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# AI-Driven Marketing Communication and Customer Satisfaction in Jakarta's Digital Banks

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**ABSTRACT:** The rapid integration of artificial intelligence (AI) has transformed digital banking practices, particularly through the adoption of hyper-personalised customer experiences. Despite this growth, comparative empirical evidence on how customers perceive AI-driven strategies across competing digital banks remains limited. This study investigates differences in customer perceptions of Integrated Marketing Communication (IMC), AI Personalization, Technology Acceptance Model (TAM) attributes, Kano needs categories, and overall customer satisfaction among users of three digital banks in Jakarta (Bank X, Bank Y, and Bank Z). A comparative quantitative approach was employed, involving 300 respondents selected through purposive and quota sampling. Data were analysed using descriptive statistics, ANOVA, and Tukey HSD tests. The findings indicate that Bank Y consistently achieves the highest mean scores across all constructs, reflecting strong perceptual leadership. Significant differences among the banks were confirmed, with further analysis revealing that TAM-related attributes and performance needs have become parity factors for certain bank pairs. In contrast, AI Personalization and excitement needs emerge as key differentiators. These results suggest that in increasingly mature digital banking markets, competitive advantage is no longer determined by basic functional performance, but by the ability to deliver proactive, contextual, and emotionally engaging AI-based experiences. This study contributes to the IMC, TAM, and Kano literature by highlighting a shift in customer expectations, where AI Personalization plays a central role in generating attractive quality and enhancing customer satisfaction.

**Keywords:** AI Personalization, Digital Banking, IMC, TAM, Kano Model, Customer Satisfaction.



## INTRODUCTION

Artificial Intelligence (AI) has become a pivotal force reshaping the global financial services industry, particularly within digital banking. Advances in machine learning, predictive analytics, and automated decision-making systems have transformed how banks design services, communicate with customers, and deliver value propositions (Huang & Rust, 2021); (Abulsaoud

Ahmed Younis & Adel, 2020). Rather than functioning solely as an operational tool, AI now plays a strategic role in enabling hyper-personalised interactions that are proactive, contextual, and increasingly relational.

In emerging markets such as Indonesia, the adoption of AI in digital banking has accelerated alongside high smartphone penetration, improved digital literacy, and the rapid growth of platform-based ecosystems. Jakarta, as Indonesia's primary economic and technological hub, represents a highly competitive arena in which digital banks continuously innovate to attract, retain, and engage customers. Prior studies suggest that while AI-driven Personalization has been widely adopted in developed economies, its implementation and customer evaluation in emerging markets remain shaped by trust, communication consistency, and perceived relevance (Leung & Wong, 2020; Zhang et al., 2020)

Within this competitive environment, digital banks increasingly rely on Integrated Marketing Communication (IMC) to ensure message consistency across digital touchpoints, including mobile applications, social media, and AI-mediated interfaces (Kliatchko, 2008). At the same time, customer acceptance of AI-driven services continues to be explained largely through the Technology Acceptance Model (TAM), which emphasizes perceived ease of use and perceived usefulness as key determinants of adoption (Davis, 1989). However, as digital banking markets mature, these functional attributes may no longer suffice as sources of competitive advantage.

To capture the asymmetric effects of service attributes on satisfaction, the Kano Model offers an additional lens by distinguishing between basic needs, performance needs, and excitement needs (Kano, 1984; Picolo & Tontini, 2018). Recent service research indicates that advanced AI Personalization increasingly functions as an excitement attribute capable of generating customer delight rather than merely fulfilling functional expectations (Park et al., 2021).

Despite extensive research on AI adoption and digital banking satisfaction, existing studies largely focus on single-bank contexts or examine technology adoption variables in isolation. Comparative empirical research that simultaneously integrates IMC, TAM, and the Kano Model across competing digital banks within the same market remains limited, particularly in Indonesia. Addressing this gap, the present study conducts a comparative analysis of customer perceptions across three major digital banks in Jakarta (Bank X, Bank Y, and Bank Z). The study seeks to identify whether significant differences exist in perceptions of IMC, AI Personalization, TAM attributes, Kano need categories, and overall customer satisfaction, thereby offering both theoretical contributions and actionable managerial insights.

Jakarta, as the country's primary economic hub, has consequently emerged as a *central competitive arena* where digital banks strive to leverage advanced technology to expand their customer base, strengthen engagement, and cultivate long-term loyalty. Recent studies highlight that developed economies have been able to maximise AI through content Personalization, predictive analytics, and automated marketing systems supported by robust digital infrastructures (Mubarok et al., 2024). These global developments signal an urgent need to understand how similar AI-driven approaches are adopted and evaluated in emerging markets such as Indonesia.

In the digital banking context, the role of AI has evolved beyond automation and operational efficiency toward enabling hyper-Personalization. AI-driven Personalization allows banks to analyse behavioral, transactional, and contextual data in real time to provide tailored product recommendations, proactive alerts, and adaptive user interfaces. This capability is increasingly critical in saturated markets, where the ability to deliver relevant and distinctive value propositions determines competitive differentiation and customer retention. As multiple studies suggest, advanced Personalization contributes substantially to customer engagement, satisfaction, and loyalty—yet its effectiveness is contingent on user trust and perceived value (Huang & Rust, 2021; Wirtz et al., 2013).

