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Intelligence, Trust, and Transparency in Young Consumers' Adoption of AI Marketing Applications in Medan

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Abstract

Purpose: This study examines associations between perceived intelligence, trust, usefulness, ease of use, social influence, and young consumers' intention to adopt Artificial Intelligence (AI) marketing applications in Medan, Indonesia.

Research methodology: A cross-sectional online survey collected 373 responses from consumers aged 18–35 between January and March 2025. Partial least squares structural equation modeling in SmartPLS 4 used 5,000 bootstrap subsamples to assess direct and indirect relationships.

Results: Perceived intelligence, trust in AI, perceived usefulness, and social influence were positively associated with adoption intention. Algorithmic transparency was positively associated with trust. The reported indirect effect through trust was 0.129. Ease of use was associated with usefulness and indirectly with adoption intention, but its direct path to intention was not significant. The model explained 58.4% of the variance in adoption intention.

Conclusions: The findings support examining functional benefits, trust, and social endorsement together when explaining AI marketing adoption intentions.

Limitations: Cross-sectional self-reports from one city restrict causal inference and generalizability. The reported model does not establish whether transparency's association with intention is fully mediated.

Contribution: The study connects acceptance models with the updated signaling-theory perspective and explainable-AI research, positioning perceived transparency as a potential trust signal and distinguishing it from perceived intelligence and functional usefulness in a young Indonesian consumer sample.

Keywords: *AI Marketing, Adoption Intention, Algorithmic Transparency, Perceived Intelligence, Trust in AI*

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1. Introduction

Artificial intelligence (AI) supports product recommendations, conversational interfaces, and personalized advertising. Marketing frameworks describe how these applications can support information processing and customer interaction (Davenport, Guha, Grewal, & Bressgott, 2020; Huang, & Rust, 2021). Their consumer implications extend beyond efficiency: data collection,

automated classification, delegation, and social interaction can create both benefits and costs (Puntoni, Reczek, Giesler, & Botti, 2021). Understanding consumers' willingness to use these applications therefore requires attention to how they evaluate their usefulness, intelligence, and trustworthiness.

Consumer responses to AI vary across tasks and interaction settings. Research on chatbot disclosure and task-dependent algorithm aversion shows that AI presence alone does not guarantee acceptance (Castelo, Bos, & Lehmann, 2019; Luo, Tong, Fang, & Qu, 2019). Consumers may evaluate the same type of technology differently depending on what it is expected to do and how they encounter it. A review of consumer interaction with emerging technologies identifies generational differences, privacy, and ethical concerns as relevant research areas (Ameen, Hosany, & Tarhini, 2021). The present study focuses on consumers aged 18–35 without assuming that this age group is uniformly digitally skilled or receptive to AI.

Medan, North Sumatra, Indonesia, provides the setting for examining these relationships in a specific urban consumer population. Recent evidence from other markets helps frame the inquiry but cannot establish the local relationships in advance. For example, a review of AI personalization in Nigerian small and medium-sized enterprises links marketing content with consumer behavior, whereas research in Bangladeshi retail examines organizational adoption and customer outcomes (Zerine, Biswas, Doha, Meghla, & Polas, 2025; Nnanna-Ohuonu, Chikwesiri, Okudo, & Chikwesiri, 2026). Differences in geography and unit of analysis motivate a consumer-level test in Medan.

Technology acceptance models provide a useful starting point, while later theoretical evaluations emphasize the importance of context and model specification (Dwivedi, Rana, Jeyaraj, Clement, & Williams, 2019; Tamilmani, Rana, Wamba, & Dwivedi, 2021). AI-service and robo-advisor studies likewise extend acceptance research to systems that make recommendations or perform tasks with some autonomy (Belanche, Casaló, & Flavián, 2019; Gursoy, Chi, Lu, & Nunkoo, 2019). Within this perspective, perceived usefulness concerns the benefits consumers expect from an application, while ease of use concerns the effort associated with interacting with it. Social influence addresses the role of others' views in consumers' willingness to adopt the technology. Perceived intelligence concerns users' assessments of system capabilities, whereas algorithmic transparency concerns their understanding of system operations. A system can be regarded as capable without its decision processes being clearly understood, and understanding those processes is not identical to judging the system useful. Including both constructs allows the study to examine capability perceptions separately from explanations that may support trust (Moussawi, Koufaris, & Benbunan-Fich, 2021; Shin, 2021).

Trust in AI concerns users' willingness to rely on systems whose performance and decisions they cannot fully inspect. Empirical reviews and acceptance research indicate that trust is multidimensional and interacts with other technology evaluations (Choung, David, & Ross, 2023; Glikson, & Woolley, 2020). In AI marketing, a consumer's evaluation of reliability may therefore be considered alongside perceptions of usefulness, system intelligence, and understandable operations. Research on Gen Z online purchasing further distinguishes platform trust from retailer trust, reinforcing the need to specify the object of trust (Lady, Ariyanto, & Olivia, 2026). Here, the object is the AI marketing application, rather than the retailer or platform considered more broadly. Trust is examined as both a correlate of adoption intention and a potential intermediary between perceived transparency and intention. This distinction is important when interpreting the proposed indirect relationship.

