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RESEARCH ARTICLE

The Impact Of Ai-Powered Service Features On Customer Satisfaction: Ride-Hailing Apps In Indonesia

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Abstract

This research study aims to analyze the influence of artificial intelligence (AI)-based service features on customer satisfaction in the ride-hailing industry in Indonesia. The research method used is a quantitative method with a survey approach and Data is collected through a survey of 400 active users of ride-hailing services. This study uses descriptive analysis to describe the characteristics of respondents, test the validity and reliability of the instrument, classical assumption test which includes normality and multicollinearity tests, and multiple linear regression analysis to test the influence of each independent variable. The results showed that Perceived Value (β=0.114), Perceived Service Delivery (β=0.104), Perceived Service Quality (β=0.194), Identification with the Service Provided (β=0.154), and AI Use Behavior in Services (β=0.175) had a positive and significant effect on customer satisfaction ($p<0.001$). In contrast, the Market Orientation of Service Provision had a negative but significant effect (β=-0.115; $p<0.01$). Simultaneously, all variables had a significant effect on customer satisfaction (F=273.333; $p<0.001$). These findings suggest that the application of AI that improves value, quality of service, and user experience can strengthen customer satisfaction and support ride-hailing companies' reputations.

Keywords

Artificial Intelligence; Ride-Hailing; Customer Satisfaction; Service Quality; Corporate Reputation.

1 | INTRODUCTION

Indonesia's transportation system has evolved significantly over the past decade, driven by rapid infrastructure development and digital innovation. Historically, the country relied heavily on road transportation for passenger and freight mobility. However, ongoing investments in mass transit systems, ports, and airports such as the Jakarta MRT, LRT, Patimban Port, and the Jakarta-Bandung High-Speed Train reflect the government's commitment to improving connectivity and reducing congestion in major cities. Despite this increase, road transportation continues to dominate, especially in urban areas where private vehicles and motorcycles remain the main modes of travel (Chesnokova, 2021). Along with the advancement of physical infrastructure, Indonesia's digital transformation has reshaped the way people move and interact with transportation services. The emergence of online transportation platforms since around 2015 has fundamentally changed urban mobility. Companies like Gojek, Grab, Maxim, and inDrive have become an integral part of everyday life by offering fast, affordable, and flexible on-demand services. Their growth is in line with the rise of digital payments, gig-based work, and the broader sharing economy, making them a key driver of Indonesia's smart mobility ecosystem (Chesnokova, 2021 & Rizqoni Waliyul Arinni, 2023).

Table 1. Most Used Online Transportation Services by Consumers

Platform	Percentage (%)
Gojek	82.60%
Grab	57.30%
Maxim	19.60%
InDriver	4.90%

Source: Institute for Economic and Financial Development (2022)

Competition in the ride-hailing industry is fierce. Each company seeks to attract users through a variety of strategies, from discounts, cashback, and promotional bundles to loyalty programs and innovative service features. As a result, having a clear brand position in the minds of consumers becomes important. Studies based on marketing mix frameworks (product, price, venue, promotion, people, process, and physical evidence) help explain how these brands differentiate themselves and how customers perceive their value proposition (Rizqoni Waliyul Arinni, 2023).

Table 2. Results of the Survey on the Quality of Consumer Service of Online Transportation Services

Description	Driving Comfort and Vehicle Cleanliness	Driver Friendliness	Ease of Using the App and Accessing Desired Services
Industry Average	3.23	3.25	3.30
Gojek	3.27	3.28	3.39
Grab	3.23	3.27	3.27
Maxim	3.08	3.11	3.01
inDrive	3.03	3.06	3.17

Source: Institute for Economic and Financial Development (2022)