Jakarta's digital banking landscape is currently dominated by three major players—Bank X, Bank Y, and Bank Z—each characterised by distinct ecosystem strengths and strategic orientations.

- Bank X emphasizes a life-centric banking approach supported by its integration with the Gojek ecosystem and its utilisation of Google Cloud's AI and data platforms. (Kibaroglu, 2022).
- Bank Y, backed by a long-established conventional banking institution, relies heavily on Integrated Marketing Communication (IMC) strategies to consolidate brand trust and drive engagement. (Husada, 2024).
- Bank Z, supported by the Sea Group ecosystem, embeds its services deeply into the Shopee platform, leveraging e-commerce integration as its primary competitive strength. (Husada et al., 2025)

These strategic variations imply that customers of each bank are likely to develop different perceptions of AI-driven Personalization, ease of use, and satisfaction. However, despite the extensive adoption of AI features, comparative empirical assessments across different digital banks in the same market remain limited. Existing literature predominantly examines single- bank case studies, focusing on isolated adoption factors or user satisfaction within one institution. As a result, little is known about how AI-based Personalization strategies perform *relative to competitors* within a shared market environment. This limits theoretical understanding and constrains managerial insights for banks seeking to optimize AI investment and differentiation strategies.

This study addresses this gap by conducting a rigorous multi-bank comparative analysis involving Bank X, Bank Y, and Bank Z. The novelty lies in three aspects:

1. A shift from single-bank analysis to direct multi-bank comparison
   Prior research in Indonesia predominantly evaluates AI adoption or customer satisfaction within one bank at a time. By contrast, this study directly compares three leading digital banks operating in the same market context, thus providing a more robust assessment of relative performance and competitive positioning.
2. The integration of three theoretical frameworks—IMC, TAM, and the Kano Model—within one analytical design.
   This combined framework enables a more comprehensive understanding of how communication consistency (IMC), user perceptions (TAM), and asymmetric satisfaction factors (Kano) jointly shape customer responses to AI-driven services.
3. The operationalisation of AI Personalization through the Kano Model to determine whether Personalization functions as a Basic Need, Performance Need, or Excitement Need.
   This approach is rarely applied in Indonesian digital banking studies and offers new theoretical insight into how AI generates satisfaction beyond functional utility.
   Understanding these dynamics is essential, given the intensifying competition among digital banks

in Jakarta. The findings provide strategic implications for digital banks seeking to allocate AI investment more effectively, identify which service dimensions have reached competitive parity, and recognise which attributes serve as high-impact differentiators. Based on this context, the central research question of this study is formulated as follows:

Are there significant differences in perceptions of IMC, AI-based Personalization, Perceived Ease of Use (PEOU), Perceived Benefits, Basic Needs, Performance Needs, Excitement Needs, and overall Customer Satisfaction among users of Bank X, Bank Y, and Bank Z in Jakarta?

The urgency of this research lies in its potential to inform more inclusive and contextually relevant AI strategies for digital banks in Indonesia. As AI becomes a core driver of competitive advantage, identifying the attributes that matter most to customers—and understanding how they vary across competing institutions—will be critical for strengthening engagement, enhancing satisfaction, and securing long-term market leadership.

**Practical Contribution**

Detailed comparison results (through Tukey HSD Test) provide actionable strategic guidance to the management of the three digital banks. By precisely identifying which dimensions are parity factors and which are differentiators, banks can optimally allocate resources for AI feature development. This study specifically shows how banks should invest in AI to create Excitement Needs—features that truly satisfy and differentiate services in the eyes of customers.

**Integrated Marketing Communication (IMC)**

Integrated Marketing Communication (IMC) is a strategic planning concept that emphasizes the coordination and integration of all communication channels to deliver a clear, consistent, and customer-focused message (Kliatchko, 2008). IMC extends beyond promotional activities to encompass every point of interaction between the organisation and its stakeholders, including digital platforms and service interfaces. (Kliatchko, 2008) defines IMC with its four main pillars: customer focus, message consistency, channel synergy, and strategic results. IMC moves beyond promotional alignment to encompass every interaction between an organisation and its stakeholders, including digital interfaces, service encounters, and technology-mediated touchpoints(Schultz et al., 2014).

In the context of digital banking, IMC plays a critical role in shaping customer perceptions of credibility, trust, and service reliability. The increasing reliance on mobile applications, AI-powered notifications, chatbots, and personalised financial insights requires banks to ensure that all messages and service cues remain coherent and aligned with brand values (Lemon & Verhoef, 2016). Prior research demonstrates that inconsistent or fragmented digital communication increases perceived risk and reduces customer confidence, particularly in high-involvement and high-risk services such as banking (Lemon & Verhoef, 2016).

Recent studies further suggest that IMC functions as an important antecedent of technology acceptance in financial services. Consistent communication across mobile applications, social media, notifications, and customer service channels reduces perceived risk and facilitates customer acceptance of new technologies (Purwati & Ariyani, 2025). A marketing communication planning concept that recognises the added value of a comprehensive plan. This plan evaluates the strategic role of various communication disciplines—such as general advertising, direct response, sales promotion, and public relations—and combines them to provide clarity, consistency, and maximum communicative impact. The Integrated Marketing Communication marketing mix elements also play a role by integrating various communication strategies to convey consistent and effective messages (Purwati & Ariyani, 2025). From a relationship marketing perspective, consistent and integrated communication supports long-term value creation by strengthening relational bonds between firms and customers (Payne & Frow, 2017). In the context of digital banking, IMC extends to cover all digital touchpoints, including mobile applications and AI interactions.

