 6 shows the revised prototype following the design revisions described below.

Figure 6

Prototype Instantiation of the CBIF Interaction Model (Revised)



Note. Screens from the revised prototype, following Stage One design revisions. From left: contact disambiguation, pending confirmation with visible cancel control, biometric authentication, balance query response, and card freeze confirmation.

Results

Conversational Banking Framework

Design Principles for Conversational Banking UX

The conversational banking framework proposed is based on three underlying design principles: human-like dialog interaction, transparency and trust, and strong error prevention and recovery. These principles come from Human-Computer Interaction research and conversational UX design literature, which assert that a well-functioning digital system should adopt natural patterns of human communication while expending the least amount of cognitive effort (Norman, 2013). Rather than having users navigate through endless menu options and rigid pathways, natural language interaction allows users to interact with banking apps using natural human

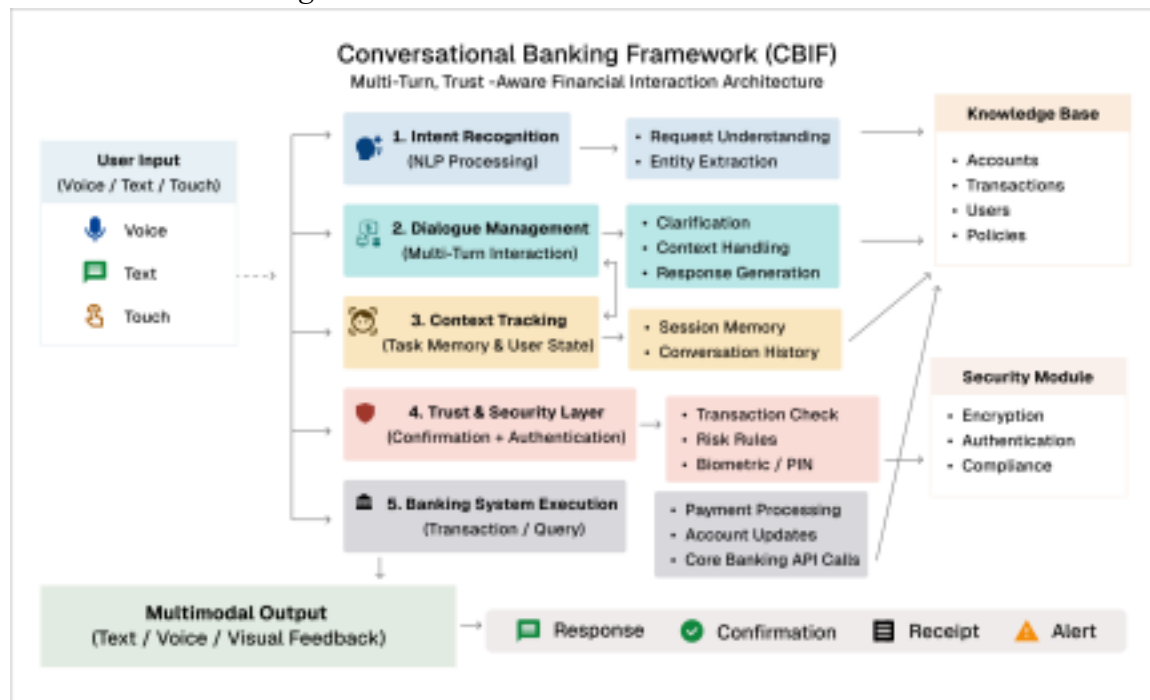
language (Hua et al., 2025). Traditional banking interfaces often require that users find a specific function before performing actions, which adds unnecessary stress and complexity. On the other hand, conversational interaction allows the user to get straight to the point, whether they are asking things like “send money to John” or questioning “why was my card declined?” This intent can then be understood by the system, which will help to guide the user in following the next steps. Transparency and trust are especially critical in financial contexts, where transactions have direct economic implications (Ashfin, 2024). This is a concern users are likely to have when it comes to using conversational banking interfaces. In order to build that trust, conversational systems must be incredibly clear about actions they take so that users will also know what exactly is happening. This means confirming transaction details back to the user and providing meaningful information at each stage of interaction. Without this level of reliability, users may be reluctant to initiate financial transactions (Felipe et al., 2025).

