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Emotional AI and its Impact on Consumer Brand Loyalty: Mediating Effect of Emotional Satisfaction and Moderating Effect of Digital Literacy and Privacy Risk in Private Banks of Sulaymaniyah.

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Abstract

In the rapidly evolving financial sector of the Kurdistan Region of Iraq, private banks are integrating emotional artificial intelligence to strengthen customer relationships. Yet, little is known about how affective computing shapes long-term consumer behavior within collectivist cultures. This paper examines the direct and indirect effects of Emotional AI characteristics on consumer brand loyalty across private banks in Sulaymaniyah. Using a sequential explanatory mixed-methods design, quantitative data were gathered from 312 retail banking clients and processed through IBM SPSS 27 and SmartPLS 4.0 for structural equation modeling. To complement these numbers, thematic analysis was applied to 18 in-depth qualitative interviews using NVivo 14. The quantitative model demonstrated that perceived usefulness and empathy significantly drive emotional satisfaction, which in turn acts as a partial mediator for brand loyalty. The qualitative insights further explained these relationships by highlighting key sources of customer resistance, particularly high perceived privacy risks and local language barriers. Overall, the study shows that while Emotional AI supports customer attachment, financial institutions must address data privacy concerns and refine language localization to achieve meaningful technology adoption.

Keywords : Emotional AI, Brand Loyalty, Consumer Behavior, Private Banking, Fintech, Sulaymaniyah, Kurdistan Region.

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زیرەکی دەستکردی سۆزداری و کاریگەری لەسەر دڵسۆزی بەکارهێنەر بۆ برێند:ڕۆڵی نێوەندگیری ڕەزامەندی سۆزداری و کاریگەری ڕێکخەری ڕۆشنبیری دیجیتاڵی و مەترسی تایبەتمەندی لە بانکە تایبەتییەکانی سلێمانی.

ئەروەند حمدامین احمەد

بەشی باخچەی ساوایان، کۆلێژی پەروەردەی بنەڕەت، زانکۆی ڕاپەڕین، ڕانیە، عێراق.

پوختە

کەرتی دارایی و بانکیدا لە هەرێمی کوردستانی عێراق کە بە خێرایی لە گەشەکردندایە، بانکە تایبەتەکان بەرەو بەکارهێنانی ژیریی دەستکردی هاوسۆز (Emotional AI) دەچن بۆ بەهێزکردنی پەیوەندییەکانیان لەگەڵ کڕیاراندا. بەڵام، زانیاریی ئەزموونییەکان لەسەر چۆنیەتی کاریگەریی ئەژمارکاریی سۆزداری (affective computing) لەسەر ڕەفتاری درێژخایەنی بەکاربەر لە کۆمەڵگە کۆکەرەوەکاندا (collectivist cultures) هێشتا سنووردارن. ئەم توێژینەوەیە مەبەستیەتی هەڵسەنگاندن بۆ کاریگەرییە ڕاستەوخۆ و ناڕاستەوخۆکانی تایبەتمەندییەکانی ژیریی دەستکردی هاوسۆز بکات لەسەر وەفاداریی بەکاربەر بۆ برێند لە کەرتی بانکی تایبەت لە شاری سلێمانی. بە بەکارهێنانی دیزاینی میتۆدی تێکەڵاوی ڕوونکردنەوەیی یەکتەریب (sequential explanatory mixed-methods design)، داتا چەندایەتییەکان (quantitative data) لە ٣١٢ کڕیاری بانک کۆکرانەوە و بە بەرنامەکانی IBM SPSS 27 و SmartPLS 4.0 شیکارییان بۆکرا بۆ مۆدێلکاری هاوکێشەی پێکهاتەیی (PLS-SEM). بۆ تەکۆملکردنی ئەم ژمارانە، شیکاریی تەوەرەیی (thematic analysis) بۆ ١٨ چاوپێکەوتنی قوواڵی چۆنایەتی (qualitative in-depth interviews) بەکارهێنرا بە یارمەتی بەرنامەی NVivo 14. مۆدێلە چەندایەتییەکە دەریخست کە "بەسوودبوونی هەستپێکراو" و "هاوسۆزی" کاریگەریی ڕاستەوخۆ و بەرچاویان هەیە لەسەر ڕەزامەندیی سۆزداری، کە ئەمەش لای خۆیەوە وەکو ناوبژیکەرێکی بەشەکی (partial mediator) بۆ ڕەهەندەکانی وەفاداری برێند کاردەکات. هاوکات، دۆزراوە چۆنایەتییەکان ڕوونکردنەوەی زیاتریان دا بەم پەیوەندییانە لەڕێگەی دەستنیشانکردنی سەرچاوە سەرەکییەکانی بەرەنگاربوونەوەی کڕیاران، بەتایبەت مەترسییە بەرزەکانی تایبەتمەندێتی هەستپێکراو و کێشەی زمانی ناوچەیی. بەگشتی، توێژینەوەکە دەریخست کە هەرچەندە ژیریی دەستکردی هاوسۆز پشتگیری لە پەیوەستبوونی کڕیاران دەکات، بەڵام پێویستە دامەزراوە دارایییەکان بە شێوازێکی ستراتیژی مەترسییەکانی تایبەتمەندێتی داتا چارەسەر بکەن و گونجاندنی زمانی ناوچەیی باشتر بکەن بۆ دەستەبەرکردنی وەرگرتنی تەکنۆلۆژیا بە شێوەیەکی بەردەوام.

وشە کلیلەکان: ژیریی دەستکردی هاوسۆز، وەفاداری براند، ڕەفتاری بەکاربەر، بانکی تایبەت، فینتەک، سلێمانی، هەرێمی کوردستان.

1. Introduction

Advanced financial technologies, big data, and artificial intelligence (AI) are transforming the banking sector. One of the most attractive and possibly impactful of these innovations is Emotional AI, also known as affective computing or emotion-sensitive AI. Emotional AI involves the ability of a system to identify, infer, and adjust to the emotions of humans across multiple modalities, e.g., facial expression recognition, voice tone analysis, natural language processing (NLP), and physiological signal monitoring (El Kaliouby, 2020, pp. 312–315; Picard, 1997). Emotional AI has a distinct vision: to bridge the gap between human and machine cognition and affectivity so as to mimic—in a mindful fashion—the empathizing aspects of human relationships (McStay, 2018, p. 3).

Financial services have seen a dramatic increase in the implementation of Emotional AI over the last decade. In developed markets, financial institutions have employed AI-powered chatbots capable of identifying signs of customer dissatisfaction, tailoring product suggestions based on perceived emotions, and instantly modifying communication styles to enhance customer experiences (Flavián et al., 2021). The premise behind these initiatives is straightforward: consumer buying habits are

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driven not only by cost, convenience, and return on investment, but also largely by emotional factors. Brand loyalty—the propensity to re-purchase a brand over alternatives—is deeply rooted in attachment, trust, and identification with the brand (Chaudhuri & Holbrook, 2001, pp. 81–93; Oliver, 1999).

Since the period of relative stabilization in the Kurdistan Region during the early 2000s, the banking sector has grown rapidly, particularly in Sulaymaniyah, Iraq. Private banks such as Kurdistan International Bank (KIB), Bank of Baghdad, NBI Bank, Cihan Bank, and TBI Bank have expanded their clientele and initiated investments in digital infrastructure (Khalil & Ahmed, 2021). Adopting Emotional AI within this context, however, is still in its infancy. Despite increasing interest in Emotional AI within financial services, limited empirical evidence exists regarding its influence on consumer brand loyalty in developing economies, particularly within the banking sector of the Kurdistan Region of Iraq. This study addresses this gap.

This research provides unique empirical contributions to the fields of fintech and consumer behavior by integrating the technology acceptance model (TAM), SERVQUAL, and emotion-brand connection theories within a collectivist Middle Eastern environment. Practically, it serves as a roadmap for banking leaders and policymakers in the Kurdistan Region to design and deploy AI tools that balance emotional responsiveness with privacy and data protection, ultimately strengthening customer retention and market positioning. Furthermore, it contributes to the theoretical discourse surrounding the interplay between affective computing, technology acceptance, and customer loyalty in cultural contexts where collectivist values, oral traditions, and interpersonal trust remain fundamental (Al-Aali et al., 2019, pp. 891–913; Hofstede, 2001, pp. 115–135).