This study examines five direct predictors of adoption intention, the association between algorithmic transparency and trust, and the indirect transparency trust intention pathway. Its theoretical contribution is to connect acceptance constructs with the updated signalling-theory account of observable and credible information (Connelly, Certo, Reutzel, DesJardine, & Zhou, 2024) and explainable-AI research (Rai, 2020; Shin, 2021). These perspectives provide complementary ways to consider how consumers assess an application and the information available about its operations. The model distinguishes perceived intelligence from functional usefulness and treats perceived transparency as a possible trust signal. Examining these constructs together allows their relationships with adoption intention to be evaluated within one specified framework. The contribution is a

context-specific test of these relationships, rather than a claim to establish a new general theory or causal mechanism.

Section 2 develops the theoretical background and hypotheses. Section 3 describes the research design, sampling, measures, and analysis. Section 4 presents the results and discusses their theoretical and practical implications. Section 5 concludes with limitations and directions for future research.

2. Literature Review and Hypotheses Development

2.1 Theoretical foundations

The Technology Acceptance Model (TAM) distinguishes perceived usefulness from perceived ease of use (Davis, 1989). Perceived usefulness refers to the expected benefits of using technology to improve task performance, while perceived ease of use concerns the effort required to learn and operate a technological system. Both constructs are important for understanding individuals' willingness to adopt technology. Later evaluations of acceptance theory emphasize that the relevance and strength of these relationships depend on the model and its context (Dwivedi et al., 2019; Tamilmani et al., 2021). In AI marketing, perceived usefulness refers to benefits associated with shopping efficiency, product recommendations, and purchasing decisions, whereas perceived ease of use reflects how easily consumers can interact with AI-powered applications. Examining these constructs separately allows the study to distinguish functional benefits from the effort required to access them.

The Unified Theory of Acceptance and Use of Technology (UTAUT) contributes social influence, defined as perceived endorsement or encouragement from important others (Venkatesh, Morris, Davis, & Davis, 2003). Social influence recognizes that technology adoption decisions may be shaped not only by individual evaluations but also by the opinions and experiences of people considered important. In AI marketing, these social evaluations may influence consumers' willingness to use AI-powered applications. This study incorporates social influence alongside TAM variables without claiming to test the complete UTAUT or UTAUT2 model. Evidence from mobile banking in Jordan and Indonesia illustrates how social and trust-related variables can be examined within context-specific acceptance models (Alalwan, Dwivedi, & Rana, 2017; Putro & Sugiat, 2025). Whether similar relationships emerge in AI marketing applications remains an empirical question.

The updated signaling-theory review by Connelly et al. (2024) emphasizes the characteristics of signals, signalers, receivers, and their context. In AI marketing, firms may provide explanations of recommendation logic, data use, and automated decisions to reduce information asymmetry between providers and consumers. Such explanations may help consumers understand how applications operate and evaluate their reliability. However, for these explanations to function as useful signals, consumers must be able to observe, interpret, and assess their credibility. Perceived algorithmic transparency is therefore proposed as an antecedent of trust in AI. Nevertheless, the present measures do not directly assess signal cost or objective accuracy. Accordingly, this study examines a limited application of signaling theory rather than testing all its mechanisms.

2.2 Perceived intelligence and adoption intention

Perceived intelligence is the extent to which users attribute learning, reasoning, adaptability, and responsive capabilities to an AI system (Moussawi et al., 2021). It differs conceptually from usefulness: a system may appear intelligent without delivering benefits relevant to a particular shopping task. Perceptions of intelligence may nevertheless support adoption intention when consumers expect the application to interpret their needs and respond appropriately. Moussawi et al. (2021) examine perceived intelligence and anthropomorphism in the adoption of personal intelligent agents. Related work on voice-assistant personality addresses how humanization shapes consumer attitudes and behavior (Poushneh, 2021). These perspectives motivate examining perceived intelligence in AI marketing while keeping intelligence, anthropomorphism, and personality conceptually distinct. Accordingly:

> H_1: Perceived intelligence has a significant positive effect on young consumers' intention to adopt AI-powered marketing applications

2.3 Trust in AI and adoption intention

Trust in AI reflects confidence in relying on an AI system under uncertainty. Its foundations can include assessments of reliability, performance, and the way the system is presented to users (Glikson & Woolley, 2020). For marketing applications that process personal information or make recommendations, users may also consider data security and responsible data use. These evaluations can shape willingness to interact with the application. Research on trust and AI acceptance indicates that trust can operate alongside perceived usefulness and attitudes (Choung et al., 2023). In Indonesian e-commerce, studies of retailer trust and continued buy-now-pay-later use also place trust within broader behavioral models (Lady et al., 2026; Wahyuningtyastuti & Ariyanti, 2025). Those settings differ from AI marketing, but they support examining trust explicitly rather than assuming that functional benefits alone explain intention. Thus:

H_2: Trust in AI has a significant positive effect on young consumers' intention to adopt AI-powered marketing applications

2.4 Algorithmic transparency and trust in AI

Algorithmic transparency concerns users' perceived access to understandable information about system logic, data use, and decision criteria. Explainable-AI research examines how explanations help users interpret automated outputs and evaluate whether to rely on them (Rai, 2020; Shin, 2021). An explanation such as a reason for a product recommendation may improve understanding, but disclosure alone does not establish that an algorithm is accurate, fair, or worthy of trust. From a signaling perspective, understandable disclosures can supply information that consumers use to evaluate a system (Connelly et al., 2024). Their influence should depend on how credible and relevant users find them. Evidence linking explainability, perception, and trust motivates the proposed positive relationship (Shin, 2021); it does not imply that every disclosure necessarily increases trust. Therefore:

H_3: Algorithmic transparency has a significant positive effect on trust in AI

2.5 Mediating role of trust in AI

Trust is proposed as an intermediary between perceived algorithmic transparency and adoption intention. Explanations may inform trust judgments, and those judgments may be associated with willingness to use the application (Choung et al., 2023; Shin, 2021). This proposed sequence connects signaling and acceptance perspectives. A significant indirect effect would support the specified pathway but classifying it as full or partial mediation additionally requires an estimated direct transparency-to-intention path (Carrión, Nitzl, & Roldán, 2017). The current hypothesis concerns the indirect relationship:

H_4: Trust in AI mediates the relationship between algorithmic transparency and adoption intention

2.6 Perceived usefulness and adoption intention

Perceived usefulness concerns expected improvements in task performance (Davis, 1989). In AI marketing, these benefits may include efficient product search, more relevant recommendations, time savings, and better purchase decisions. Shopping-chatbot research examines usefulness alongside other attitudes and acceptance variables (Kasilingam, 2020). Indonesian marketplace evidence also links perceived benefits and convenience with purchase intention, although purchasing and technology adoption are distinct outcomes (Ahyani & Solihin, 2025). These perspectives motivate the following hypothesis:

H_5: Perceived usefulness has a significant positive effect on adoption intention

2.7 Perceived ease of use, usefulness, and adoption intention

Perceived ease of use concerns the effort required to learn and operate a system (Davis, 1989). TAM extensions provide a rationale for examining both its relationship with usefulness and its direct relationship with intention (Venkatesh & Davis, 2000). An accessible interface may help users realize functional benefits. However, evidence from Indonesian mobile banking and continued BNPL use

illustrates that effort-related relationships vary across settings and behavioral outcomes (Putro & Sugiat, 2025; Wahyuningtyastuti & Ariyanti, 2025). The study therefore tests both paths.

$H_{6}a$: Perceived ease of use has a significant positive effect on perceived usefulness

$H_{6}b$: Perceived ease of use has a significant positive effect on adoption intention

2.8 Social influence and adoption intention

Social influence concerns perceived expectations or endorsement from important referents (Venkatesh et al., 2003). Family members, peers, and online contacts may provide information about AI marketing applications or affect their perceived acceptability. Contemporary UTAUT evaluations and Indonesian mobile-banking evidence motivate including this construct (Putro & Sugiat, 2025; Tamilmani et al., 2021). The study tests the relationship in Medan without treating collectivism or peer influence as measured characteristics of every respondent. Thus:

H_{7}: Social influence has a significant positive effect on young consumers' intention to adopt AI-powered marketing applications

Figure 1 presents the proposed conceptual model, including the direct hypotheses and the indirect transparency–trust–adoption intention pathway specified in *H_{4}*.