Architecture of the Conversational Framework

Conversational banking architecture consists of three axiomatic components: intent recognition, dialogue management, and contextual state tracking. As shown in Figure 3, these components work together to allow conversational systems to understand user requests, handle multi-turn conversations, and maintain context across financial tasks (Rustamov et al., 2021). The process begins with Intent recognition, which is the first interface between the user and the conversational system. The system first leverages natural language processing techniques to analyze the user input in order to understand the underlying financial intention of the user. For instance, requests like “send \$200 to Sarah” or “show my last transactions” are mapped onto corresponding banking functions. Then again, intent recognition is not enough to manage complex financial interactions, as many requests require extra details and specific contexts before any action can be safely executed. That is where dialogue management functions come in as the main coordination mechanism in the framework. It coordinates the entire exchange, gathering information bit by bit, confirming relevant data, and assisting users through the whole process. The management of dialogue is also responsible for determining when clarification on the user’s request is needed, and when authentication procedures should be invoked.

Figure 3

Conversational Banking Framework Architecture



Note. Authors' creation, 2026.

Trust-Aware and Multi-modal Interaction Design

Although most digital services can get away with standard security, banking requires a much higher level of reliability. Hence, conversational banking systems need to include interaction mechanisms that are trust-aware and prevent unintended actions while reassuring users about their decisions (Singh & Namin, 2025). Confirmation patterns are a critical aspect of design. Before money moves from the user's account, the system should clearly play back exactly what it is about to do. A user should clearly confirm with the system what action is being taken before doing any financial transaction. This confirmation stage helps users ensure the specifics of the transaction are correct and may correct possible mistakes. Authentication mechanisms are also an important component of security. Instead of forcing users to use conventional passwords, conversational systems can also support biometric authentication methods like fingerprint authentication or face verification with smartphones. These mechanisms allow users to validate sensitive actions without breaking the conversation flow (Omarini, 2022).

Finally, this framework also includes multi-modal interaction capabilities. Conversational banking does not have to be voice or text input only. Rather, modern systems leverage multi-modal interaction, such as voice commands for input, chatbots to provide details in text format, touch clickers for confirmations, and biometric login to ensure an accurate reduction of the response area (Iniesto et al., 2023). This multi-modal strategy allows users the flexibility of engaging with financial systems as suits their environment and privacy needs.

Framework Model and Operational Flow

The previously described components are integrated into a conceptual model of a goal-oriented conversational interaction involving digital banking. As shown in Figure 4, the process starts with user input via one or more interaction modalities, e.g., voice or text. This input is handled by the intent recognition component, which determines what financial task the user is requesting. Once the intent is identified, the dialogue management component begins a structured dialog flow meant to extract required information and drive users through the transaction pipeline. Throughout this entire exchange, state tracking acts as the system's memory, keeping track of things like account numbers and dollar amounts so the user never has to repeat themselves.

Figure 4

Multi-Turn Financial Dialogue Flow



Note. Authors' creation, 2026.