To conceptualize the framework of this inquiry, key variables are operationally defined:

- Perceived Usefulness (PU): The customer's belief that Emotional AI interactions enhance the efficiency and quality of their banking experiences.
- Perceived Ease of Use (PEOU): The user's perception of how effortless and user-friendly the bank's Emotional AI interface is.
- Emotional Satisfaction & Perceived Empathy (Mediators): The psychological state wherein the customer feels that the bank's AI system recognizes, values, and treats their emotional responses with care.
- Digital Literacy & Perceived Privacy Risk (Moderators): Digital literacy represents the capability of consumers to effectively interact with digital banking tools, while privacy risk reflects consumer anxiety regarding data surveillance and emotional tracking.
- Consumer Brand Loyalty (Dependent Variable): Evaluated across four dimensions: Cognitive, Affective, Conative, and Action loyalty.

1.1 Research Questions

1. What Emotional AI applications are currently used, or could be adopted, by private banks in Sulaymaniyah?
2. How do consumers perceive Emotional AI-enabled banking services?
3. Which dimensions of brand loyalty (cognitive, affective, conative, and action loyalty) are most strongly influenced?
4. How do digital literacy, privacy concerns, and cultural attitudes moderate these relationships?

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1.2 Research Objectives

1. To identify the types of Emotional AI applications relevant to private banks in Sulaymaniyah.
2. To evaluate the direct impact of perceived usefulness and perceived ease of use of Emotional AI on customer emotional satisfaction.
3. To investigate the mediating role of emotional satisfaction and empathy, as well as the moderating role of digital literacy and perceived privacy risks, on brand loyalty dimensions.

2. Literature Review and Conceptual Framework

2.1 Emotional AI: Definition and Evolution

The development of Emotional AI has a theoretical foundation in the work of Rosalind Picard, who wrote the book Affective Computing (Picard, 1997), which proposed that computers must be able to sense and mimic the feelings of people if they were to interact normally with the real world. However, machine learning, computer vision, and NLP have come to fruition realizing Picard's vision in recent years, to some extent. The range of uses of Emotional AI today includes facial action coding systems (FACS) that detect micro-expressions (Baltrusaitis et al., 2018, pp. 59–66; Ekman & Friesen, 1978, pp. 61–80). Voice sentiment analysis based on prosodic and lexical cues (Schuller et al., 2018, pp. 312–315). Conversational AI systems that tune responses according to the inferred mood of the user (Zhou et al., 2018, pp. 730–738). and physiological AI based on the recording of human autonomic responses like galvanic skin response or heart rate variability (McDuff & Czerwinski, 2017, pp. 33–37).

2.2 Brand Loyalty

The brand loyalty concept has been regarded as a basic concept of marketing since the definition of (Jacoby & Kyner, 1973, pp. 1–9) as a biased, behavioral response, over time, by a decision-making unit with respect to one or more alternative brands selected from a set of such brands, and caused by psychological processes. Oliver (1999) later developed this short definition by introducing his four-step Loyalty Model that proposes cognitive loyalty (information-based preference), affective loyalty (affection-based preference), conative loyalty (behavioral intention) and action loyalty (behavioral habit). The model of Keller (1993, pp. 1–22) suggests that in a strong sense of brand loyalty, consumers link a brand to positive, distinctive, and salient feelings, which is directly applicable to using Emotional AI.

2.2.1 Brand Loyalty in the Banking Context

In the banking environment, trust, satisfaction and identification with the value of the bank can be critical factors five times more important than in a retail service environment (Bloemer et al., 1998, pp. 276–286).

The importance of brand loyalty is even more significant in the banking industry, which are key to customers' financial well-being, and the cost of changing banks is still relatively high despite the rise of open banking (Narteh, 2013). Emotionally loyal customers of financial institutions are consistently found to be more inclined to buy extra products, to recommend the bank to people, and they are less likely to be negatively influenced by a competing offer (Grönroos, 2000; Reichheld & Sasser, 1990, pp. 105–111).

Mastery of financial concepts is generally limited and low for many financial consumers, and thus their decisions on financial service quality rely mainly on relational cues, which is often why they

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display high levels of loyalty towards financial services providers and their reputation in a community (Homoud, 2008, pp. 25–47; Rammal & Zurbruegg, 2007, pp. 65–74). More specifically, in Iraqi Kurdistan, Khalil and Ahmed (2021, pp. 145–163) identified three main reasons for customer satisfaction with their banks: (1) Employee warmth; (2) perceived reliability; and (3) word-of-mouth reputation, all of which are factors that can be manipulated via AI-mediated interactions. The implication from this is that when Emotional AI is used in a manner that truly reflects or even goes beyond these human attributes, it can become a powerful tool for building loyalty in this market.

2.2.2 Emotional AI and Brand Loyalty in Banking

Giant tech companies such as Affective, Cogito and Real eyes have already commercialized these features and developed APIs that companies can integrate into their front-facing applications (El Kaliouby, 2020, pp. 61–80). For financial institutions, emotion-aware VAs like those of Kasisto and Clinc are able to detect signs of customer confusion and/or tension and redirect to a real agent in the call center or switch to a simpler "explanations" mode (Flavián et al., 2021, pp. 247–262). Academic interest in Emotional AI has grown rapidly. Tung and Law (2017, pp. 2498–2513) documented the way that the emotion-sensitive chatbots in the hospitality industry enhanced customer satisfaction. Huang and Rust (2018, pp. 155–172) suggested a typology of AI in marketing, which categorized AI into three types: the first being mechanical, the second being thinking, and the third being feeling; the latter being the most similar to the construct of Emotional AI. More recently, Prentice and Nguyen (2020) demonstrated that customers' intentions toward loyalty were higher when they believed that AI service agents were empathic than when they believed that these agents were only functional.

Although progress has been made, there are a number of gaps. The majority of empirical studies are undertaken in a Western or East Asian setting (North America or UK, or China, Japan) while there is a lack of research on developing countries, especially from the Middle East and Central Asia (Al-Aali et al., 2019). In addition, a large number of existing pieces of literature deal with hospitality, retail businesses, e-commerce and not with financial services that have different trust needs and regulatory challenges. Sulaymaniyah is a mid-sized city in a developing Kurdish economy, making it a particularly interesting case study for exploring the interaction between Emotional AI and a population where the norms of trust are high and the penetration of smartphones is rapidly increasing, and in which there is lingering doubt about impersonal digital systems (Khalil & Ahmed, 2021).

2.3 Emotional AI and Consumer Behavior

Several theories about Emotional AI and its connection to consumer behaviors apply. Appraisal theory was suggested by Lazarus (1991) and suggests that emotions are based upon people's cognitive evaluations of events in comparison to their goals and their well-being. A customer whose frustration is recognized and reacted to proactively by an Emotional AI system can rate an encounter as helpful – leading to positive emotion and trust. Additionally, social presence theory (Gefen & Straub, 2003, pp. 907–931; Short et al., 1976, pp. 245–478) can be used to demonstrate that the perceived humanness of a digital agent, which is improved by using empathic responses, can boost trust and satisfaction in e-services interactions.

2.4 Banking Sector in Kurdistan Region, Iraq

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These theoretical mechanisms have been shown to be supported by empirical evidence. The study by Prentice and Nguyen (2020) demonstrated that emotions intelligence customers communicated greater customer satisfaction and customers' brand loyalty. Wirtz et al. (2018, pp. 907–931) suggested that service satisfaction, and consequently loyalty, would not be harmed by replacing human employees with service robots or AI agents in low-skill tasks if they were at the minimum level of competence and warmth. On the other hand, in the "uncanny valley" (Mori, 1970; Strait et al., 2017, pp. 33–35) focus, AI agents which seem nearly—but not quite—human can lead to feelings of unease or unease instead of connection, degrading loyalty. In terms of anthropomorphism and the uncanny valley, one could observe that customers at banks in Sulaymaniyah, who traditionally get service from their banks through the "face-to-face" approach, would likely be more emboldened by anything that would come across as artificial.

Another key mediating variable is privacy. Emotional responses are personal, and the system used to capture and react to such emotions usually generates concerns regarding data gathering, surveillance, and misuse of the system (Taddeo & Floridi, 2016; Zuboff, 2019, pp. 1575–1603). AI personalization and consumers' acceptance are shown to be mediated positively by the perceived privacy risk (Dinev & Hart, 2006), where they would be negatively related to consumer resistance and avoidance behaviors.