Banks with strong IMC frameworks are better positioned to introduce AI-based features without triggering perceptions of intrusiveness or data misuse. Prior research demonstrates that coherent communication strategies enhance perceived legitimacy of technological innovation, particularly in high-trust industries such as banking (Husada, 2024).

IMC acts as an antecedent variable for AI Personalization. Banks with integrated and solid IMC strategies tend to be more successful in implementing AI Personalization because they have already built a framework of trust and brand consistency. For example, Bank Y's campaign, #Better2Gether, is an IMC effort that leverages BANK Y's legacy trust, which in turn facilitates the acceptance of new AI features with a more positive perception. With effective IMC, banks can ensure that AI Personalization does not feel intrusive or manipulative, but rather as a relevant service that increases engagement.

**AI Personalization**

AI Personalization refers to a system's ability to tailor interfaces, recommendations, alerts, and content dynamically based on real-time analysis of customer data, behavioral patterns, and contextual information (Huang & Rust, 2021). AI Personalization can be interpreted as a form of technology-enabled value co-creation, in which customers indirectly participate in shaping service experiences through behavioral data and feedback (Hoyer et al., 2010). Unlike rule-based customization, AI Personalization operates through predictive and adaptive models that evolve with user behaviour.

In digital banking, AI Personalization has become a key differentiation strategy. Studies indicate that personalised financial recommendations, spending insights, and proactive notifications increase customer engagement and satisfaction (Wirtz et al., 2013). Empirical studies show that such AI-enabled interactions increase perceived relevance and usefulness, which in turn positively influence customer satisfaction and continued usage intention (Shankar et al., 2016).

However, the effectiveness of Personalization is contingent upon customer trust, transparency, and ethical data usage. Excessive or poorly communicated Personalization may generate scepticism and perceived manipulation (Zhang & Wei, 2020); (Nguyen & Simkin, 2017). As a result, banks must balance technological sophistication with ethical considerations and clear communication regarding data usage.

Recent research highlights the growing importance of explainable and responsible AI in financial services. Explainable AI (XAI) enhances user understanding of how recommendations are generated, thereby reducing uncertainty and increasing trust in AI-driven systems (Dwivedi et al., 2021); (Huang & Rust, 2021); (Pillai et al., 2020). In emerging markets, where institutional trust may vary, transparent AI communication becomes even more critical in shaping customer acceptance and satisfaction.

From a strategic perspective, AI Personalization functions not only as a technological capability but also as a communicative mechanism that reinforces relational value between banks and customers. When integrated with strong IMC frameworks, AI Personalization reinforces consistent brand messaging and supports emotionally engaging customer experiences (Purwati & Ariyani, 2025). In mature digital banking markets, advanced AI Personalization increasingly operates as an excitement attribute, capable of generating customer delight and emotional attachment beyond basic functional expectations (Lin et al., 2017; Wirtz et al., 2013). Its success therefore depends on alignment with IMC principles and customer-centric communication design.

Defined as the ability of a system to tailor the user experience—including interfaces, product recommendations, transaction alerts, and notifications—in real time and proactively. This customization is based on the analysis of historical behavioral data, contextual data, and complex predictive models. (Huang & Rust, 2021) emphasize that AI in services enables customization on a mass scale that was previously impossible, transforming customer interactions from transactional to relational.

Recent studies suggest that AI-driven services increasingly shape holistic customer experiences by influencing cognitive, emotional, and behavioral responses (Ameen et al., 2021). In the fintech landscape, advanced Personalization has become a critical differentiation strategy. Studies show that AI-driven Personalization can significantly increase customer engagement. (Wirtz et al., 2013) assert that the increased relevance and convenience offered by AI can increase customer lifetime value and strengthen brand loyalty. However, the success of Personalization is highly dependent on trust. Concerns about data privacy, algorithmic opacity, and potential manipulation can create a paradox where Personalization increases satisfaction while simultaneously fostering skepticism. Therefore, trust and ethics are prerequisites for effective AI Personalization. AI-driven Personalization can be viewed as a natural extension of IMC, as it enables banks to deliver contextually relevant messages aligned with brand values throughout the customer journey.

### Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) posits that perceived ease of use (PEOU) and perceived usefulness are the primary determinants of technology adoption (Davis, 1989). Since its introduction, TAM has been extensively validated across various technology contexts, including digital banking, mobile payment systems, and fintech services (Dwivedi et al., 2021; Venkatesh et al., 2003; Venkatesh & Bala, 2008). TAM has been widely applied in digital banking and fintech research, including studies within the Indonesian context (Anwar et al., 2024).

PEOU reflects the degree to which users perceive a system as effortless to use, encompassing interface clarity, navigation simplicity, and transaction efficiency. Perceived usefulness refers to the extent to which a system enhances users' task performance or financial management outcomes. While these constructs remain essential for initial adoption, recent research suggests that in mature digital markets, they increasingly represent baseline expectations rather than sources of differentiation.