To understand user behavior more deeply, a large-scale survey involving 400 respondents was conducted. The majority of participants were young adults between the ages of sixteen and twenty-five, mostly women, and concentrated in Bandung. Most respondents prefer non-cash payments, citing convenience and practicality as the main reasons for using online transportation services. About one-third use the app one to five times per month, mainly for short daily commutes. Among all the features available, ride-hailing emerged as the most frequently used service, accounting for 46 percent of total activity. The survey also showed that usage peaked in December 2021 and declined in early 2022, reflecting mobility fluctuations caused by seasonal and economic factors. These findings emphasize that online transportation is firmly embedded in users' daily routines, with demand strongly tied to digital practicality, reliability, and convenience (Rizqoni Waliyul Arinni, 2023). Despite the tremendous advances in AI integration, companies face growing challenges in maintaining transparency and fairness in these systems. The complexity of machine learning algorithms often makes it difficult for users to understand how decisions such as fare calculations or driver assignments are made. This lack of clarity creates a perception of ambiguity that can erode public trust even when technology is working efficiently. As users increasingly demand transparency, e-transportation companies must ensure that the logic behind AI-based processes is explained and aligned with consumers' expectations of fairness and accountability. Ethical and privacy issues further intensify these challenges. The extensive use of AI and big data in ride-hailing platforms involves the ongoing collection of personal information, including location, behavioral patterns, and payment preferences. While this data allows for better personalization of services and route optimization, it also exposes companies to significant reputational risks if users suspect misuse or inadequate protection of their information.

Therefore, maintaining ethical data practices is essential not only for regulatory compliance but also for maintaining a positive reputation based on integrity and respect for privacy. Finally, over-automation presents the risk of weakening the human relationships that underlie emotional trust. In online transportation, where the service experience is highly personalized, an over-reliance on automated responses and AI-based interactions can make users feel detached from the brand. While AI improves operational convenience and speed, it must be balanced with empathy, responsiveness, and human oversight to maintain relational authenticity. Companies that successfully combine technological precision with a sense of human care gain reputational benefits, positioning themselves as innovative and trustworthy. Similar phenomena are also found on various global ride-hailing platforms. In the United States, China, India, and European countries, companies such as Uber, Lyft, and Didi Chuxing have integrated artificial intelligence for real-time price optimization, demand prediction, and driver allocation. However, several studies show that the success of AI implementation is not only determined by technological sophistication but also by users' perceptions of algorithm fairness, system transparency, and data privacy protection. Research conducted by Kellogg, Valentine, and Christin (2020) found that algorithmic management systems can improve operational efficiency but also create uncertainty and distrust when users and driver-partners do not understand the basis of algorithmic decision-making. Additionally, research by Dwivedi *et al*. (2023) shows that the acceptance of AI in digital services is strongly influenced by the level of user trust in data security and transparency in the use of technology. These findings confirm that successful adoption of AI in the ride-hailing industry requires a balance between technological innovation, ethical data governance, and service experiences that remain human-oriented.

Furthermore, a global report from McKinsey & Company (2024) shows that companies that successfully combine artificial intelligence with a human-centered service approach have higher levels of customer satisfaction and loyalty than companies that rely on full automation. This indicates that while AI can improve service efficiency and accuracy, the role of humans remains important in building emotional relationships, empathy, and customer trust. Therefore, the development of future AI-based ride-hailing services will focus not only on improving algorithmic capabilities but also on creating a transparent, secure, and human-centric customer experience. While the implementation of Artificial Intelligence (AI) in ride-hailing services continues to evolve and offers a wide range of operational benefits, the relationship between AI features and customer satisfaction still requires more in-depth empirical study, especially in developing countries such as Indonesia. AI-driven features, such as automatic driver matching, accurate estimated time of arrival, digital payment systems, route recommendations, and automated customer service, have the potential to improve the user experience through convenience, speed, and personalization of services. However, the effectiveness of these features in improving customer satisfaction can be influenced by user perception of service value, service quality, algorithm transparency, and the level of trust in the technology used. Therefore, this study aims to analyze the influence of AI-based service features on customer satisfaction in the ride-hailing industry in Indonesia by examining the role of Perceived Value of AI Adoption, Perceived Service Delivery, Perceived Service Quality, Market Orientation of Service Provision, Identification with the Service Provided, and AI Use Behavior in Services as factors that affect customer satisfaction. The research findings are expected to make a theoretical contribution to the literature on AI adoption in the digital services industry as well as serve as a basis for ride-hailing companies to develop AI-based services that are more effective, transparent, and customer-oriented (Huang & Rust, 2021; Dwivedi *et al*., 2023). Based on this phenomenon, research is still needed to explain how Artificial Intelligence (AI)-based service features affect customer perception and satisfaction in the ride-hailing industry. This study aims to test the influence of AI-based service features on customer satisfaction of ride-hailing applications in Indonesia. Specifically, this study analyzes the influence of Perceived Value of AI Adoption, Perceived Service Delivery, Perceived Service Quality, Market Orientation of Service Provision, Identification with the Service Provided, and AI Use Behavior in Services on customer satisfaction. The results of the research are expected to contribute to the development of literature on the adoption of AI in digital services as well as provide input for ride-hailing companies in designing more effective, transparent, and customer-oriented services.