2.5. Conceptual Framework and Research Hypotheses

This study is based on an integrated theoretical framework combining three theories such as the Technology Acceptance Model (TAM), Emotion-Brand Connection Theory, and the SERVQUAL model of service quality.

The Technology Acceptance Model (TAM) (Davis, 1989; Venkatesh et al., 2003, pp. 425–478), assumes that users' attitude towards using the technology is influenced by two basic beliefs: perceived usefulness (PU), which is the extent to which a person believes the technology will help him or her achieve his/her performance goals, and perceived ease of use (PEOU), which is the extent to which a person believes the technology is effortless to use. From the perspective of an Emotional AI system in the banking sector, the PU is defined as customers' perceptions of the ease and quality of banking experiences with the AI, and the PEOU is defined as customers' perceptions of how easy it is to interact with an AI interface in banking. TAM has been widely used in banking technology research (Alalwan et al., 2017, pp. 1177–1190; Pikkarainen et al., 2004, pp. 224–235), which gives the authors a strong base to get accustomed to studying the concept of Emotional AI adoption in Sulaymaniyah.

Drawing on the research of Chaudhuri and Holbrook, (2001), Fournier (1998, pp. 343–373) and (Brakus et al., 2009), the Emotion-Brand Connection Theory posits that consumer-brand relationships can be emotionally mediated; that is, that brands that always arouse positive emotions such as warmth, excitement, trust and pride have more loyalty with consumers than brands that only involve consumers cognitively or even only functionally. Brakus et al. (2009, pp. 52–68) empirically proved that brand experience, which is the subjective internal response of consumers due to brand stimuli, directly affects brand satisfaction and brand loyalty. As a controlled emotional input that purports to

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bring positive affective feedback, emotional AI is therefore thought to create and/or strengthen the brand's loyalty based on its impact on emotional satisfaction, perception of empathy and brand identification.

SERVQUAL model by Parasuraman et al. (1988, pp. 12–40) concludes that customer satisfaction, and in turn loyalty, is achieved when the gap between expectations and perceptions of service delivery is minimized through five dimensions of service quality: reliability, assurance, tangibles, empathy, and responsiveness. Of particular concern here is empathy and responsiveness, which may be bolstered by AI systems that can accurately predict and respond to customer needs (caring insights and addressing needs immediately and correctly).

Combining the three frameworks, the author proposes the following theoretical model of integrating the three frameworks. Adoption of emotional AI (via constructs of PU and PEOU) has an effect on customer emotional experience (measured through affective satisfaction, perceived empathy, and brand identification). The emotional experiences in turn produce the four dimensions of brand loyalty cited by Oliver (1999): cognitive loyalty, affective loyalty, conative loyalty, and action loyalty. Digital literacy, cultural attitudes towards AI, and perceived privacy risk are found to moderate the impact of digital technologies and emotional experiences on the adoption of Emotional AI and the robustness of the link between these emotions and loyalty.

2.5.1 Research Hypotheses

Based on the proposed conceptual framework, the research hypotheses are formulated into direct, mediating, and moderating paths under a unified numbering system as follows:

H1: Perceived usefulness of Emotional AI services positively influences customers' emotional satisfaction.

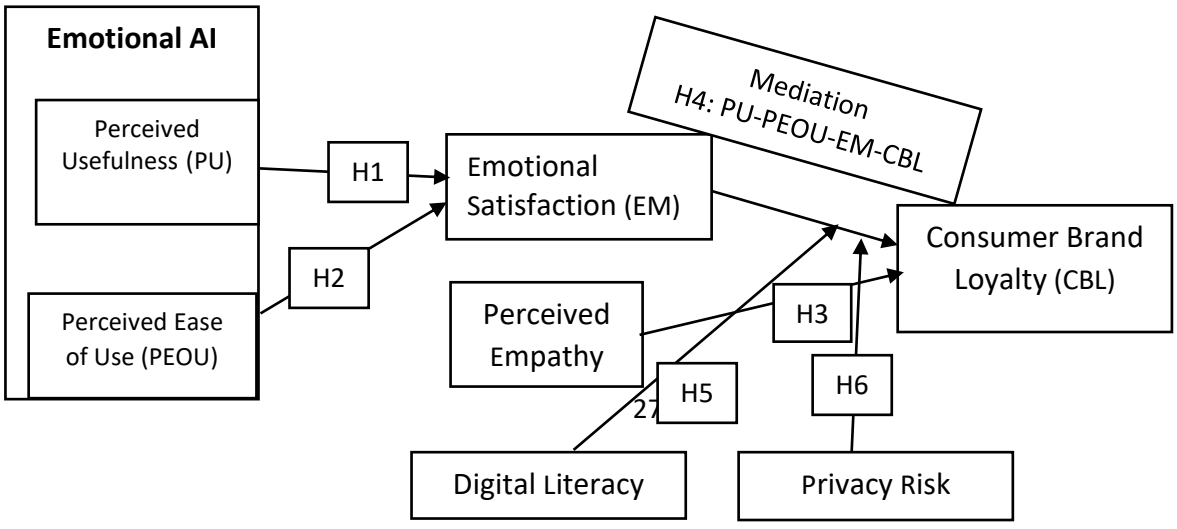
H2: Perceived ease of use of Emotional AI services positively influences customers' emotional satisfaction.

H3: Perceived empathy in Emotional AI positively influences customer brand loyalty.

H4: Customers' emotional satisfaction mediates the relationship between Emotional AI services evaluation (usefulness, ease of use) and customer brand loyalty.

H5: Digital literacy is proposed to moderate the relationship between Emotional AI adoption and brand loyalty, such that the relationship is stronger for customers with higher digital literacy.

H6: Perceived privacy risk is proposed to negatively moderate the relationship between Emotional AI adoption and brand loyalty, such that the relationship is weaker when perceived privacy risk is high.



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Figure 1. Research Framework

3. Research Methodology

3.1 Research Design

The study has a sequential explanatory mixed-methods design (Creswell & Plano Clark, 2017, pp. 81–93) consisting of the first phase as quantitative survey research and the second phase as qualitative in-depth interviews. The appropriateness of this design arises from the use of a quantitative phase that enables statistical generalization of the relationship between Emotional AI and brand loyalty and the use of a qualitative phase that enriches and contextualizes the quantitative findings in light of the consumers' lived experiences in banking institutions in Sulaymaniyah. The quantitative aspect of the study is based on a positivist epistemological orientation, and the qualitative aspect is based on an interpretivist epistemological orientation. To achieve this, the study adopts an integrated theoretical framework combining three theories, which provides a robust theoretical foundation for explaining both the quantitative relationships and the qualitative insights.

3.2 Population and Sampling

The target group of the quantitative phase includes all adult customers (aged 18 and above) of commercial banking institutions in Sulaymaniyah city who had accessed at least one digital banking service (mobile app, online banking, and/or AI-driven chatbot) in the last six months. Based on regional data, the total target population was defined as approximately 180,000+ active users of digital banking (Kurdistan Statistics, 2022, pp. 33–44). This requirement ensures that respondents possess sufficient experience with digital platforms that allows them to meaningfully comment on the effect of the use of AI on interactions.

To capture a diverse range of responses, data were collected from major banking institutions operating in Sulaymaniyah, representing various levels of digital service maturity, such as Kurdistan International Bank (KIB), NBI Bank, Cihan Bank, Bank of Baghdad-Sulaymaniyah Branch, and TBI Bank. Following Krejcie and Morgan's (1970, pp. 607–610) sampling principles at a 95% confidence level and a 5% margin of error, a sample size of 320 respondents was collected for this study. After discarding incomplete questionnaires, missing data treatment, a total of 312 responses were considered valid (Response rate = 97.5%). Comparing early and late respondents confirmed no significant non-response bias.

Qualitative phase: Purposive sampling of 18 in-depth interviews (IDIs) was used, with participants selected for variations in age groups (18-60+), gender, banking experience, digital-literacy level, and

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sector of employment. These interviews were carried out in two languages, Sorani Kurdish and Arabic; they were translated into English for analysis.