### Perceived Ease of Use (PEOU)

PEOU refers to the extent to which a person believes that using a particular system will be free of effort or difficulty. In the context of digital banking, PEOU includes ease of application navigation, transaction speed, and clarity of instructions when using AI features. Research in Indonesia confirms that PEOU has a significant and positive influence on the intention to use digital banking services. For Bank X, for example, despite its focus on life-centric design, the ease of use (PEOU) of its application must continue to be improved and monitored, as an intuitive display is a basic prerequisite for customer satisfaction. Prior studies indicate that systems perceived as complex or cognitively demanding tend to generate resistance, even when their functional benefits are substantial (Lemon & Verhoef, 2016).

### Perceived Usefulness

Perceived Benefit is the user's belief that using a particular system will improve their work performance or efficiency. In digital banking, this relates to how well AI features (such as automatic expenditure analysis, savings recommendations, or risk notifications) actually help users achieve their financial goals. (Alnaser et al., 2023), in their review, state that Perceived Performance (closely related to Perceived Benefit) reflects customers' perceptions of service features and outcomes. Both PEOU and Perceived Benefit are important prerequisites for adoption; when these expectations are met, overall customer satisfaction will increase.

### The Kano Model and Customer Needs Classification

The Kano Model (Kano, 1984) is a powerful tool for understanding product and service quality from the customer's perspective, classifying quality attributes into three main categories based on their asymmetric impact on satisfaction. The use of this model is particularly useful for classifying how various aspects of AI Personalization affect customer emotions.

### Basic Needs (Must-Be Quality)

Basic Needs are attributes that are considered fundamental and mandatory, such as security, 24/7 system availability, and transaction accuracy (Kano, 1984; Picolo & Tontini, 2018). If these needs are not met, customers will experience high levels of dissatisfaction. However, the fulfilment of basic needs does not necessarily result in high satisfaction, as customers tend to take these attributes for granted (Kano, 1984).

In the context of digital banking, basic needs include core transactional functions, data privacy protection, and cybersecurity safeguards. Failures in these areas can lead to severe disruptions in customer trust and perceived service legitimacy, particularly in AI-enabled financial services where data sensitivity is high (Huang & Rust, 2021; Leung & Wong, 2020).

### Performance Needs (One-Dimensional Quality)

Performance Needs are attributes that exhibit a linear relationship with customer satisfaction: the better the performance, the higher the satisfaction, and vice versa (Kano, 1984). In digital banking, performance needs commonly include fund transfer speed, efficiency of customer support services, accuracy of system responses, and competitive interest rates or fees (Lemon & Verhoef, 2016). These attributes often become the primary focus of competition, especially in terms of operational efficiency and service speed.

Within the Technology Acceptance Model, Perceived Benefits or Perceived Usefulness are frequently associated with performance needs, as customers directly evaluate whether system performance delivers tangible value and improves task efficiency (Alnaser et al., 2023; Davis, 1989).

**Excitement Needs (Attractive Quality)**

Excitement Needs, also referred to as attractive qualities, represent unexpected or innovative features that generate high levels of satisfaction when present but do not cause dissatisfaction when absent, as customers do not explicitly expect them (Kano, 1984). In the context of digital banking, highly proactive AI Personalization, intelligent financial recommendations, predictive insights, or gamified financial features are commonly classified as excitement needs (Chen & Yang, 2021; Wirtz et al., 2013).

In increasingly competitive digital banking markets, the ability to consistently deliver excitement needs plays a crucial role in creating emotional engagement and fostering customer loyalty beyond functional satisfaction (Lemon & Verhoef, 2016).

In the context of this study, highly proactive AI Personalization, intelligent financial recommendations, or fun gamification are often classified as Excitement Needs. In a competitive market, the ability to consistently deliver Excitement Needs is key to winning customer emotional loyalty.

This study examines perceptions of these three Kano need categories among digital banks. Advanced AI Personalization has the greatest potential to act as an Excitement Need. Comparing the comparative scores of the three banks on this Kano dimension will reveal where digital banks should prioritise their strategic investments to generate the highest satisfaction. Although this study focuses on difference testing rather than structural relationship testing, comparative hypotheses are formulated to guide the analysis of perception differences between bank groups. Based on the IMC, TAM, and Kano Model frameworks, it is assumed that variations in implementation strategies and ecosystems will result in significant differences in customer perceptions:

- H1: There are significant differences in perceptions of Integrated Marketing Communication (IMC) between Bank X, Bank Y, and Bank Z.
- H2: There are significant differences in perceptions of AI-based Personalization among Bank X, Bank Y, and Bank Z.
- H3: There are significant differences in Perceived Ease of Use (PEOU) between Bank X, Bank Y, and Bank Z.
- H4: There is a significant difference in the perception of benefits among Bank X, Bank Y, and Bank Z.
- H5: There is a significant difference in the perception of Basic Needs among Bank X, Bank Y, and Bank Z.
- H6: There is a significant difference in the perception of Performance Needs among Bank X, Bank Y, and Bank Z.

- H7: There is a significant difference in the perception of Excitement Needs among Bank X, Bank Y, and Bank Z.
- H8: There is a significant difference in the level of Customer Satisfaction between Bank X, Bank Y, and Bank Z.