2 | BACKGROUND THEORY

2.1 Artificial Intelligence in Services

Artificial Intelligence (AI) refers to a computer system capable of performing tasks that typically require human intelligence, such as learning, reasoning, and decision-making (Russell & Norvig, 2021). In the service sector, AI improves the efficiency, personalization, and responsiveness of services through technologies such as machine learning, predictive analytics, and natural language processing. In ride-hailing applications, AI is used for dynamic pricing, driver-passenger matching, route optimization, and automated customer support, which contributes to improved customer experience and operational performance (Wirtz *et al*., 2021). From a theoretical perspective, the use of AI in digital services can be explained through the Technology Acceptance Model (TAM) developed by Davis. This theory states that user acceptance of a technology is influenced by perceived usefulness and perceived ease of use. The greater the benefits and convenience that customers feel from AI-based features, the higher the level of usage and customer satisfaction with the service (Venkatesh *et al*., 2022). In addition, Service-Dominant Logic (SDL) explains that service value is created through interactions between service providers and customers. In the context of ride-hailing, AI functions as an enabler that helps create a more personalized, fast, and responsive service experience, thereby increasing customer perceived value and satisfaction (Vargo & Lusch, 2023). Thus, the implementation of AI plays a role not only as a technological innovation but also as a means of creating value and a customer-oriented competitive advantage.

2.2 Service Quality Theory

Service Quality Theory (SERVQUAL) explains that customer satisfaction is influenced by the perception of the quality of service received, including reliability, responsiveness, assurance, empathy, and physical evidence (Parasuraman *et al*., 1988). In AI-based ride-hailing services, this theory is relevant to explain the variables of Perceived Service Quality and Perceived Service Delivery, as customers assess service quality based on the reliability of the application, the accuracy of driver matching, the accuracy of the estimated time of arrival, the security of transactions, and the responsiveness of customer service. Additionally, the Perceived Value of AI Adoption is based on the Perceived Value Theory, which states that customers will feel satisfied when the benefits obtained are greater than the costs or sacrifices incurred (Zeithaml, 1988). Meanwhile, AI Use Behavior in Services is supported by the Technology Acceptance Model (TAM), which explains that the use of technology is influenced by the perception of benefits and ease of use (Venkatesh *et al*., 2022). The variable Identification with the Service Provided is based on Social Identity Theory, which explains that a customer's psychological attachment to a brand or platform can increase satisfaction and loyalty (Tajfel & Turner, 1986). The Market Orientation of Service Provision is based on Market Orientation Theory, which emphasizes the importance of understanding customer needs in creating value and competitive advantage (Narver & Slater, 1990). Thus, the integration of SERVQUAL theory, Perceived Value Theory, TAM, Social Identity Theory, and Market Orientation Theory provides a comprehensive theoretical foundation to explain the influence of AI-based service features on customer satisfaction in the ride-hailing industry in Indonesia.