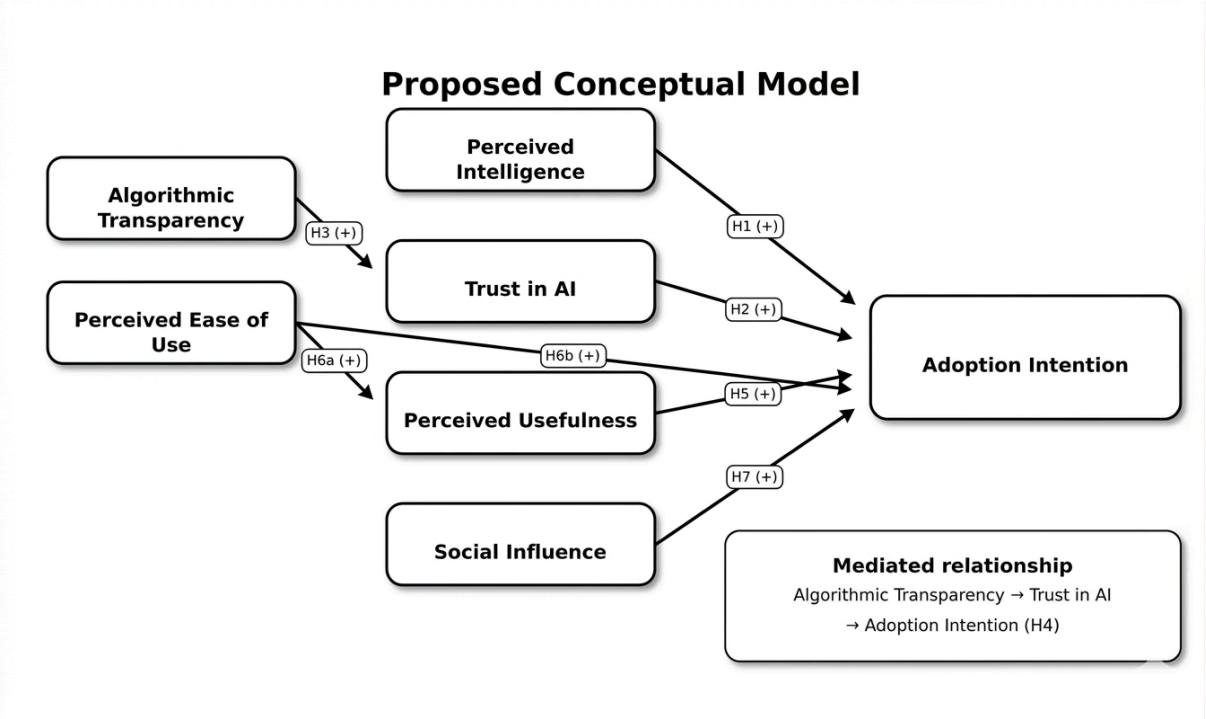


Figure 1. Proposed conceptual model of AI marketing adoption

3. Research Methodology

3.1 Research design

The study uses a quantitative, cross-sectional survey to examine the proposed relationships at one point in time. A deductive approach links the hypotheses to survey measures and Partial Least Squares Structural Equation Modeling (PLS-SEM). The design estimates associations and does not establish temporal ordering or causal effects.

3.2 Population, sample, and sampling technique

The target population comprises consumers aged 18–35 residing in Medan, North Sumatra, Indonesia, with prior exposure to or experience with AI marketing applications, such as product recommendations, chatbots, or algorithm-driven advertising. This age range defines the study population; the findings do not represent all consumer age groups. The analysis uses 373 valid

responses. Adoption intention has five incoming direct paths, so the ten-times heuristic would yield a minimum of 50 observations. This heuristic is only a rough check and does not establish adequate statistical power or representativeness. More defensible sample-size justification depends on the smallest effect of interest and the desired significance and power levels (Hair, Risher, Sarstedt, & Ringle, 2019; Kock & Hadaya, 2018). No a priori power calculation is reported for this study.

The study used simple random selection from a sampling frame assembled from online community registries, university student databases, and digital platform user panels in Medan. Random numbers were used to select eligible individuals from that frame. Population coverage depends on the sources included in the frame, and the resulting sample cannot be assumed to represent every young consumer in Medan. Nonresponse may also affect the final respondent composition.

3.3 Data collection procedure

Data were collected through a structured online questionnaire distributed via Google Forms between January and March 2025. A pretest with 30 respondents assessed item clarity, completion time, and face validity and led to minor wording refinements. The questionnaire was administered in Bahasa Indonesia after back-translation of the English-language wording. Before participation, respondents received an informed-consent statement describing the study purpose, voluntary participation, and confidentiality.

3.4 Measurement instruments

The questionnaire comprised 30 items across seven constructs. Responses used a five-point Likert scale from 1 (strongly disagree) to 5 (strongly agree). The following descriptions identify the conceptual and measurement sources reported for each construct; adaptation to this setting requires assessment of the resulting measures. Perceived Intelligence (PI) comprised five items concerning learning ability, adaptability, reasoning, contextual understanding, and intelligent responsiveness, drawing on research on intelligent agents and voice assistants (Moussawi et al., 2021; Poushneh, 2021).

Trust in AI (TAI) comprised five items concerning reliability, data security, accuracy, ethical data use, and benevolent intent, drawing on trust and explainability research (Glikson & Woolley, 2020; Shin, 2021). Algorithmic Transparency (AT) comprised four items addressing the clarity of data collection, recommendation logic, decision criteria, and user control over personalization, with conceptual sources in explainability and algorithmic accountability (Diakopoulos, 2016; Shin, 2021). Perceived Usefulness (PU) comprised four adapted items on shopping efficiency, decision quality, time savings, and overall benefits (Davis, 1989; Venkatesh & Davis, 2000).

Perceived Ease of Use (PEOU) comprised four adapted items on operational simplicity, ease of learning, interface intuitiveness, and required effort (Davis, 1989). Social Influence (SI) comprised four adapted items concerning family members, peers, social media contacts, and opinion leaders (Venkatesh et al., 2003). Adoption Intention (AI_INT) comprised four adapted items on intention to use, continued use, increased use, and recommending the application (Venkatesh et al., 2003). These items broaden the outcome beyond initial adoption, which should be considered when interpreting the construct.

3.5 Data analysis technique

PLS-SEM was implemented in SmartPLS 4. The analysis first examined indicator loadings, internal consistency, convergent validity, and discriminant validity, followed by structural paths, explained variance, and effect sizes (Hair et al., 2019). Reported inference used 5,000 bootstrap subsamples with Bias-Corrected and Accelerated (BCa) confidence intervals. Indirect effects were evaluated from their bootstrap intervals (Carrión et al., 2017). Explanatory fit and out-of-sample predictive performance are distinct assessment tasks (Shmueli et al., 2019).

4. Results and Discussions

4.1 Respondent demographics

Of the 373 valid responses obtained, the demographic profile of the sample is as follows. In terms of gender distribution, 198 respondents (53.1%) were female and 175 (46.9%) were male. Regarding age, the largest group consisted of respondents aged 22–25 (40.5%), followed by 18–21 (28.4%), 26–30 (20.1%), and 31–35 (11.0%). In terms of educational attainment, 52.3% held a bachelor's degree, 31.4% were current undergraduate students, 10.7% held a diploma, and 5.6% had completed a master's degree or above. Monthly income distribution indicated that 38.6% earned below IDR 3 million, 33.5% earned IDR 3–6 million, 18.5% earned IDR 6–10 million, and 9.4% earned above IDR 10 million. Regarding AI marketing application experience, 67.8% reported having used AI-powered recommendation features on e-commerce platforms, 18.8% had interacted with AI chatbots, and 13.4% had engaged with other AI marketing tools.