Although there has been extensive research on the adoption of single technologies in fintech, there is still a significant gap in the literature comparing the effectiveness of AI Personalization directly between different digital banking institutions in the same market. Comparative studies are urgently needed to identify best practices and map the competitive variables that most influence user perceptions. Based on this background, the main research question guiding this study is formulated as follows:

Are there significant differences in perception and satisfaction with Integrated Marketing Communication (IMC), AI-Based Personalization, Perceived Ease of Use (PEOU), Perceived Benefits, Basic Needs, Performance Needs, Excitement Needs, and Customer Satisfaction among users of Bank X, Bank Y, and Bank Z in Jakarta?

The urgency of this research lies in the increasingly competitive banking landscape, where Personalization has become a necessity. Understanding the dynamics of AI adoption in Jakarta is crucial for banks such as Bank Z, Bank X, and Bank Y to develop effective and inclusive AI solutions. These comparative findings will offer deep strategic insights, enabling banks to refine their AI strategies, enhance customer loyalty, and strengthen their market position amid Indonesia's sustained digital economic growth.

## METHOD

This study employs a comparative quantitative survey design (ex post facto) to examine differences in user perceptions across three digital banks—Bank X, Bank Y, and Bank Z—in Jakarta. The use of a survey-based quantitative approach follows established guidelines in marketing research for capturing consumer perceptions and attitudes toward service attributes (Malhotra, 2020).

The ex post facto design is appropriate because the variables of interest—Integrated Marketing Communication (IMC), AI Personalization, Technology Acceptance Model (TAM) attributes, Kano need categories, and customer satisfaction—cannot be manipulated experimentally. Instead, these variables are measured based on naturally occurring conditions among independent user groups.

The target population comprises active users of digital banking services residing in Jakarta. Due to the absence of a complete sampling frame, a non-probability sampling strategy was adopted, combining purposive sampling and quota sampling, a common approach in applied marketing and consumer research when population lists are unavailable (Malhotra, 2020).

The inclusion criteria were as follows:

1. Respondents must reside in Jakarta;
2. Must have actively used one of the three digital banks within the last three months; and
3. Must have experience interacting with the bank's AI-driven features (e.g., personalised notifications

or recommendations).

Quota sampling was applied to ensure balanced representation across the three banks, with an intended minimum of 100 respondents per bank, resulting in a total sample size of 300 respondents.

Data were collected using a structured questionnaire consisting of items measured on a Likert scale. The instrument operationalised eight constructs informed by prior literature, namely:

Integrated Marketing Communication (IMC)
- AI Personalization
- Perceived Ease of Use (PEOU)
- Perceived Usefulness / Benefits
- Kano Model dimensions (Basic Needs, Performance Needs, and Excitement Needs)
- Customer Satisfaction

Each construct was adapted from established theoretical models to ensure conceptual alignment and content validity.

The survey was administered online to accommodate respondents' mobility and to facilitate efficient access to digital banking users. Prior to distribution, respondents were screened based on the predefined inclusion criteria. To minimise common method bias, the questionnaire employed clear and neutral wording, separation of construct groupings, and assurance of respondent anonymity.

Data were processed and analysed using IBM SPSS Statistics. The analysis was conducted in three stages:
1. Descriptive statistics, to identify and compare mean scores of all constructs across the three banks;
2. One-way ANOVA, to test whether statistically significant differences exist among the three independent groups for each construct; and
3. Tukey HSD post-hoc tests, to determine which specific bank pairs differ significantly, thereby distinguishing differentiating attributes from those reflecting competitive parity.

Given the relatively low internal reliability observed in several constructs, interpretation focused on patterns of mean differences rather than causal inference. This approach maintains analytical rigor while acknowledging measurement limitations, consistent with exploratory and comparative research practices in marketing studies (Malhotra, 2020).

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- AI Personalization
- PEOU (Perceived Ease of Use)
- Perceived Usefulness/Benefits
- Kano Model Dimensions: Basic Needs, Performance Needs, and Excitement Needs
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1. Descriptive Statistics
   Used to identify and compare mean scores of all constructs across the three banks.
2. One-Way ANOVA
   Conducted to test whether statistically significant differences exist among the three independent groups for each construct.
3. Tukey HSD Post-Hoc Test
   Employed to determine which specific pairs of banks differ significantly, thereby distinguishing differentiating factors from competitive parity attributes.

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## RESULT AND DISCUSSION

The internal reliability test results showed low Cronbach's Alpha values for most constructs (such as IMC: 0.072; PEOU: 0.076), indicating that the questionnaire instrument was highly inconsistent in measuring the intended constructs. This low reliability may be due to factors such as overly heterogeneous construct items, ambiguous interpretation of items by respondents, or a small number of items per construct. Given the low reliability of some constructs, this analysis focused on describing and comparing *mean* differences between groups, rather than testing causal relationships between variables. Therefore, this study focuses on descriptive analysis and mean difference tests (ANOVA and Tukey HSD test) to identify patterns and differences in perceptions between respondent groups.

### Comparative Descriptive Analysis

Descriptive statistical analysis presents the average user perception of the eight constructs among the three banks. Average scores were calculated to determine the perception rankings among competitors.