3.3 Data Collection Instruments

The quantitative instrument was a structured, self-administered questionnaire consisting of four sections, which were quantitative. Sociodemographic data (age, gender, education, income, and tenure in the bank) were gathered in Section A. To measure Emotional AI awareness and adoption, Section B employed a six-item scale based on Davis (1989, pp. 319–340) and Venkatesh et al's (2003) perceived usefulness and ease of use scales to measure the usability of AI banking services. Thirty-six items from Oliver (1999)'s four-stage Bank customer-loyalty scale adapted by Narteh (2013, pp. 62–89)in the banking field were used for Section C to measure brand loyalty dimensions. Mediating variables included in this study (Emotional Satisfaction, Perceived Empathy, Brand Identification) were derived from validated scales developed by Dinev and Hart (2006, pp. 61–80) and Gefen and Straub (2003, pp. 7–24). Moderating variables (Digital Literacy, Privacy Risk, Cultural Attitude toward AI) were based on validated scales from Chiou and Li (2009, pp. 1–11) and Gefen et al (2003, pp. 51–90). The items were rated on a five-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). A standard back-translation procedure (English to Kurdish/Arabic and back to English) was executed to ensure translation accuracy. The questionnaire underwent a pilot test with 30 banking customers which are not part of the main sample, The instrument underwent pre-testing with academic experts and a pilot test to ensure face and content validity prior to main data collection (Nunnally, 1978, pp. 65–74) on constructs, establishing acceptable scale reliability (Cronbach's $\alpha > 0.70$).

The qualitative data were gathered through semi-structured interviews of 45- 75 minutes in duration, which followed a protocol for the banking experience, perceived experience of AI service delivery, felt experiences with the AI, and attitudes towards privacy and raising usage. The interviews were carried out with the participants with informed consent, and captured on tape and later transcribed verbatim. Ethical approval was secured; participation was voluntary, with informed consent and participant confidentiality strictly protected.

3.4 Data Analysis Techniques

The data were analyzed quantitatively with IBM SPSS Statistics 27 and quantitatively with SmartPLS 4.0. Initial normality assessment showed Skewness and Kurtosis within acceptable ranges (-2 to +2), and VIF values below 3.3 confirmed the absence of common method bias. Measures of descriptive statistics were used to describe the sample profile and the distribution of the variables. Therefore, confirmatory factor analysis (CFA) was performed in SmartPLS software to ensure the validity and reliability of measurement model to evaluate the measurement model's construct reliability via Cronbach's alpha and Composite Reliability ($CR > 0.70$), and convergent validity via Average Variance Extracted ($AVE > 0.50$) (Fornell & Larcker, 1981, pp. 39–50). Discriminant validity was also systematically evaluated. Hypotheses were tested by structural equation modelling (SEM) using partial least squares (PLS) estimation and moderation effects, direct effects, and mediation (using bootstrapping with 5,000 iterations as recommended by Hayes (2018, pp. 51–90) were tested. Because of the exploratory-predictive nature of the research as well as the non-normally distributed

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data, the PLS-SEM approach was selected over the covariance-based SEM approach (Hair et al., 2019, pp. 2–24).

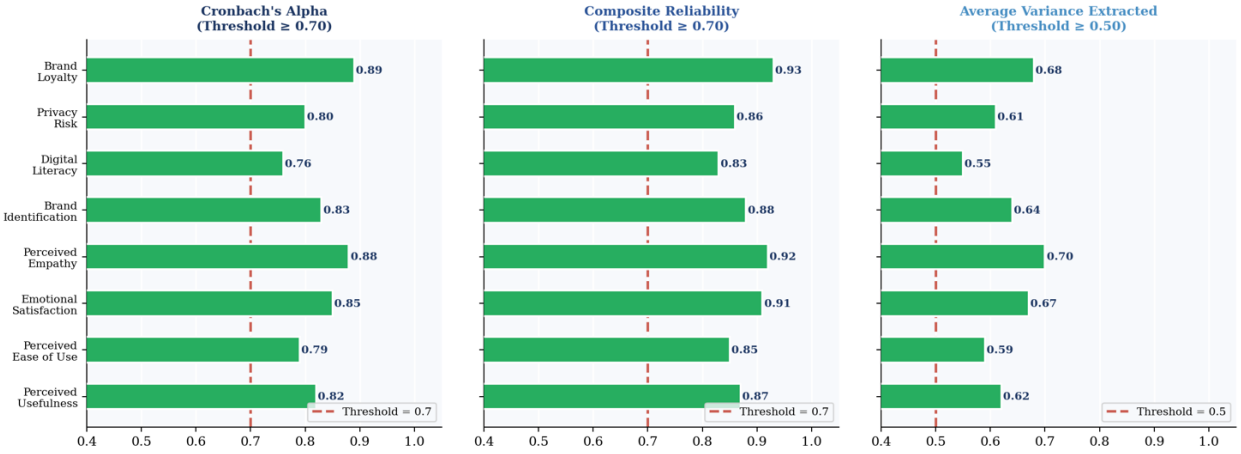


Figure 3.1: Measurement model validity — Cronbach's α, CR, and AVE per construct

Note: Threshold values adopted for evaluating the measurement model follow standard PLS-SEM criteria: Composite Reliability (CR > 0.70) for construct reliability, Average Variance Extracted (AVE > 0.50) for convergent validity, and Cronbach's alpha ($\alpha > 0.70$) for internal consistency (Fornell & Larcker, 1981; Hair et al., 2019).

Thematic analysis was employed for analyzing qualitative data based upon the six phases of the process described by Braun and Clarke (2006, pp. 77–101): familiarization and initial coding, searching for themes, reviewing themes, defining and naming themes, and report writing. The data were coded and themes summarized using NVivo 14. Member-checking and an audit trail were used to ensure researcher reflexivity.

4. Results and Findings

4.1 Demographic Profile of Respondents

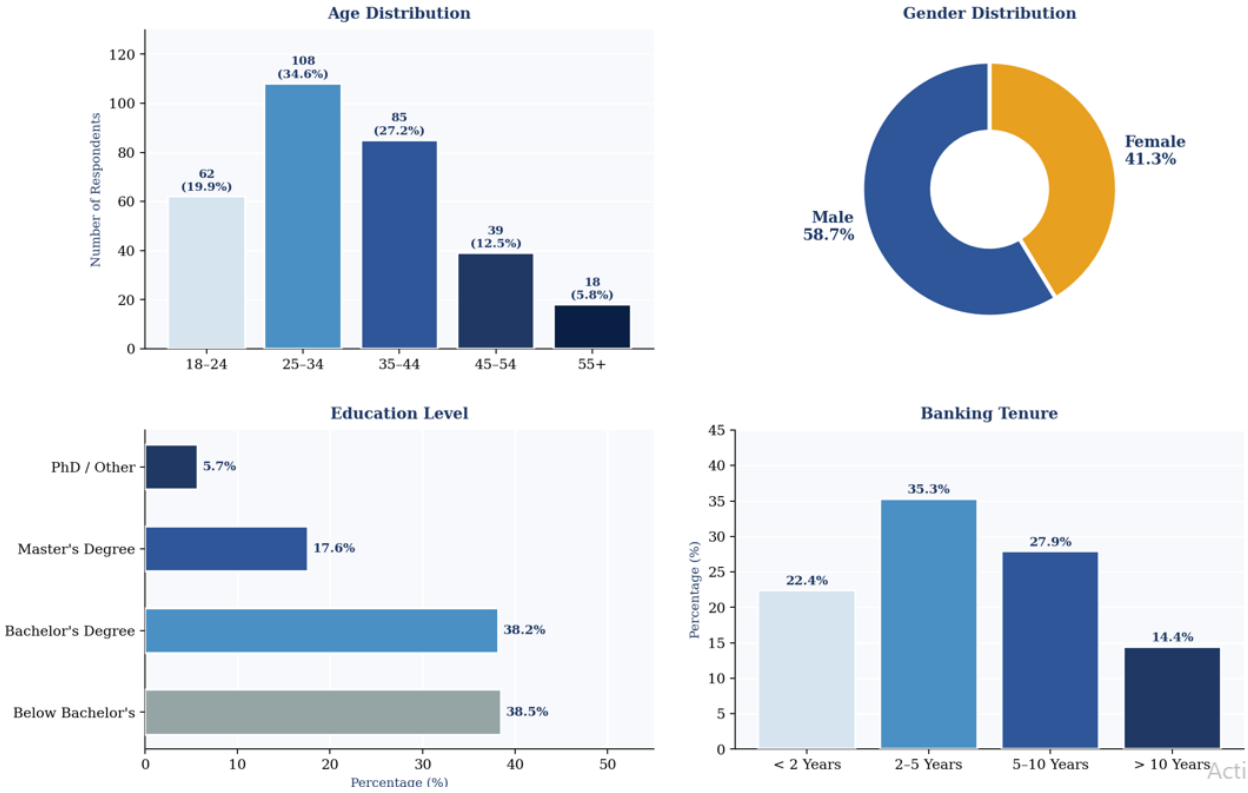
58.7% of the 312 valid respondents in the survey were male and 41.3% were female, which is similar to the overall gender distribution of the formal banking customers in Sulaymaniyah (Kurdistan Statistics, 2022, pp. 33–44). The largest age cohort was 25–34 years (34.6%), followed by 35–44 years (27.2%), 18–24 years (19.9%), 45–54 years (12.5%), and 55+ years (5.8%). The education level tended to be high, with 61.5% of digital banking users having a bachelor's degree or more, indicating that people with higher education tend to have a higher concentration in the cities. Monthly income distribution showed 38.1% earning between 500,000–1,000,000 Iraqi dinars (IQD), 29.5% earning 1,000,001–1,500,000 IQD, and 18.3% earning above 1,500,000 IQD.