4.2 Measurement model evaluation

Table 1 summarizes the measurement model assessment results, including indicator loadings, Cronbach alpha, composite reliability, average variance extracted, and indicator variance inflation factors. These statistics were evaluated using the reporting criteria discussed by Hair et al. (2019).

Table 1. Measurement model assessment results

Construct / Item	Loading	CA	CR	AVE	VIF
Perceived Intelligence		0.891	0.920	0.699	
PI1	0.842				2.134
PI2	0.858				2.387
PI3	0.831				2.056
PI4	0.819				1.945
PI5	0.836				2.211
Trust in AI		0.903	0.928	0.720	
TAI1	0.867				2.456
TAI2	0.851				2.312
TAI3	0.838				2.198
TAI4	0.844				2.267
TAI5	0.849				2.341
Algorithmic Transparency		0.872	0.913	0.724	
AT1	0.856				2.089
AT2	0.871				2.156
AT3	0.842				1.967
AT4	0.834				1.923
Perceived Usefulness		0.884	0.920	0.742	
PU1	0.868				2.234
PU2	0.879				2.356
PU3	0.851				2.123
PU4	0.847				2.078
Perceived Ease of Use		0.876	0.915	0.729	
PEOU1	0.862				2.145
PEOU2	0.854				2.089
PEOU3	0.848				2.012
PEOU4	0.851				2.067
Social Influence		0.862	0.906	0.707	
SI1	0.839				1.956

Construct / Item	Loading	CA	CR	AVE	VIF
SI2	0.856				2.034
SI3	0.842				1.989
SI4	0.827				1.912
Adoption Intention		0.895	0.927	0.760	
AI_INT1	0.876				2.356
AI_INT2	0.882				2.412
AI_INT3	0.861				2.234
AI_INT4	0.868				2.289

The reported loadings range from 0.819 to 0.882 and exceed 0.708. Cronbach alpha ranges from 0.862 to 0.903, composite reliability from 0.906 to 0.928, and AVE from 0.699 to 0.760. These reported values exceed the conventional 0.70 reliability and 0.50 AVE thresholds (Hair et al., 2019). Indicator VIF values range from 1.912 to 2.456. Table 2 presents the reported construct correlations and square roots of AVE for the discriminant-validity assessment.

Table 2. Fornell–Larcker criterion for discriminant validity

	PI	TAI	AT	PU	PEOU	SI	AI_INT
PI	0.837						
TAI	0.612	0.849					
AT	0.534	0.648	0.851				
PU	0.587	0.601	0.512	0.861			
PEOU	0.498	0.489	0.467	0.634	0.854		
SI	0.423	0.478	0.398	0.456	0.412	0.841	
AI_INT	0.645	0.672	0.578	0.658	0.523	0.512	0.872

In Table 2, every reported square root of AVE exceeds the corresponding construct correlations. This pattern meets the Fornell–Larcker criterion. However, that criterion alone is insufficient to establish discriminant validity. HTMT ratios were reported to be below 0.85, but the matrix and confidence intervals are not presented. Inference should therefore remain qualified until those results can be evaluated alongside the correlations (Franke & Sarstedt, 2019; Hair et al., 2019).

4.3 Structural model assessment

The structural model assessment considered predictor collinearity, standardized paths, explained variance (R^2), and effect sizes (f^2), following (Hair et al., 2019). Inner VIF values were reported to be below 3.0. Path inference used 5,000 bootstrap subsamples with BCa intervals. Table 3 reports the direct paths; Table 4 reports the indirect effects.

Table 3. Structural model results for direct effects

Hypothesis / Path	β	SE	t-value	p-value	f^2	Decision
H_1: PI → AI_INT	0.218	0.048	4.542	< 0.001	0.058	Supported
H_2: TAI → AI_INT	0.264	0.052	5.077	< 0.001	0.072	Supported
H3: AT → TAI	0.487	0.043	11.326	< 0.001	0.312	Supported
H_5: PU → AI_INT	0.231	0.049	4.714	< 0.001	0.063	Supported
H_6a: PEOU → PU	0.498	0.042	11.857	< 0.001	0.331	Supported
H_6b: PEOU → AI_INT	0.078	0.046	1.696	0.090	0.007	Not Supported
H_7: SI → AI_INT	0.156	0.044	3.545	< 0.001	0.032	Supported

Six of the seven direct hypotheses were supported by the reported estimates. Perceived intelligence (H_1: $\beta = 0.218$, $t = 4.542$), trust in AI (H_2: $\beta = 0.264$, $t = 5.077$), perceived usefulness (H_5: $\beta = 0.231$, $t = 4.714$), and social influence (H_7: $\beta = 0.156$, $t = 3.545$) were positively associated with adoption intention (all $p < 0.001$). Algorithmic transparency was positively associated with trust (H_3: $\beta = 0.487$, $t = 11.326$, $p < 0.001$), and ease of use was positively associated with usefulness (H_6a: $\beta = 0.498$, $t = 11.857$, $p <$

0.001). The direct ease-of-use path to intention was not significant (*H₆b*: $\beta = 0.078$, $t = 1.696$, $p = 0.090$).