**Table 1.** Descriptive Statistics of Average Constructs per Digital Bank

| Construct | Bank X (Mean) | Bank B (Mean) | Bank C (Mean) | Standard Deviation (Mean) | Leadership Ranking | Data Source |
|---|---|---|---|---|---|---|
| IMC | 3,130 | 3,590 | 3,405 | 0.30 | Bank X > Bank Z > Bank Y | 1 |
| AI Personalization | 3,442 | 3,802 | 3,200 | 0.34 | Bank X > Bank Y > Bank Z | 1 |

| Construct | Bank X (Mean) | Bank B (Mean) | Bank C (Mean) | Standard Deviation (Mean) | Leadership Ranking | Data Source |
|---|---|---|---|---|---|---|
| PEOU | 3,292 | 3,652 | 3,565 | 0.32 | Bank X > Bank Z > Bank Y | 1 |
| Perceived Benefits | 3,228 | 3,605 | 3,310 | 0.35 | Bank X > Bank Z > Bank Y | 1 |
| Basic Needs | 3,338 | 3,848 | 3,635 | 0.32 | Bank X > Bank Z > Bank Y | 1 |
| Performance Requirements | 3,230 | 3,670 | 3,300 | 0.34 | Bank X > Bank Z > Bank Y | 1 |
| Excitement Needs | 3,132 | 3,378 | 2,975 | 0.31 | Bank X > Bank Y > Bank Z | 1 |
| Satisfaction | 3,228 | 3,745 | 3,430 | 0.33 | Bank X > Bank Z > Bank Y | 1 |

Table 2 shows that Bank Y consistently obtained the highest Mean score across all 8 constructs. Bank X's leadership is most prominent in Basic Needs (3.848) and AI Personalization (3.802), as well as Customer Satisfaction (3.745). In general, Bank Z ranks second, followed by Bank X. However, there are important exceptions in the dimensions of AI Personalization and *Excitement Needs*, where Bank X (AI Personalization: 3.442; Excitement Needs: 3.132) outperforms Bank Z (AI Personalization: 3.200; Excitement Needs: 2.975). This indicates that Bank X's AI-supported *life-centric* strategy, despite its lower PEOU, successfully produced Personalization that was more highly valued than Bank Z's.

**ANOVA Test Results**

The ANOVA test was used to test eight hypotheses (to) regarding the differences in overall customer perception averages among the three banks.

**Table 2.** ANOVA Test Results (Average Differences Between Bank Groups)

| Construct | F-value | p-value | Conclusion (Significance) | Data Source |
|---|---|---|---|---|
| IMC | 59.8243 | 0.000 | Significant difference. Supported. | 1 |
| AI Personalization | 76.5770 | 0 | Significant difference. Supported. | 1 |
| PEOU | 33.2945 | 0.000 | Significant difference. Supported. | 1 |
| Perceived Benefits | 31.8989 | 0.000 | Significant difference. Supported. | 1 |
| Basic Needs | 60.9840 | 0 | Significant difference. Supported. | 1 |
| Performance Needs | 48.1994 | 0 | Significant difference. Supported. | 1 |
| Excitement Needs | 43.9414 | 0.00 | Significant difference. Supported. | 1 |
| Satisfaction | 61.8724 | 0.000 | Significant difference. Supported. | 1 |

All constructs show a p-value of 0.000. Therefore, the null hypothesis (which states that there is no difference in means) is rejected for all variables. This confirms that, overall, there is a highly significant difference in perception among users of Bank X, Bank Y, and Bank Z across all measured service dimensions.

**Results of the Tukey HSD Post-Hoc Test**

To determine which pairs of banks have significant differences (True/False), the Tukey HSD Post-Hoc Test was conducted. The results of this test are the core of the comparative analysis, which distinguishes between differentiating competitive factors (differentiators) and factors that achieve parity (parity factors).

**Table 3.** Summary of Tukey HSD Post-Hoc Test Results (Pattern of Differences Between Banks)

| Construct | Bank Y vs Bank X (reject) | Bank Y vs Bank Z (reject) | Bank X vs Bank Z (reject) | Pattern of Differences (Equivalent Groups) | Data Source |
|---|---|---|---|---|---|
| IMC | True | True | True | Bank X > Bank Z > Bank Y | 1 |
| AI Personalization | True | True | True | Bank X > Bank Y > Bank Z | 1 |
| PEOU (TAM) | True | True | **False** | Bank X Bank Z > Bank Y | 1 |
| Perceived Benefits (TAM) | True | **False** | True | Bank X > Bank Y Bank Z | 1 |
| Basic Needs (Kano) | True | True | True | Bank X > Bank Z > Bank Y | 1 |
| **Performance Needs (Kano)** | True | **False** | True | Bank X > Bank Y Bank Z | 1 |
| Excitement Needs (Kano) | True | True | True | Bank X > Expert > Bank Z | 1 |
| Satisfaction | True | True | True | Bank X > Bank Z > Bank Y | 1 |

The Tukey HSD test analysis divides the eight constructs into two main categories based on their significance patterns:

**Strong Differentiators**

These variables show significant differences between all bank pairs. This category includes IMC, AI Personalization, Basic Needs, *Excitement* Needs, and Satisfaction. In this dimension, Bank Y consistently ranks at the top. The difference in average scores for Satisfaction, for example, is 0.5175 points higher for Bank X than for Bank Y. The pattern of Bank X > Bank Y > Bank Z in AI Personalization and Excitement Needs shows that in creating a unique and proactive experience, Bank Xlebih is more successful than Bank Z, even though Bank Z has the support of Shopee's large ecosystem. This pattern confirms that *brand* and AI strategies greatly influence customer perception.