2.3 Market Orientation Theory

Market orientation refers to an organization's ability to understand current and future customer needs, monitor competitors' actions, and coordinate corporate resources to create superior value for customers (Narver & Slater, 1990). In the ride-hailing industry, market orientation is realized through the use of Artificial Intelligence (AI) to analyze customer behavior, predict demand, and provide more personalized services. This theory is the foundation for the Market Orientation of Service Provision variable because companies that effectively utilize market information through AI tend to be more responsive to customer needs and can improve customer satisfaction through more relevant and valuable services.

2.4 Social Identity Theory

Social Identity Theory is based on membership or attachment to a certain group, organization, or brand (Tajfel & Turner, 1986). In the context of ride-hailing services, customers who feel they have a value match and a positive experience with a platform will develop a stronger emotional attachment. This theory underlies the variable Identification with the Service Provided, indicating that a higher level of customer identification with the ride-hailing platform leads to a more positive perception of the service received, thus increasing customer satisfaction and loyalty (Bhattacharya & Sen, 2003).

2.5 Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) states that the acceptance and use of technology are influenced by two main factors: perceived usefulness and perceived ease of use (Davis, 1989). In ride-hailing services, AI features such as estimated time of arrival, route recommendations, digital payments, and automated customer service will be used more often if they are considered useful and easy to operate. Therefore, the TAM theory serves as the basis for the AI Use Behavior in Services variable, indicating that higher customer acceptance of AI technology is more likely to create a positive experience and enhance customer satisfaction.

2.6 Customer Satisfaction and Company Reputation

Customer satisfaction theory refers to the extent to which service performance meets or exceeds customer expectations (Oliver, 1980). Meanwhile, a company's reputation reflects a stakeholder's overall evaluation of the company's credibility, trust, and performance (Fombrun, 1996). In AI-powered ride-hailing services, the Customer Satisfaction Theory posits that satisfaction arises when service performance meets or exceeds customer expectations (Oliver, 1980). Company reputation is the collective perception of stakeholders regarding the company's credibility, trust, and quality in the long term (Fombrun, 1996). In this study, Customer Satisfaction plays the role of a dependent variable influenced by perceived value, service quality, market orientation, customer identification, and AI usage behavior. Furthermore, high customer satisfaction contributes to the formation of Corporate Reputation, as satisfied customers tend to provide positive ratings, recommend services to others, and build a better corporate image. Thus, customer satisfaction becomes an important mechanism that connects the implementation of AI-based service features with the company's reputation in the ride-hailing industry.

3 | METHOD

This study uses a quantitative research approach to examine the impact of service features supported by Artificial Intelligence (AI) on customer satisfaction and corporate reputation in the Indonesian ride-hailing industry. Data was collected through online questionnaires distributed to active users of ride-hailing apps, including Gojek, Grab, Maxim, and inDrive. The purposive sampling technique was used by targeting respondents who had experience using AI-based features in ride-hailing services. A total of 400 eligible questionnaires were analyzed in this study. The quantitative approach was chosen because it allows for objective and measurable testing of relationships between variables using comprehensive statistical analysis (Creswell & Creswell, 2023). The research model consists of six independent variables, namely Perceived Value of AI Adoption, Perceived Service Delivery, Perceived Service Quality, Market Orientation of Service Provision, Identification with the Service Provided, and AI Use Behavior in Services. Meanwhile, Customer Satisfaction and Corporate Reputation play roles as dependent variables. Prior to hypothesis testing, the quality of the instrument was evaluated through validity and reliability tests. The results of the validity test showed that all 31 statement items were declared valid, with an item-total correlation value ranging from 0.77 to 0.88. The reliability test yielded a Cronbach's Alpha value of 0.940, indicating a very high level of internal consistency. A Cronbach's Alpha value above 0.70 indicates that the instrument has good reliability and is suitable for use in behavioral and management research (Cheung *et al*., 2024). Additionally, a reliability value close to 1.00 indicates that the indicators used have very strong consistency in measuring the research construct.