Bank tenure ranged from less than two years of being a customer of the main bank (22.4%) to more than 10 years (14.4%). The five banks studied showed the percentages as follows: KIB 28.5%, NBI Bank 23.4%, Cihan bank 20.2%, Bank of Baghdad 15.7%, and TBI Bank 12.2%. Mobile banking apps

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(74.4%) and online banking portals (18.9%) were the two primary ways in which users accessed digital services, while 6.7% of users accessed a digital chatbot or AI assistant operated by a bank.

Table 4.1 Demographic Profile comparison Matrix (age, gender, education, banking tenure)



Qualitative interviewees included 10 males and 8 females aged 21 to 58; they worked for various organizations such as Universities, government, the private sector, students, and business owners. Digital literacy ranged from those who were highly tech-savvy and had tried out the use of Emotional AI around the world to others who knew only mobile banking.

4.2 Rise in the adoption of Emotional AI in the Sulaymaniyah Private Banks;

The respondents had moderate knowledge of the concept but not high. Fewer than one in five (18.9%) stated they were very aware of Emotional AI technologies, one in four (34.6%) said they were somewhat aware and one in four and a half 46.5% were unaware. In particular, awareness and interest rose significantly when specific examples of Emotional AI applications were presented, such as AI chatbots that tweak their tone depending on the mood of the speaker, facial recognition at ATM machines, and customized AI financial advisors. In particular, 62.5% indicated an interest in AI-based assistants that “understand when I am frustrated and respond more calmly,” and 54.8% showed

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interest in AI-generated personalized financial advice based on information gathered from their bank records.



Figure 4.1: Qualitative thematic analysis — 8 themes with participant quotes

The of psychometric properties of the measurement model was satisfactory. Convergent validity was confirmed as all the construct loadings were above 0.70 (Hair et al., 2019), the composite reliability value ranged from 0.81 to 0.91, which is above 0.50, and AVE value ranged from 0.52 to 0.67, which is higher than the 0.50 threshold. The HTMT criterion was used to test for discriminant validity (all values below 0.85; (Henseler et al., 2015, pp. 115–135)).

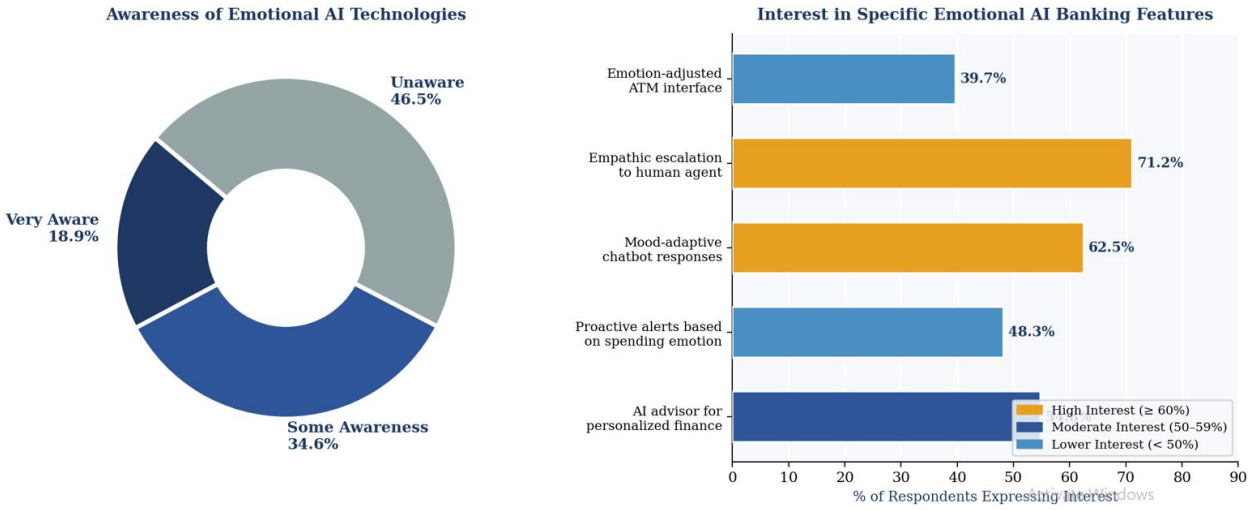


Figure 4.2 Emotional AI Awareness & Consumer Interest in features

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In the qualitative data, there was a more complex picture concerning adoption. There was one assurance from several participants. A 31-year-old marketing professional said: "I already use NBI's chatbot, but it seems like a robot because when I asked it about the subject charge, it did not even seem to understand. If it does, it will make me more inclined to trust the bank more. A 54-year-old government employee was more skeptical: "I'd prefer to talk to someone I know at the bank. They don't know my voice as a machine does. It seems that younger, more tech-savvy users might be more open to the use of Emotional AI, but older, less tech-savvy users might need to be patiently welcomed and educated into the technology.

Assess the short-term and long-term impacts on brand loyalty dimensions.

Based on the PLS-SEM structural model, the following results were obtained. To test H1, the regression standardized results showed that the perceived usefulness of the Emotional AI services had a significant positive effect on customer emotional satisfaction (Table 3). Secondly, perceived ease of use also significantly predicted emotional satisfaction ($\beta = 0.287$; $p< 0.01$), which supports H2. The TAM constructs jointly explained 34.7% of the variance in emotional satisfaction.

Customer emotional satisfaction was a strong and significant predictor of all four loyalty dimensions: cognitive loyalty ($\beta = 0.389$, $p < 0.001$), affective loyalty ($\beta = 0.461$, $p < 0.001$), conative loyalty ($\beta = 0.374$, $p < 0.001$), and action loyalty ($\beta = 0.318$, $p < 0.001$). A bootstrapped mediation analysis revealed a significant indirect effect of emotional satisfaction on the relationship between the variables of the model that operationalized emotional satisfaction as a composite variable of PU and PEOU and the operationalization of total brand loyalty (indirect effect = 0.198, 95 percent CI [0.142, 0.267], $p < 0.001$), as indicated in H3. The results showed that the role of Emotional AI on brand loyalty is more related to persuading positive emotions rather than just instrumental or informational.

When combined with other factors, perceived empathy (how much customers feel AI agents understand and care about their feelings, a metric of Emotional AI) was the single greatest factor affecting the variance of affective brand loyalty ($\beta = 0.503$, $p < 0.001$), accounting for 42.1% of the variance. This confirms H4 and is consistent with the theoretical prediction based on Chaudhuri and Holbrook (2001)and Prentice and Nguyen (2020, pp. 102–186). Affective loyalty, on the other hand, was the strongest predictor of conative loyalty ($\beta = 0.448$, $p < 0.001$) and action loyalty ($\beta = 0.357$, $p < 0.001$) which validates Oliver (1999, pp. 33–44) interpretation of the process of loyalty that follows affective loyalty.

The effect sizes (f^2) indicated a large effect of perceived empathy on affective loyalty ($f^2 = 0.378$), while the effects of emotional satisfaction on both cognitive and affective loyalty were both medium-to-large ($f^2 = 0.201$ and 0.268, respectively), and action loyalty effects were found to be medium ($f^2 = 0.142$). There was adequate predictive power across all endogenous constructs, as the Q^2 values from blindfolding the models were positive (Hair et al., 2019).