Table 4. Indirect-effect results

Indirect Path	Indirect β	95% CI LL	95% CI UL	p-value	Decision
H₄: AT → TAI → AI_INT	0.129	0.082	0.184	< 0.001	Supported
PEOU → PU → AI_INT	0.115	0.071	0.168	< 0.001	Significant

Table 4 reports a positive indirect transparency–trust–intention relationship (*H₄*: $\beta = 0.129$, 95% BCa CI [0.082, 0.184], $p < 0.001$). Because a direct transparency-to-intention path was not estimated in the reported model, this result cannot establish full or partial mediation. The indirect ease-of-use–usefulness–intention effect was also significant ($\beta = 0.115$, 95% BCa CI [0.071, 0.168], $p < 0.001$). Together with the nonsignificant direct ease-of-use path, that pattern is consistent with indirect-only mediation within the specified model. Neither result establishes a causal sequence in these cross-sectional data.

The reported R^2 values are 0.584 for adoption intention, 0.237 for trust, and 0.248 for usefulness. These describe the variance explained within the analyzed sample. They do not establish predictive performance for new observations. Assessing that performance requires documented prediction settings and indicator-level prediction errors against an appropriate benchmark (Shmueli et al., 2019). Such results are not available in the reported tables, so out-of-sample predictive performance remains unestablished here. Figure 2 summarizes the significant direct paths, indirect effects, and reported R^2 values. It omits the nonsignificant direct ease-of-use–intention path ($\beta = 0.078$, $p = 0.090$), which is retained in Table 3.

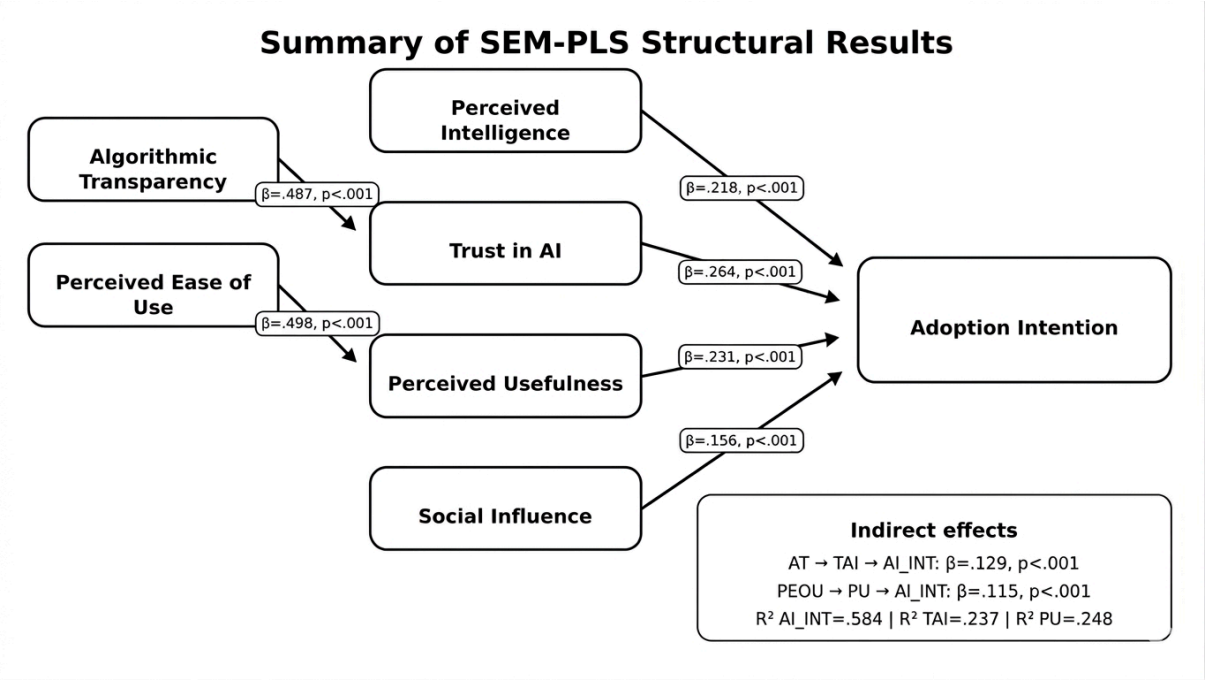


Figure 2. Summary of reported structural model results

4.4 Discussion

4.4.1 Theoretical implications

The positive perceived-intelligence coefficient ($\beta = 0.218$) supports treating perceived capability as distinct from functional usefulness in the specified AI marketing model. This interpretation is consistent with intelligent-agent adoption research (Moussawi et al., 2021). It also complements the consumer-experience perspective, which recognizes that responses to AI involve more than task efficiency (Puntoni et al., 2021). The result is an incremental association after accounting for the

included predictors; it does not show that intelligence perceptions are universally more important than usefulness or trust.

Trust has the largest reported standardized direct coefficient among the predictors of adoption intention ($\beta = 0.264$), although differences between coefficients were not formally tested. The positive transparency-trust path and indirect transparency-intention effect is consistent with a trust-related interpretation of explanation provision (Choung et al., 2023; Shin, 2021). The omitted direct transparency-to-intention path prevents classifying the relationship as full mediation. Consequently, the contribution is evidence consistent with the specified indirect pathway rather than proof that transparency operates exclusively through trust.