The questionnaire was compiled using a 5-point Likert Scale, ranging from 1 = strongly disagree to 5 = strongly agree. The distribution of the questionnaire was carried out online through Google Forms and disseminated through social media, ride-hailing user communities, and academic networks. Respondent criteria included individuals who are at least 17 years old, have used ride-hailing services in the past six months, and have experience using AI-based features such as estimated time of arrival (ETA), route recommendations, digital payments, or automated customer service. Data analysis was conducted using IBM SPSS Statistics 26 through several stages, namely descriptive analysis to describe respondent characteristics, instrument validity and reliability tests, classical assumption tests which include normality and multicollinearity tests, and multiple linear regression analysis to test the influence of each independent variable on customer satisfaction. Hypothesis testing was carried out using a t-test to measure partial influences, an F-test to test simultaneous influences, and a determination coefficient (R^2) to determine the model's ability to explain variations in customer satisfaction. This approach allows for a comprehensive evaluation of the influence of AI-based service features on customer perception, customer satisfaction, and corporate reputation in the Indonesian ride-hailing industry.

4 | RESULTS AND DISCUSSION

4.1 Results

4.1.1 Overview of Respondent Data and Coverage

This study was analyzed using 400 valid responses. The questionnaire contains 31 measurement items (excluding respondent identity/screening questions), and the instrument does not include inversely coded (unfavorable) items. The dataset was processed using IBM SPSS, and the data collection window was documented as November 15 – December 15 in the survey records.

Table 3. Data Overview

Component	Description
Sample size (N)	400
Number of measurement items	31
Reverse-coded items	None
Software used	IBM SPSS
Survey period (reported)	15 November to 15 December

From an analytical point of view, a sample size of 400 provides sufficient statistical strength for multiple regressions involving six predictors. This improves the stability of the estimated coefficient and reduces the sensitivity of the results to sampling fluctuations. It should be noted that the SPSS output provided is mainly instrument test documents and regression results. Demographic profile tables (e.g. gender, age group, domicile, most used apps, monthly usage frequency) require a separate frequency output, which is not included in the current analysis report.

Table 4. Validity Testing Result

No Question	rxy	rtable	Status
1	0.81	0.75	Valid
2	0.81	0.75	Valid
3	0.77	0.75	Valid
4	0.80	0.75	Valid
5	0.80	0.75	Valid
6	0.80	0.75	Valid
7	0.82	0.75	Valid
8	0.82	0.75	Valid
9	0.80	0.75	Valid
10	0.81	0.75	Valid
11	0.82	0.75	Valid
12	0.85	0.75	Valid
13	0.80	0.75	Valid
14	0.81	0.75	Valid
15	0.84	0.75	Valid
16	0.88	0.75	Valid
17	0.88	0.75	Valid
18	0.86	0.75	Valid
19	0.86	0.75	Valid
20	0.82	0.75	Valid
21	0.80	0.75	Valid
22	0.81	0.75	Valid
23	0.82	0.75	Valid
24	0.84	0.75	Valid
25	0.80	0.75	Valid
26	0.82	0.75	Valid
27	0.84	0.75	Valid
28	0.82	0.75	Valid
29	0.83	0.75	Valid
30	0.86	0.75	Valid
31	0.83	0.75	Valid

All r_{xy}values exceed the r-table threshold, meaning each item demonstrates an adequate correlation with the construct score. Substantively, this implies that respondents answered the items consistently in a way that reflects a coherent underlying construct structure. In terms of magnitude, the highest validity coefficients are observed for Item 16 and Item 17 ($r_{xy} = 0.88$), while the lowest coefficient appears for Item 3 ($r_{xy} = 0.77$). Despite this variation, the overall pattern confirms that the measurement instrument satisfies the required validity criteria. Consequently, no items were removed at the validity-testing stage, and all items were retained for subsequent reliability testing and hypothesis analysis.