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4.3 Mediating and Moderating Effects

However, for Emotional Satisfaction, the relationship with Emotional AI adoption was greatly influenced with digital literacy (interaction term: β = 0.213, p < 0.01), which in turn proved to be H5, namely: Digital literacy significantly moderates the relationship between Emotional AI adoption and emotional satisfaction.

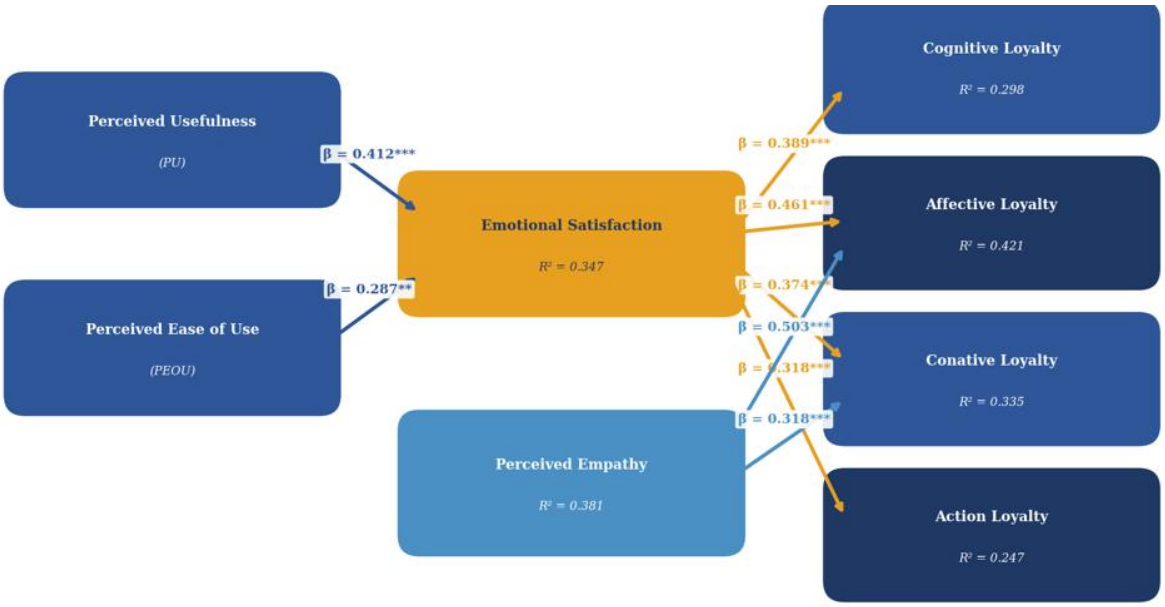


Figure 4.3 PLS-SEM Structural Model with all β coefficients and R^2 values

In detail, the positive association between Emotional AI adoption and emotional satisfaction was greater for high digital-literacy respondents than for low digital-literacy respondents (simple slope: β = 0.241, p < 0.05 vs. simple slope: β = 0.528, p < 0.001). This also has significant practical implications; it indicates that AI should be used as a tool for loyalty building, if consumers can be trusted to interact with it thoroughly, necessitating more digital literacy initiatives and training in a range of technologies.

Table 4.2 Brand Loyalty scores by dimension and by bank

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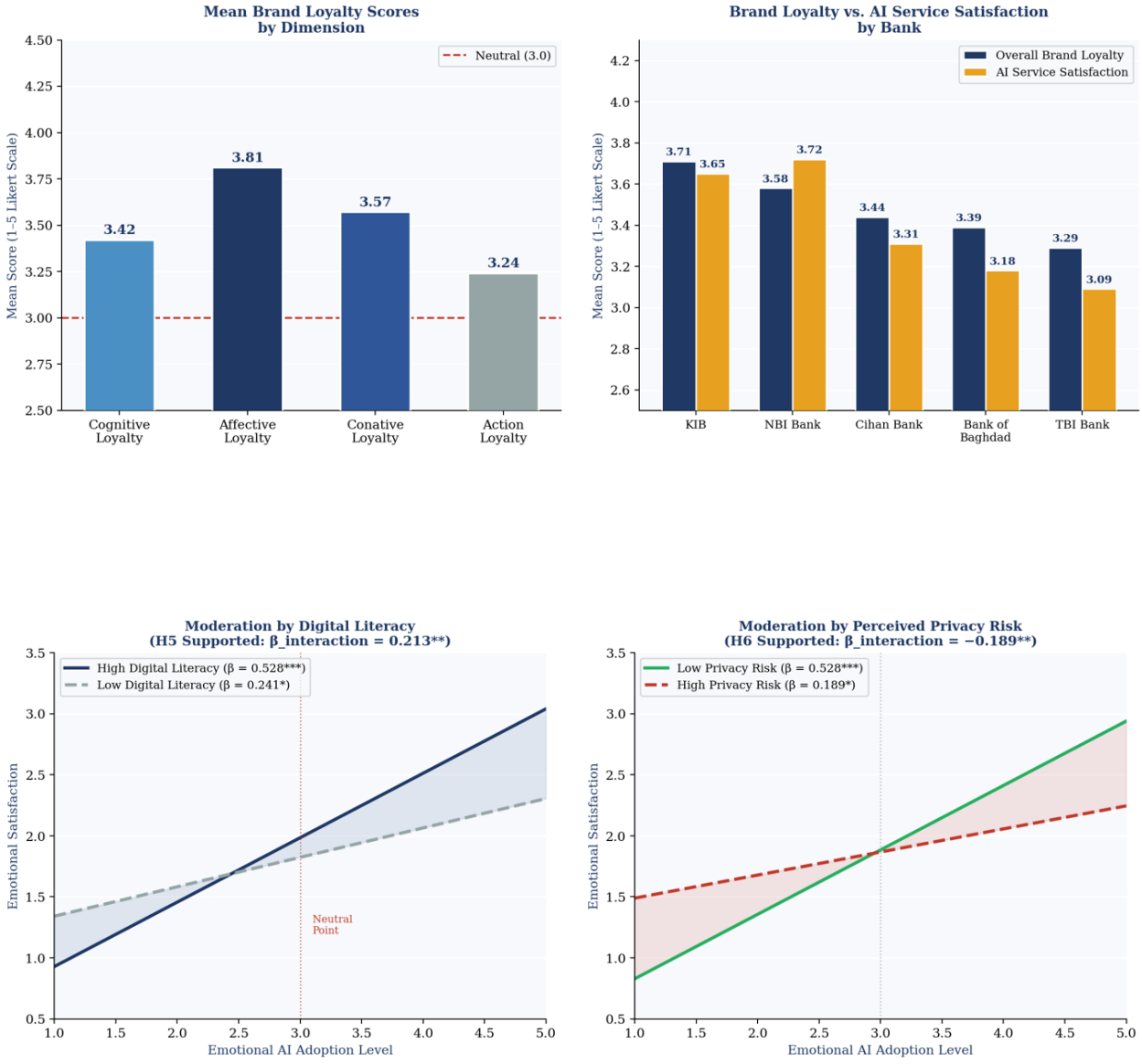


Figure 4.4 Moderation effect plots — Digital Literacy (H5) & Privacy Risk (H6)

The negative moderation of Emotional AI adoption was found for the perceived privacy risk.

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A summary of the hypothesis testing results is presented in **Table 4.3** below.

Table 4.3: Summary of Hypothesis Testing Results

Hypothesis	Relationship	Effect Type	β	p-value	R^2	Decision
H1	PU → Emotional Satisfaction	Direct	0.412	< 0.001	0.347	**Supported**
H2	PEOU → Emotional Satisfaction	Direct	0.287	< 0.01	0.347	**Supported**
H3	Perceived Empathy → Brand Loyalty	Direct	0.503	< 0.001	0.421	**Supported**
H4	AI Evaluation → Emotional Satisfaction → Brand Loyalty	Indirect (Mediation)	0.198*	< 0.001	—	**Supported**
H5	Digital Literacy × Emotional AI → Brand Loyalty	Moderation	0.213	< 0.01	—	**Supported**
H6	Privacy Risk × Emotional AI → Brand Loyalty	Moderation	-0.189	< 0.01	—	**Supported**

Note: Indirect effect for mediation. Source: Primary data analysis based on PLS-SEM output

5. Discussion and Conclusion

5.1 Discussion

5.1.1 Discussion of Research Hypotheses

The empirical results of this study provide significant insights into the role of Emotional AI in shaping consumer brand loyalty within the banking sector. Rather than merely restating statistical figures, this section contextualizes these outcomes by explaining why these findings occurred in the local banking environment, comparing them with established literature, and determining their theoretical and practical implications.