Prototype Interaction Scenarios

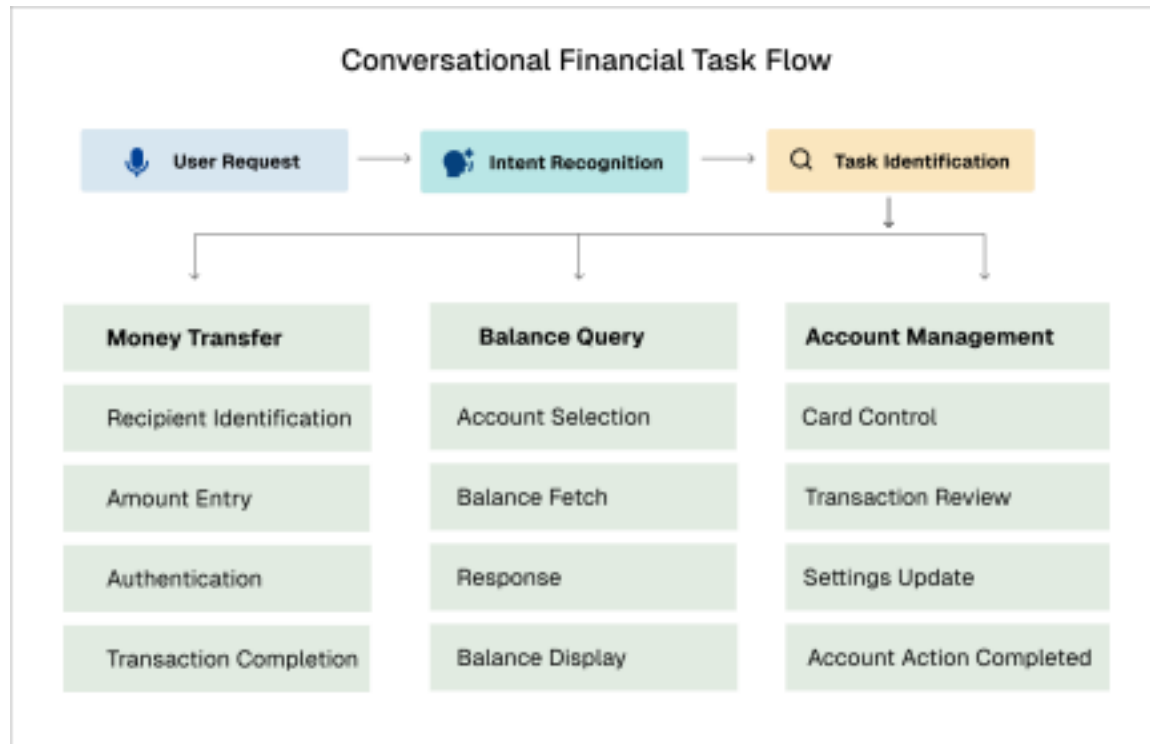
Financial Task Flows

In order to examine how this conversational banking framework actually functions in the real world, it was tested with common financial interaction scenarios. These scenarios show how these standard banking operations can be conducted in a structured conversation and dialogue instead of through menu-based navigation logic, as highlighted in Figure 5. For this purpose, three broad types of financial tasks were identified: transfer funds, check balance, and account management. One of the most sophisticated interactions is money transfers, which involve several steps: identifying users, selecting the account to withdraw from, confirming transactions, and validating security. Balance queries are an easier informational task, whereas account management actions can involve card locks and transaction review or payment preferences

(Allouch et al., 2021; Ntoa, 2024).

Figure 5

Conversational Financial Task Flow



Note. Authors' creation, 2026.

Dialogue Interaction

Prototype scenarios were developed to demonstrate how multi-turn conversational interactions could facilitate the completion of financial tasks. Unlike typical command-based chatbot systems, the framework organizes interactions as a series of dialogue exchanges that help users toward their goal. A designed flow between the human and the machine was made to feel structured yet flexible. One of the biggest hurdles in automated banking is handling uncertainty. Instead of forcing a restart from the user's side, in case of ambiguity, it asks for more information using clarification prompts. This approach mimics how two people talk to each other, "negotiating" the meaning until both sides are on the same page, allowing for financial transactions to be executed through iterative conversations rather than one-off commands (Feine et al., 2019; McTear et al., 2016).

Handling Errors and Security-Sensitive Interactions

Error management and secure transaction execution are essential elements of financial systems (Norman, 2013; Ntoa, 2024). In the proposed model, the processes of ambiguity resolution and authentication are directly integrated with conversational interaction sequences. Clarification prompts act as a safety net. They are used when the system is not confident about user input as a means of disambiguating before processing a transaction. For example, when multiple recipients share the same name, the system requests more identifying information to confirm accuracy. This minimizes the risk of incorrect transactions and prevents users from mistakenly performing actions they did not intend to perform. Furthermore, sensitive security operations require explicit authentication before finalization. By embedding authentication into the conversational workflow, as opposed to keeping it separate from interaction, security and usability are both retained by the scheme. Confirmation modalities further ensure that users have ongoing control of financial actions before the completion of a transaction (Allouch et al., 2021; Ntoa, 2024).

Both evaluators independently rated the lack of cancel, back, or edit controls that were visually available on the pending confirmation card as a severity level 3, and the single severity level 4 finding by the Computer Science evaluator, where a misrecognized amount was corrected by the user, acknowledged by the system, and executed at the original value. A visible cancellation option was added before the second stage, but the recognition and state-propagation defects were platform limitations and therefore remediable.

System Usability Scale scores were 78.75 for the conversational condition and 86.25 for the menu-driven condition. Both are above the reference point of approximately 68 for average usability (Sauro & Lewis, 2016). Median workload scores were 1.7 against 2.1 on a zero-to-ten scale. Errors were concentrated in the conversational condition, where two participants experienced speech recognition failures.

Across the seven measures recorded, none favored the conversational condition for a majority of participants, most clearly on the two single-function tasks, where input via voice provides no navigational advantage over one or two taps. When read in absolute rather than comparative terms, however, the conversational condition was rated higher than the usability

reference point on first exposure, by participants who are habituated to menu-driven banking, and under conditions where voice input is unavailable to at least half of the sample.