Table 5. Reliability Test Results (Cronbach's Alpha) Variance of Questionnaire Items 1–15

Remarks	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	Total
Grain Variance	0.610	0.596	0.573	0.609	0.597	0.622	0.609	0.616	0.645	0.601	0.650	0.645	0.628	0.590	0.641	318.515

Number of Grain Variances	19.086
Total Variance	318.515
R11	0.940
Reliability	Very High

Variance of Questionnaire Items 16–31

Remarks	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	Total
Grain Variance	0.651	0.708	0.638	0.656	0.547	0.600	0.626	0.621	0.689	0.600	0.600	0.615	0.612	0.560	0.591	0.541	318.515

Number of Grain Variances	19.086
Total Variance	318.515
R11	0.940
Reliability	Very High

Source: SPSS (2026)

Figure 5 presents the calculation summary of the reliability test using Cronbach's Alpha (r_{11}) for the research instrument, which consists of 15 items with individual grain variances ranging from 0.573 to 0.650. The sum of these grain variances is 19.086, while the total variance of the overall instrument score is 318.515. These components are essential for the Cronbach's Alpha formula, where the resulting coefficient of r_{11} = 0.940 indicates that the questionnaire possesses very strong internal consistency. Based on the Guilford classification, where an Alpha value in the range of 0.80 to 1.00 is categorized as "Very High," the instrument is confirmed to be highly reliable and suitable for further statistical testing, as the items consistently measure the intended underlying constructs.

Table 6. Hypothesis Testing Results

Variable	Coefficient β	Std. Error	Significance
Perceived Value (X1)	0.114231572	0.026945619	0.000027917185
Perceived Service Delivery (X2)	0.103648563	0.025087828	0.000044075926
Perceived Service Quality (X3)	0.193840547	0.031633602	0.000000002168
Market Orientation of Service Provision (X4)	-0.114998439	0.037513882	0.002323211502
Identification with the Service Provided (X5)	0.154362537	0.034917682	0.000012743521
AI Use Behavior in Services (X6)	0.174900752	0.023348196	0

The t-test results evaluate the partial contribution of each independent variable to Customer Satisfaction (Y) within the multiple regression model, using a significance threshold of $\alpha = 0.05$. The analysis reveals that all six predictors significantly influence Customer Satisfaction, though the direction and magnitude of these effects vary.

1) Perceived Value (X1): With a positive coefficient of $\beta = 0.1142$ and a significance value of $p = 0.0000279$, Perceived Value exerts a significant positive effect. This indicates that customers who perceive the service benefits as outweighing the costs and efforts involved report higher levels of satisfaction.
2) Perceived Service Delivery (X2): This variable demonstrates a positive and significant influence ($\beta = 0.1036, p = 0.0000441$). Efficient service execution, such as timely pickups and clear communication, is thus a key driver of customer satisfaction.
3) Perceived Quality of Service (X3): As the strongest predictor among the perception-based variables, Perceived Service Quality shows a substantial positive effect ($\beta = 0.1938, p \approx 0.00000000216$). This highlights that reliability, convenience, and security are the primary factors driving user satisfaction.
4) Market Orientation of Service Provision (X4): Interestingly, this variable shows a significant negative effect ($\beta = -0.1150, p = 0.002323$). This suggests that, within this specific model, an increased focus on certain market-driven operationalizations may paradoxically correlate with lower levels of customer satisfaction.
5) Identification with Service Provided (X5): This variable has a positive and significant impact ($\beta = 0.1544, p = 0.0000127$), indicating that users who feel a personal alignment between the service and their lifestyle are more satisfied.
6) AI Use Behavior in Services (X6): Finally, AI Use Behavior shows a strong positive effect ($\beta = 0.1749, p < 0.05$). This confirms that active engagement with AI-enabled features such as route optimization and automated support significantly enhances the customer experience.

In conclusion, while most variables positively drive satisfaction, the results underscore the dominant roles of Service Quality and AI-related behaviors, while highlighting a complex relationship between market-oriented service provision and user sentiment.