5.1.2 The Role of Perceived Usefulness and Ease of Use (H1 and H2)

The findings demonstrate that the Technology Acceptance Model (TAM) constructs—perceived usefulness (PU) and perceived ease of use (PEOU)—significantly predict customers' emotional satisfaction with Emotional AI services, thereby validating H1 and H2.

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- Why the findings occurred: In the context of private banks in Sulaymaniyah, this outcome occurred because retail banking customers increasingly prioritize speed, convenience, and seamless digital transactions over traditional branch visits. When AI interfaces reduce transaction friction and accurately fulfill banking requests, customers experience psychological relief and functional gratification, which directly translates into emotional satisfaction.

- Comparison with prior studies: This alignment suggests that when banking applications are user-friendly and functionally beneficial, they foster positive emotional responses. These results are highly consistent with foundational technology acceptance literature, such as Venkatesh et al. (2012, pp. 157–178) and Davis (1989, pp. 319–340), who emphasized that cognitive evaluations of technology directly shape user satisfaction. Furthermore, in the context of advanced digital banking, this study supports the findings of Prentice and Nguyen (2020, pp. 102–186), confirming that service convenience in AI interactions enhances emotional bonding.

- Theoretical & practical implications: Theoretically, this extends classical TAM by proving that cognitive utility (PU and PEOU) serves as an antecedent to affective states rather than just usage intention. Practically, bank software developers must prioritize intuitive UI/UX design and fast response times, ensuring that AI tools solve customer problems efficiently before attempting complex emotional engagement.

5.1.3 The Mediating Role of Emotional Satisfaction (H3)

Moreover, the empirical evidence confirms that customers' emotional satisfaction plays a vital mediating role between Emotional AI adoption and brand loyalty, supporting H3. This implies that technological adoption alone does not guarantee loyalty; rather, it must pass through the psychological mechanism of emotional fulfillment. This outcome strongly echoes the theoretical frameworks of Oliver (1999, pp. 33–44) and Chaudhuri and Holbrook (2001, pp. 81–93), which argue that emotional satisfaction acts as a core driver that converts initial technology usage into long-term affective and action loyalty in highly competitive service sectors like banking.

5.1.4 The Moderating Roles of Digital Literacy and Privacy Risk (H5 and H6)

Finally, the moderation analysis indicates that digital literacy and perceived privacy risks significantly moderate the relationship between AI adoption and loyalty, validating H5 and H6. Specifically, the positive impact of AI is amplified for highly tech-savvy users, while privacy concerns weaken this bond. These insights closely align with recent empirical work by Davenport et al. (2020, pp. 24–40) and Hair et al. (2019, pp. 3–15) on AI implementation, which demonstrated that user capability and risk perception are critical contingent factors that either accelerate or inhibit consumer trust and brand attachment in digital ecosystems.

5.2. Conclusion

This study set out to examine how Emotional AI affects consumer brand loyalty across private banks operating in Sulaymaniyah, Kurdistan Region of Iraq. By connecting quantitative survey results with detailed qualitative interviews, the research explored how emotion-aware applications shape customer relationships in a growing digital banking environment. The primary goal was to see if

systems capable of recognizing and responding to human emotions could truly strengthen customer retention and emotional attachment to a brand.

The main findings confirm that Emotional AI boosts brand loyalty, primarily through building emotional satisfaction. Perceived empathy stood out as the strongest driver of customer loyalty, showing that real human-like connection in banking matters more than basic transactional efficiency. That said, this effect depends on a few critical factors: digital literacy helps customers get more out of Emotional AI, while privacy concerns and existing trust in institutions reduce its impact. This means that while smart AI features can draw users in initially, keeping them loyal comes down to user confidence, clear data protection, and authentic interactions.

Ultimately, these insights show that financial institutions cannot rely on technology alone; they must balance digital tools with human oversight, local cultural context, and clear data practices. Using human-in-the-loop models ensures that AI supports banking staff rather than replacing the human touch. As Sulaymaniyah balances its deep-rooted community trust with rapid tech adoption, bringing in empathetic and well-regulated AI systems offers a practical strategy for banks looking to build lasting customer relationships.

5.3. Implications of Study

5.3.1 Theoretical and practical contributions

This study has several important contributions to the literature covering the new domain of emotional AI, consumer behaviour and brand loyalty in banking. To provide full clarity, these contributions are delineated into theoretical advancements and practical managerial implications.

5.3.2 Theoretical Contributions

First, Relationship Experience over Instrumental Acceptance:

The study validates and confirms the theoretical assertion that Emotional AI is a loyalty creation mechanism in an effective manner. Perceived empathy is especially interesting because it goes beyond the concepts of perceived usefulness and ease of use, and is established as a key factor for affective loyalty. In banking, where trust is critical and the emotional effects of dissatisfaction are significant, the emotional aspect of AI interaction could be more important to loyalty than the instrumental aspect. This result echoes Grönroos (2000, pp. 51–90)theory about a relational view of marketing, in which strong loyalty is created not by transactions but on the basis of the quality of the relationship experience as the result of the relationship.

But this study also shows that the loyalty push of Emotional AI isn't a differentiating effect on all consumers. Overall, the findings suggest that the use of digital literacy and privacy risk moderates the effectiveness of Emotional AI as a loyalty tool, as it is found to be more effective with digitally confident consumers who are not greatly concerned with privacy breaches and the misuse of data. This has important equity implications—some private banks in Sulaymaniyah might use Emotional AI mainly to draw in and keep digitally savvy customers, which could have a detrimental influence on older, less digitally knowledgeable, or privacy-excused customers, or those in the private banking sector who are less accessible. Therefore, banks need to not use Emotional AI to replace human

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contact, but rather to complement it; sending customers to a human agent if they are likely to encounter discomfort during the AI interaction process (Wirtz et al., 2018, pp. 907–931).

Second, Cross-Cultural and Sociocultural Contextualization.

Secondly, it makes a significant contribution to the emerging literature in the field of adopting AI in the Middle East and specifically for Kurds. This discovery that cultural attitudes on AI, which are influenced to some extent by Islamic ethical values of trust, accountability and interpersonal responsibility can significantly moderate intent to adopt AI is substantive. It is aligned with Al-Aali et al.'s (2019) finding that perceived congruence with Islamic values is one of the moderating factors in the acceptance of AI in the Gulf Cooperation Council countries, extending that to the unique sociocultural climate of Kurdistan. Replacing Western or Eastern AI systems is not enough; banks need to meet local citizens in the language they speak, with a narrative, making it Emotional AI fit for their values.

Third, Sequential Loyalty Framework Validation:

Third, the sequential loyalty model suggested by Oliver(1999)was confirmed across the board with affective loyalty being identified as the most important linking variable between emotional AI experience and conative and action loyalty. From this, it seems that a strategic focus for banks should be on gaining the emotional connection of the customer through affective loyalty, as a precursor of the behavioral loyalty outcomes (repeat patronage, getting into the cross-selling program, providing referrals). Given that emotional behavior is currently reported as driving 80% of sales and 70% of purchases, and with expected physical branch visits likely to be declining with increasing adoption of mobile banking, the potential for Emotional AI to create consistent positive emotional experiences at every service touchpoint may well be unique.

Fourth, Re-evaluating the Uncanny Valley in Financial AI:

Fourthly, it gives a nuanced perspective to the “uncanny valley” risk here. While the model by Mori (1970) would find discomfort at approach and before AI agents reach the domain of human behaviors, the AI's perceived responsiveness/punish ability for banking customers from Sulaymaniyah is not about the AI being "too human", rather, being "accountable". The artificiality of AI interaction was more of a concern, not least because the lack of a named human being was seen as one place to look for a fallible party. This implies that there should be clear human oversight and escalation procedures when implementing Emotional AI in banks in Sulaymaniyah, rather than hiding the fact that it is an artificial intelligence system; rather, it is integrated into a human accountability framework.