**Competitive Parity Factors**

These variables indicate that some bank pairs are not significantly different (value 'False' in the reject column), signifying that these banks have achieved a level of similarity as perceived by customers. This category includes Perceived Ease of Use (PEOU), Perceived Benefits, and Performance Needs. PEOU: Tukey's test shows that the Perceived Ease of Use between Bank X and Bank Z is not significantly different (-adj 0.14). This indicates that although Bank X is in the lead, the ease of use of Bank Z's application has reached parity with Bank X in the eyes of customers. However, Bank X lags significantly behind both.

Perceived Benefits and Performance Needs: Perceived Benefits and Performance Needs between Bank X and Bank Z also did not differ significantly (adj 0.2224 and 0.315, respectively). This is a critical finding, indicating that the functional benefits and performance attributes offered by these two banks are considered equivalent by users. Only Bank X has managed to maintain a significant advantage in Perceived Benefits and Performance Needs compared to its two competitors.

Before discussing the theoretical implications, it is necessary to emphasize once again the methodological limitations caused by the very low reliability of the instruments. In an ideal quantitative study, a low Cronbach's Alpha would preclude conclusions about internal validity. Given the low reliability of some constructs, this analysis focused on describing and comparing *mean* differences between groups, rather than testing causal relationships between variables**.**

Therefore, even though there are statistically significant test results (confirmed through ANOVA and Tukey HSD), the interpretation of the results in this study must be done very carefully and focus on the observed differences in *average* customer *perception scores*. The low Cronbach's Alpha (such as IMC: 0.072; PEOU: 0.076) may be due to several factors, including. Heterogeneous Construct Items: Items formulated to measure a single construct (e.g., IMC or PEOU) may be too diverse or ambiguous, causing respondents to interpret the items differently. Different Experience Contexts: Users' experiences may vary greatly between digital banks, even when measured with the same instrument, resulting in extreme response variations and reduced internal consistency. Few Items Per Construct: A limited number of items per construct can make reliability unstable.

**Analysis of Bank X BANK Y Digital's Advantages: Dominance in Trust and IMC**

Bank Y shows undeniable dominance, leading in all eight variables, with a significant difference in Satisfaction scores (Mean Bank X 3.745; Mean Bank Y 3.228). This advantage can be explained through the integration of three theoretical frameworks: strong IMC, inherited *legacy trust*, and its AI capabilities to fulfil *Excitement Needs*.

Bank X's superiority in IMC stems not only from their digital marketing strategies (such as integrated, user- centred campaigns), but more importantly, from their most valuable intangible asset: *the legacy trust* of their parent bank, BANK Y. Studies show that trust is a prerequisite, not just a by-product, of successful Personalization. Consumers in emerging markets such as Indonesia tend to trust banks backed by established conventional institutions more. Bank X's IMC leverages this historical trust to communicate AI- driven Personalization features as a secure and reliable service. This established trust reduces customer scepticism about the use of data for Personalization, a critical issue that often hinders AI adoption in other financial institutions.

### Perceptions of AI Personalization and Satisfaction

Bank X also excels significantly in AI Personalization (Mean 3.802). This advantage correlates directly with their leadership in Customer Satisfaction. This reinforces the view that banks that successfully implement AI Personalization effectively (proactively and relevantly) will lead in terms of market satisfaction. Bank X's ability to deliver these benefits may be supported by its access to BANK Y's extensive customer data and stable infrastructure, enabling its AI to offer truly contextual financial advice or recommendations.

### Shift in Competitive Factors: From Parity to Differentiation

One of the most strategic findings from the Tukey Test is the identification of parity factors vs. differentiation factors, particularly within the TAM and Kano Model frameworks.

### TAM Model: PEOU and Perceived Benefits Become Parity

According to the TAM Model, PEOU and Perceived Benefits are the main drivers of adoption. However, comparative analysis shows that in this mature Jakarta market, these variables have shifted from differentiators to parity factors for some banks: **PEOU Parity (Bank X Bank Z):** Although PEOU is considered important, the results show that the ease of use of Bank Z and Bank X applications are at an equivalent level in the eyes of customers.[1] This indicates that core functions and basic user interfaces have become standard expectations (*Basic Needs*) that both banks have successfully fulfilled. Bank X must address its lower PEOU perception (Mean 3.292), a challenge that requires them to conduct a UX/UI audit to ensure *that* their life-centric user experience is truly intuitive and barrier-free, in line with previous study findings on Bank Y.

**Parity in Perceived Benefits and Performance Needs (Bank Y Bank Z):** The perception that AI services or bank features will improve financial efficiency (Perceived Benefits) and Performance Needs (such as speed) is considered equal between Bank X and Bank Z. This is a critical finding, indicating that the functional benefits and performance attributes offered by these two banks are considered equal by users. Only Bank X managed to maintain a significant advantage in Perceived Benefits and Performance Needs compared to its two competitors.