The updated signaling framework provides a contemporary theoretical interpretation: explanations may communicate information that consumers use to judge an AI system (Connelly et al., 2024). The transparency–trust association is compatible with this account, while explainable-AI research clarifies the importance of intelligibility (Rai, 2020). The study does not measure explanation accuracy, signal cost, or credibility separately, and transparency is the only modeled antecedent of trust. The findings therefore cannot establish which transparency feature is most effective or that transparency is the strongest possible trust antecedent.

The positive usefulness-intention and ease-of-use–usefulness paths support the relevance of acceptance constructs in this setting. The nonsignificant direct ease-of-use path suggests that ease of operation may be associated with intention primarily through perceived benefits in the specified model. Related Indonesian research reports context-dependent effort and benefit relationships in mobile banking, marketplace purchasing, and Buy Now, Pay Later (BNPL) continuance (Ahyani & Solihin, 2025; Putro & Sugiat, 2025; Wahyuningtyastuti & Ariyanti, 2025). These comparisons do not establish why the direct path is nonsignificant here; familiarity and digital skill were not tested as explanations.

Social influence remains positively associated with intention after the other included predictors are considered. This is consistent with retaining social context in acceptance research (Tamilmani et al., 2021). Recent studies of platform and retailer trust, AI personalization, and firm-level AI adoption place related consumer outcomes within broader digital-market settings (Lady et al., 2026; Nnanna-Ohuonu, Chikwesiri, Okudo, & Chikwesiri, 2026; Zerine et al., 2025). Their differing populations and units of analysis limit direct comparison. The present contribution is the joint examination of these relationships among young consumers in Medan, not evidence of a measured cultural mechanism.

4.4.2 Practical implications

Developers and marketers can use the findings to identify features worth testing with consumers. Recommendation relevance, context-sensitive responses, and reliable task completion may help users recognize application capabilities. Product evaluations should assess whether such features deliver practical benefits rather than merely create an impression of intelligence. Firms should make recommendation explanations and data-use information understandable and assess whether users find them accurate and credible. Privacy controls and accessible information can support informed decisions, but this study did not test interface features or security certifications. Their effectiveness should be evaluated directly rather than inferred from the transparency coefficient.

The social-influence association suggests evaluating peer information, authentic user experiences, and referral mechanisms as possible communication channels. Any such campaign should avoid implying universal approval and should be tested with the intended consumer group. The results do not identify the effectiveness of a particular influencer strategy or establish a cultural explanation. The indirect ease-of-use finding also supports testing clear navigation and onboarding alongside perceived usefulness. An intuitive interface may help users access application benefits, even when ease of use has no significant direct path to intention. These are design implications to evaluate prospectively; the survey does not estimate the effect of implementing them.

5. Conclusions

5.1 Conclusion

This study examined associations underlying AI marketing adoption intentions in 373 consumers aged 18–35 in Medan. Perceived intelligence, trust, usefulness, and social influence had significant positive direct paths to intention. Transparency had a positive path to trust and a positive indirect relationship with intention through trust. Ease of use was associated with usefulness and indirectly with intention, while its direct path to intention was not significant. The reported model explained 58.4% of intention variance in the sample. These findings support further examination of the combined acceptance and signaling perspective, subject to the study's measurement, reporting, and design limitations.

5.2 Research limitations

The cross-sectional design cannot establish causation or temporal mediation. The single-city age-restricted sample and coverage of the sampling frame limit generalizability. Self-reports may be affected by common method bias: reported item randomization and reverse coding do not eliminate this possibility, and low VIF values alone do not rule it out. The intention measure combines initial use, continued use, increased use, and recommendation, which may represent different behavioral outcomes. The absence of a direct transparency-to-intention path limits mediation classification. The unreported HTMT matrix and indicator-level prediction results also constrain assessment of discriminant validity and out-of-sample performance.

5.3 Suggestions for future research

Future studies should distinguish initial adoption, continued use, recommendation, and observed behavior. Longitudinal or experimental designs can test temporal relationships and manipulate explanation features while measuring their comprehensibility and credibility. Researchers should estimate the direct transparency-to-intention path, document complete measurement and prediction outputs, and assess sampling coverage and nonresponse. Comparisons across age groups, cities, and application types could test how well the relationships generalize. Privacy concerns, perceived risk, digital skill, and prior AI experience are additional candidates for prespecified extensions.

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Author Contributions

TS contributed to the conceptualization of the study, literature review, methodology, instrument development, data collection, data analysis, interpretation of the findings, and writing original draft preparation.

References

Ahyani, A., & Solihin, D. (2025). Purchase intention on Bukalapak: Role of risk, convenience, and benefits. *Annals of Human Resource Management Research*, *5*(3), 681-692. https://doi.org/10.35912/ahrmr.v5i3.3183

Alalwan, A. A., Dwivedi, Y. K., & Rana, N. P. (2017). Factors influencing adoption of mobile banking by Jordanian bank customers: Extending UTAUT2 with trust. *International journal of information management*, *37*(3), 99-110. https://doi.org/10.1016/j.ijinfomgt.2017.01.002

Ameen, N., Hosany, S., & Tarhini, A. (2021). Consumer interaction with cutting-edge technologies: Implications for future research. *Computers in Human Behavior, 120, 106761. doi:*. https://doi.org/10.1016/j.chb.2021.106761

Belanche, D., Casaló, L. V., & Flavián, C. (2019). Artificial Intelligence in FinTech: Understanding robo-advisors adoption among customers. *Industrial management & data systems*, *119*(7), 1411-1430. https://doi.org/10.1108/imds-08-2018-0368

Carrión, G. C., Nitzl, C., & Roldán, J. L. (2017). *Mediation analyses in partial least squares structural equation modeling: Guidelines and empirical examples Partial least squares path modeling: Basic concepts, methodological issues and applications (pp*.