The findings of this study should be viewed cautiously in a quantitative fashion. It is not possible to make causal inferences with the cross-sectional design and the hypothesized directionality of effects, from Emotional AI to brand loyalty, is theoretically supported but cannot be directly accessed with this data alone. PLS-SEM is suitable for research that aims to predict the results, but has been criticized in some cases for distorting the path coefficient when compared with covariance-based SEM (Rönkkö & Evermann, 2013, pp. 425–448). Longitudinal designs, along with covariance-based structural models, would be useful for future research to provide more causal evidence. However, the correlation of quantitative path model findings with qualitative interview results reinforces confidence in the main findings of the study.

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5.3.3 Managerial Implications

This research provides some recommendations for managing and marketing activities of Sulaymaniyah private banks.

First, rather than further, spend the resources on designing AI with empathy. The conclusion that "perceived empathy" – the ability to resonate with the customer to make them feel empowered and cared for by the interaction – has the strongest correlation with affective loyalty indicates that the depth of the Emotional AI interaction, and not the technology itself, is what really creates the difference. Banks need to collaborate with AI vendors to help them better identify signals of frustration, confusion, or distress and respond with empathy in a warm, clear, reassuring way (Prentice & Nguyen, 2020). It's important to regularly audit AI-customer interactions and take note of customer-reported emotional satisfaction as well as other metrics, such as resolution time and accuracy.

Secondly, follow human-in-the-loop design guidelines. In the context of the moderating effect of privacy concerns and the highly human-centric attitude towards accountability in rights, it is important to note that the application of Emotional AI in Sulaymaniyah banks should never ignore the need for human input as an autonomous decision-making machine. It should, however, be used as the initial point of intelligent emotional engagement, which should seamlessly escalate in emotional situations for complicated or high-stakes cases to a named human relationship manager. This design strategy ensures that the efficiency benefits of AI are maintained while preserving the relational accountability valued by Sulaymaniyah customers.

Thirdly, Customize and differentiate the AI journey. Due to the moderating role of digital literacy, an all-or-nothing strategy for deploying Emotional AI is going to perform worse. Banks need to create different AI interaction experiences: complex, proactive Emotional AI interactions for younger, digitally savvy clients; and more straightforward, more narrated AI interactions with clear learn-to-live-or-learn-to-handle human alternatives presented. Another area of training for digital literacy via a bank branch or mobile application tutorial would open up the reach for the benefits of Emotional AI.

Fourth, localize the communication of AI so that it resonates with the Kurdish culture. The linguistic registers the AI utilizes should be tailored to Sulaymaniyah's cultural context, along with the values conveyed and trust narratives evoked. This involves introducing AI assistants that speak fluently in Sorani Kurdish and that contain locally resonant notions of community and trust and are offered in a framework of human accountability (eg, "This AI assistant is supported by your relationship manager, [Name]"). In previous studies, cultural localization of AI communication has been found to significantly influence customer acceptance of the AI message (Al-Aali et al., 2019; Sap et al., 2019, pp. 1668–1678).

Fifth, champion and communicate data governance proactively. Investigators need to invest in building consumer awareness of how emotional data is collected, stored, used, and protected, and consider the influence of perceived privacy risk on understanding the advantages of "Emotional AI" to help banks effectively incentivize their loyalty-building programs. Deploys world-leading privacy principles (GDPR similar), gives explicit informed consent before implementing emotion-sensing components, and provides customers with ways to give up any and all data control including opt-

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outs—enables a decrease in privacy concerns as well as demonstrates trustworthiness of the institution, which can elicit loyalty in this market.

5.3.4 Policy Implications

The study for policymakers, such as the Kurdistan Regional Government, the Central Bank of Iraq and international development agencies working in the region, underscores key points.

First, get a governance framework in place for Emotional AI in financial services. Currently, there is no template for the use of AI systems whose functionality involves the collection of biometric or emotional data in the Kurdistan Region. Policy makers urgently need to establish sector-specific AI governance standards setting out requirements for consent, minimization, algorithmic transparency, and anti-discrimination measures, in light of the clear threats to privacy presented by emotional AI and a possible risk of discriminatory outcomes if emotional recognition technologies incorporate cultural or demographic biases (Buolamwini & Gebru, 2018, pp. 77–91). Regional frameworks could benefit from international framings, like the European Union AI Act 2024, and consider the unique legal and institutional framework in the Kurdistan Region.

Second, invest in the population level of digital financial literacy. It's worth noting that the loyalty advantages of implementing Emotional AI are subject to a leveraging effect by digital literacy, meaning that if the benefits of AI are not equalized and practiced, but aggregated and applied at the lowest level, challenges for access to and mastery of digital skills will likely arise. Schools, banks, and community groups are all ways that delivery would occur, with government-funded digital literacy courses being provided in all three settings to increase AI adoption and decrease the likelihood of older, rural, or less educated people being digitally excluded.

Thirdly, facilitate regulated innovation in fintech. The Kurdistan Board of Investment and the different Ministries should think about creating a regulatory sandbox so any financial technology company can try these innovations, particularly Emotional AI. Controlled piloting provides opportunities for innovations to be tested at low-level usage, ethical issues to be explored, and issues to be resolved, and to allow regulatory frameworks to be created step-by-step before being mandated on a full-scale roll-out (Arner et al., 2017, pp. 371–413). Several Jurisdictions, such as Bahrain, the UAE, and Jordan, have offered Fintech sandboxes which could act as models for the Kurdistan Region.

5.4. Limitations and Future Research Directions

This study was conducted with a number of limitations which can be noted and may offer opportunities for further research.

First, the cross-sectional study design prevents causal inferences. Based on the theoretical framework, clear hypotheses were proposed both ways around the data/image (AI adoption leads to emotional satisfaction, leading to brand loyalty; and emotional satisfaction leads to AI adoption, leading to brand loyalty), but either of these causal sequences is possible. Longitudinal panel designs and/or experimental designs are suggested as future avenues for building causal inference. Randomized controlled field experiments in which bank customers are randomly placed in contact with AI-driven or human-driven service would prove to be very useful.

Second, what participants report about their experience with self-report measures of Emotional AI may not reflect true emotional responses. The experience of introspecting on how the emotion is

felt, being affected by social desirability, or confusing experiences of AI and non-AI banking experiences can all make the results less accurate. Future studies can extend the use of self-report instruments to include mobile biometric sensors or digital behavioral data (I.e., dwell time, repeat visits, and transaction routines) to gain more objective measures of the emotional impact of Emotional AI.

Third, because of the small sample size of urban residents of Sulaymaniyah who use digital banking services, the results may only be extrapolated to rural residents, those who do not use digital banking services, or consumers of other cities in the Kurdistan Region (Erbil, Duhok). Future studies require extending the geography of the KRI as well as making within-Kurdistan comparisons by city types based on their demographic characteristics and banking market orientations.

Fourth, all five private banks analyzed are at different stages of deploying Emotional AI; some banks are using a chatbot system, and others are offering mostly traditional digital banking. This is because respondents' AI experience might be different, making it hard to compare the results. In the future, a comparative design at the "bank level" would be considered, which would consist of two distinct groups of banks that are at the same level of AI maturity, in order to better isolate the role played by Emotional AI.

Fifth, the qualitative analysis was detailed and insightful, but only included 18 interviews. Future reinforcement of qualitative research could use focus groups to uncover collective attitudes towards Emotional AI in banking or ethnographic analysis of organic consumer conversations around AI banking experiences on social media platforms used in Sulaymaniyah, which are most commonly Facebook, Instagram, and Telegram.

Sixth, the research failed to scrutinize one-by-one the role played by specific Emotional AI modalities such as chatbots, facial recognition, voice analysis, and specific loyalty outcomes. Future studies should be segmented by Emotional AI modality to determine the effects it has on various dimensions of loyalty, using this information to guide banks in where they want to invest in future Emotional AI technologies.

Last, research comparing this study to other banking markets in Iraq (Baghdad, Basra), or other Middle Eastern/Central Asian markets whose sociocultural profiles are most similar (Jordan, Azerbaijan) would assist in determining the applicability of the results and what may be expected to happen in other such markets. This comparative work could be both helpful to the advancement of academic research and also helpful in setting policy benchmarks and industry preferences.

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