### Kano Model: Excitement Needs as the Key to Future Differentiation

With PEOU and Perceived Benefits shifting to parity factors, the competitive battlefield has shifted to Excitement Needs. Although a must-be quality, differences in Basic Needs are significant among all banks, with Bank X leading substantially (Mean 3.848). Bank X's advantage here may include a higher perception of security and superior application stability, which are fundamental foundations that must be ensured before excitement features can be appreciated. The failure of Bank Y and Bank Z to match Bank X on these Basic Needs is a strategic vulnerability. This variable shows a strong differentiation pattern: Bank X > Bank Y > Bank Z (all significantly different). This pattern is parallel to the AI Personalization score, confirming that AI Personalization is the main catalyst for creating Excitement Needs in digital banking. Bank X has successfully transformed AI into an Attractive Quality that generates customer delight. The fact that Bank Xunggul significantly outperforms Bank Z in terms of Excitement Needs (Bank Y 3.132 vs Bank Z 2.975) shows that Bank Xdalam's strategy of utilising data and AI (e.g. through a partnership with Google Cloud for sentiment analysis and real-time alerts, to create a personalised, life-centric experience, despite PEOU's weaknesses, remains more effective in generating excitement than Bank Z, which may still be too focused on basic e-commerce transaction integration.

**AI Personalization and Satisfaction: A Critical Relationship**

Bank X's leadership in Customer Satisfaction (3.745) is driven by its excellence in AI Personalization (3.802) and Excitement Needs (3.378). This pattern indicates a strong relationship: in a competitive digital banking market, achieving the highest customer satisfaction requires banks to not only meet *Basic Needs* (such as security and convenience), but more importantly, to create *Excitement Needs* through proactive and meaningful AI Personalization.

Bank X, despite lagging behind Bank X in *Basic Needs* and PEOU, maintains second place in AI Personalization and *Excitement Needs*, contributing to higher satisfaction than Bank Z. This implies that for Bank Y, investing in intelligent AI technology (as done through its partnership with Google Cloud offers a clear path to increasing customer *delight*, even if their basic PEOU is not yet optimal.

Conversely, Bank Z, which has a massive user base from the Shopee ecosystem, shows the lowest scores for AI Personalization and *Excitement Needs*. This indicates that Bank Z's AI Personalization may still be limited to product recommendations within the Shopee ecosystem or basic transactional notifications, failing to achieve the level of sophistication that creates *delight* that sets it apart from its competitors.

## CONCLUSION

This study provides a comprehensive comparative assessment of customer perceptions toward AI-driven marketing communication, service quality dimensions, and overall satisfaction across three major digital banks operating in Jakarta's rapidly maturing digital ecosystem. The results strongly confirm that significant differences exist across all eight measured constructs, as indicated by the ANOVA tests ($p < .001$). These findings empirically validate that although digital banks operate within the same competitive environment, their strategic approaches to IMC execution, AI Personalization, and service innovation produce distinct perceptual outcomes among users.

A key contribution of this research is the identification of a shift in competitive dynamics within Jakarta's digital banking sector. Constructs traditionally associated with the Technology Acceptance Model—namely Perceived Ease of Use and Perceived Benefits— have reached competitive parity among several bank pairs. This suggests that core usability and functional efficiency have evolved into baseline expectations (Must-Be qualities in the Kano Model), limiting their ability to generate differentiation. As such, digital banks can no longer rely solely on TAM-based functional advantages to secure superior customer evaluations.

Conversely, the study highlights the critical role of AI Personalization and Excitement Needs as the strongest differentiating factors. Banks that successfully employ AI to provide proactive, context-aware, and emotionally engaging experiences demonstrate markedly higher satisfaction scores. This is consistent with the evolution of customer expectations in advanced digital markets, where hyper-personalised interactions serve as a primary source of perceived value and relational depth. These findings affirm the theoretical position that AI is not merely a technological enabler but a strategic lever capable of generating Attractive Quality attributes that elevate customer delight beyond functional fulfilment.

In addition, the study underscores the strategic importance of institutional trust and strong IMC. Banks with established reputational capital and consistent communication frameworks—particularly Bank Y—are more effective in legitimising AI features and mitigating customer scepticism about data use. This reinforces the notion that AI-driven Personalization yields stronger outcomes when embedded within credible and coherent communication ecosystems.

Methodological limitations must also be acknowledged. The low reliability values for several constructs indicate potential inconsistencies in item formulation and response interpretation. Accordingly, the findings should be interpreted as comparative patterns rather than causal relationships. Nevertheless, the consistency of significance across both ANOVA and Tukey HSD tests supports the robustness of the observed inter-bank differences.

Overall, this research advances the literature by integrating IMC, TAM, and the Kano Model in a multi-bank comparative framework—a perspective that remains underexplored in Indonesian digital banking studies. The findings highlight a clear strategic direction: digital banks seeking sustainable differentiation and higher customer satisfaction must prioritise AI investments that deliver Excitement Needs, supported by strong IMC and trust-building mechanisms.

Future studies are recommended to refine construct measurements, employ larger and more diverse samples, and incorporate structural modelling to explore the causal pathways between IMC strategies, AI capabilities, and customer satisfaction more rigorously.

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