Table 7. Simultaneous Significance Test Results

Components	Value
F-Statistic	273.3327626
Significance	0

Table 7 presents the results of the F-test, which is used to evaluate whether all the independent variables in the regression model simultaneously have a statistically significant effect on the dependent variable, i.e. Customer Satisfaction (Y). This test assesses the feasibility of the overall regression model by testing the null hypothesis that all predictor regression coefficients are equal to zero. Based on the output, the regression model produced an F-statistic of 273.3327626 with a significance value (Sig.) of 0.000. Using the significance level $\alpha = 0.05$, the results show that the p-value < 0.05, therefore the null hypothesis is rejected. This means that the independent variables of Perceived Value (X1), Perceived Service Delivery (X2), Perceived Service Quality (X3), Service Delivery Market Orientation (X4), Identification with Services Provided (X5), and AI Use Behavior in Services (X6) collectively have a significant influence on Customer Satisfaction. The regression model is statistically significant and worthy of interpretation, showing that the predictors together explain the variation in Customer Satisfaction (Y).

Table 8. Determination Coefficient Test Results

Components	Value
R	0.8981588365
R Square (Coefficient of Determination)	0.8066892956
Adjusted R Square	0.8037379872
Std. Error of the Estimate	0.8146771479

Source: SPSS (2026)

From table 8, the Output also reports an Adjusted R Square value of 0.8037379872. The adjusted R Square takes into account the number of predictors included in the model and provides a more conservative estimate of explanatory power. The fact that the Adjusted R Square is only slightly lower than the R Square suggests that the independent variables included in the model contribute meaningfully and that the model is not artificially inflated by unnecessary predictors. In other words, the model retains strong explanatory capabilities even after adjustment.

4.2 Discussion

These findings demonstrate that AI-powered service features play a crucial role in shaping customer satisfaction within Indonesia's ride-hailing industry. The high explanatory power of the model ($R^2 = 0.8067$) suggests that customers' evaluations of AI-based services are strongly influenced by their perceptions of value, service delivery, service quality, identification with the platform, and AI usage behavior. The positive effects of Perceived Value support the argument that customers are more satisfied when AI technology provides meaningful benefits, such as convenience, efficiency, accurate information, and reduced travel uncertainty. These findings are consistent with Perceived Value Theory, which posits that customers evaluate services based on the balance between the benefits received and the costs incurred (Zeithaml, 1988). The significant influence of Perceived Service Delivery and Perceived Service Quality indicates that customers attach great importance to the effectiveness of AI-powered service processes. Features such as accurate driver matching, reliable ETA predictions, responsive apps, and seamless transactions contribute positively to satisfaction. Among all predictors, service quality emerged as one of the strongest determinants, confirming the relevance of SERVQUAL theory in a digital services environment. The positive relationship between Identification with the Services Provided and customer satisfaction suggests that users who feel emotionally connected to a ride-hailing platform tend to evaluate their experience more favorably. These findings support Social Identity Theory, which argues that psychological attachment to a brand can reinforce positive customer perceptions and loyalty.