Discussion

In mapping our results to the three design principles, an uneven view was produced. A good realisation of the characteristics that define human-like dialogue interaction was achieved, with no severity above 1 recorded against the heuristics most closely related to it. Transparency was largely implemented through the display mechanism; however, transparency was not implemented in terms of verification since there is a distinction between displaying a parameter for confirmation purposes versus determining whether or not the value displayed represents the original value specified by the user. Error Prevention and Recovery represented the poorest realisation of all three principles.

Overall, aggregate usability and workload measures are indicative of all aspects of the instantiation, including design decisions that the framework does not address nor the behavior of a development environment whose behavior is also not addressed by the framework. Therefore, attribution is possible at the level of the individual mechanisms the framework prescribes. Both evaluators positively evaluated both the disambiguation card and the pending confirmation card. Similarly, none of the participants indicated uncertainty regarding their confirmation of actions, indicating positive support for those components of the framework that provide for those respective mechanisms. The most severe finding points the same way from the opposite direction. Where the prototype lacked a provision the framework specifies, namely the propagation of an acknowledged correction into the transaction state, the outcome was an incorrect transfer. That absence of the provision resulted in failure that is identical to that which the provision is designed to prevent, providing evidence that the provision should exist within the framework and not be dependent upon implementation.

In addition to convergence with regard to voice input and discoverability, there are two other areas that were identified during both phases of the evaluation. The first area relates to language proficiency. Although all of the evaluators and participants in this study are native speakers of languages other than English, previous studies have demonstrated variability in speech recognition performance among different linguistic populations (Koencke et al., 2020) although no cause-and-effect relationship may be inferred from this observation it is clear that if

a framework aims to decrease barriers to access then similar issues warrant further investigation at larger scales than was investigated here.

Implications, Limitations, and Future Research

To implement conversational interaction within retail banking, there are four key requirements that must exist. The corrections resulting from conversational interaction must be able to affect the transaction payload (not merely the conversation) so that a conversational acknowledgement does not necessarily imply an alteration in state. All states prior to the final commitment must also show reversibility. Conversational options and possible routes of recovery after completion of transactions must be indicated clearly. Finally, speech recognition accuracy must be tested throughout the accents and languages of the target customers' demographic base, with text-based entry available and treated as a viable option (and not a secondary choice).

Convenience sampling resulted in four subjects who participated in this study and two evaluators. Convenience sampling allows no statistical generalization. As such, we can report on our findings descriptively. Each participant was familiar with traditional banking via menus; each had their first experience with conversational banking paradigms; the artifacts assessed during the two stages of data collection were somewhat different (but related); and several devices limited the ability of at least two subjects to use voice input. Additional research will need to provide reliable voice input capabilities as well as engage customers in actual multi-step financial workflow activities (the task types used for this research did not have those aspects isolated).

Conclusion

This proposed conversational banking framework shows the importance of going beyond the current command-based chatbot systems toward structured multi-turn dialogue interactions. Classic chatbot interfaces often handle single-user requests and do not support complex transactions such as financial transactions that need clarification, confirmation, and security verification (Chau et al., 2025). The framework shows that conversational interfaces can be designed to help users carry out more complex tasks and be able to guide the user step by step through financial workflows, with full transparency. Conversational systems, as multi-step

dialogue between humans and machines, are intended to reduce the cognitive workload for users when interacting with complex banking infrastructures, although the evaluation reported here did not establish that advantage over a familiar menu-driven interface on first exposure. Such design patterns resonate with established principles in Human-Computer Interaction that emphasize feedback, error prevention, and user control as determinants of success for digital systems (Norman, 2013). The framework was evaluated through a prototype instantiation rather than in a live financial environment, and the limitations of that evaluation are set out above. This study offers a framework for the conversation design of digital banking systems where multi-turn dialogue management, contextual interaction tracking, and trust-aware security mechanisms are integrated. The framework achieves this by making the financial interactions into guided conversational workflows, thus minimizing the cognitive load required to smoothly assemble and execute complex banking transactions while providing the transparency and predictability needed in any financial environment. Designing digital banking systems to improve usability is an important factor in ensuring successful adoption and usage; thus, it is crucial that the interaction patterns used in such systems be carefully considered. As conversational technologies develop, embedding user-centred design principles into financial service platforms will be fundamental to creating banking systems that are usable and inclusive.

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