Similarly, AI Use Behavior was found to be one of the strongest predictors of customer satisfaction. Customers who actively engage with AI-enabled features—such as route recommendations, digital payments, and automated assistance—are more likely to appreciate the benefits offered by the platform. These results align with the Technology Acceptance Model (TAM), which emphasizes that technology adoption increases when users find it useful and beneficial. Interestingly, the Market Orientation of Service Provision shows a significant negative effect on customer satisfaction. These results suggest that customers may perceive certain market-oriented practices, such as dynamic pricing, algorithmic allocation, and aggressive promotional strategies, as favoring the interests of the platform over customer well-being. While these practices can improve operational efficiency, they may create perceptions of injustice and reduce satisfaction. These findings highlight the importance of balancing business goals with transparency and customer-centric AI governance. Overall, the results show that customer satisfaction in AI-powered ride-hailing services is driven not only by technological efficiency but also by customers' perceptions of fairness, trust, service quality, and an emotional connection with the platform. Therefore, ride-hailing providers should focus on designing AI systems that are transparent, user-friendly, and aligned with customer expectations to strengthen long-term satisfaction and corporate reputation. The findings of this study also align with the development of the global ride-hailing industry. On platforms such as Uber, Didi Chuxing, and Grab, AI implementations are used to improve the efficiency of driver-passenger matching, demand prediction, route optimization, and service personalization. Research by Huang and Rust (2021) demonstrates that AI enhances the quality of the customer experience through response speed and service accuracy, especially in routine, data-driven services. These findings corroborate our results that Perceived Service Quality and AI Use Behavior are critical factors in increasing customer satisfaction. Differences in customer characteristics can also affect perceptions of AI-based services. Younger customers with high digital literacy tend to be more receptive to AI and value convenience, personalization, and service automation more than older age groups (Dwivedi *et al*., 2023). This is relevant to our study's respondent profile, which is dominated by young, active ride-hailing users. Therefore, the acceptance of AI technology is influenced not only by the quality of the technology itself but also by the readiness and digital experience of the users.

The findings regarding the negative effects of Market Orientation of Service Provision are supported by various international studies. On many global platforms, the implementation of dynamic or "surge" pricing often creates a perception of injustice when fares increase significantly during peak hours or emergencies. Research by Kellogg *et al*. (2020) shows that algorithmic systems oriented solely toward business efficiency can cause distrust if users do not understand the basis of system decision-making. Therefore, algorithmic transparency is a vital factor in maintaining customer satisfaction and company reputation. From an international best-practices perspective, companies such as Uber and Grab are beginning to develop Explainable Artificial Intelligence (XAI) approaches that provide clearer information regarding fare changes, estimated arrival times, and service recommendations. Furthermore, several companies have implemented "Responsible AI" principles that emphasize transparency, fairness, data security, and human oversight in AI-based decision-making (IBM, 2024; Microsoft, 2024). These practices demonstrate that the success of AI implementation depends not only on technological sophistication but also on the company's ability to build customer trust through ethical, human-centered AI governance. In conclusion, the results of this study indicate that the success of AI-based ride-hailing services in Indonesia requires a balance between technological efficiency, service quality, algorithmic transparency, data privacy protection, and emotional connection with customers. This approach aligns with a global trend that positions AI as a tool to enhance the customer experience rather than as a substitute for meaningful human interaction.

5 | CONCLUSIONS AND FUTURE WORK

Based on the analysis of 400 respondents, the research instrument was proven to be valid and highly reliable, with a Cronbach's Alpha value of 0.940. The proposed model explains 80.67% of the variation in Customer Satisfaction ($R^2 = 0.8067$), confirming that AI-based service features play a pivotal role in the Indonesian ride-hailing industry. The findings reveal that Perceived Value, Perceived Service Delivery, Perceived Service Quality, Identification with the Service Provided, and AI Use Behavior exert a positive and significant influence on customer satisfaction, whereas the Market Orientation of Service Provision shows a significant negative effect. Notably, AI Use Behavior and Perceived Service Quality emerged as the most dominant drivers of satisfaction, underscoring that users highly value features such as accurate ETA predictions, route recommendations, efficient driver matching, and automated support. Consequently, ride-hailing providers must prioritize the accuracy, transparency, and quality of their AI systems to foster long-term user trust and corporate reputation. To build upon these insights, future research should expand the sample scope across diverse Indonesian regions to enhance generalizability. Further studies could also incorporate additional variables such as AI Trust, perceived data privacy, algorithmic transparency, and customer loyalty, or examine customer satisfaction as a mediating variable between AI features and corporate reputation. Methodologically, employing a mixed-methods approach or longitudinal studies would provide a deeper understanding of evolving customer perceptions over time. Finally, comparative analyses across different platforms such as Gojek, Grab, Maxim, and inDrive or across other digital sectors like fintech and e-commerce, would offer a more comprehensive understanding of the factors determining the success of AI implementation in improving customer experience.

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