Castelo, N., Bos, M. W., & Lehmann, D. R. (2019). Task-dependent algorithm aversion. *Journal of marketing research*, *56*(5), 809-825. https://doi.org/10.1177/0022243719851788

Choung, H., David, P., & Ross, A. (2023). Trust in AI and its role in the acceptance of AI technologies. *International Journal of Human–Computer Interaction*, *39*(9), 1727-1739. https://doi.org/10.1080/10447318.2022.2050543

Connelly, B., Certo, T., Reutzel, C., DesJardine, M., & Zhou, Y. (2024). Signaling Theory: State of the Theory and Its Future. *Journal of management, 51, 24-61*. https://doi.org/10.1177/01492063241268459

Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. *Journal of the academy of marketing science*, *48*(1), 24-42. https://doi.org/10.1007/s11747-019-00696-0

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly, 319-340. doi:*. https://doi.org/10.2307/249008

Diakopoulos, N. (2016). Accountability in algorithmic decision making. *Communications of the ACM*, *59*(2), 56-62. https://doi.org/10.1145/2844110

Dwivedi, Y. K., Rana, N. P., Jeyaraj, A., Clement, M., & Williams, M. D. (2019). Re-examining the unified theory of acceptance and use of technology (UTAUT): Towards a revised theoretical model. *Information systems frontiers*, *21*(3), 719-734. https://doi.org/10.1007/s10796-017-9774-y

Franke, G., & Sarstedt, M. (2019). Heuristics versus statistics in discriminant validity testing: A comparison of four procedures. *Internet research*, *29*(3), 430-447. https://doi.org/10.1108/intr-12-2017-0515

Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: Review of empirical research. *Academy of management annals*, *14*(2), 627-660. https://doi.org/10.5465/annals.2018.0057

Gursoy, D., Chi, O. H., Lu, L., & Nunkoo, R. (2019). Consumers acceptance of artificially intelligent (AI) device use in service delivery. *International journal of information management, 49, 157-169. doi:*. https://doi.org/10.1016/j.ijinfomgt.2019.03.008

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, *31*(1), 2-24. https://doi.org/10.1108/ebr-11-2018-0203

Huang, M.-H., & Rust, R. T. (2021). A strategic framework for artificial intelligence in marketing. *Journal of the academy of marketing science*, *49*(1), 30-50. https://doi.org/10.1007/s11747-020-00749-9

Kasilingam, D. L. (2020). Understanding the attitude and intention to use smartphone chatbots for shopping. *Technology in society, 62, 101280. doi:*. https://doi.org/10.1016/j.techsoc.2020.101280

Kock, N., & Hadaya, P. (2018). Minimum sample size estimation in PLS-SEM: The inverse square root and gamma-exponential methods. *Information systems journal*, *28*(1), 227-261. https://doi.org/10.1111/isj.12131

Lady, L., Ariyanto, H., & Olivia, C. (2026). Platform Trust, e-WOM, and Gen Z Purchase Intention: Mediating Role of Retailer Trust. *Annals of Management and Organization Research, 7, 557-570 v7i4.3854*. https://doi.org/10.35912/amor.v7i4.3854

Luo, X., Tong, S., Fang, Z., & Qu, Z. (2019). Frontiers: Machines vs. *humans: The impact of artificial intelligence chatbot disclosure on customer purchases. Marketing science*, *38*(6), 937-947. https://doi.org/10.1287/mksc.2019.1192

Moussawi, S., Koufaris, M., & Benbunan-Fich, R. (2021). How perceptions of intelligence and anthropomorphism affect adoption of personal intelligent agents: S. *Moussawi et al. Electronic Markets*, *31*(2), 343-364. https://doi.org/10.1007/s12525-020-00411-w

Nnanna-Ohuonu, O., Chikwesiri, N. P., Okudo, A., & Chikwesiri, I. V. (2026). Artificial Intelligence Personalized Marketing Content and Consumer Behavior in Nigerian SMEs. *Annals of Management and Organization Research*, *7*(3), 325-339. https://doi.org/10.35912/amor.v7i3.3418

Poushneh, A. (2021). Humanizing voice assistant: The impact of voice assistant personality on consumers' attitudes and behaviors. *Journal of Retailing and Consumer Services, 58, 102283. doi:*. https://doi.org/10.1016/j.jretconser.2020.102283

Puntoni, S., Reczek, R. W., Giesler, M., & Botti, S. (2021). Consumers and artificial intelligence: An experiential perspective. *Journal of marketing*, *85*(1), 131-151. https://doi.org/10.1177/0022242920953847

Putro, C. B. R., & Sugiat, M. A. (2025). The use of UTAUT model to understand user intention and user behavior of mobile banking BIMA PT Bank Jateng. *Journal of Multidisciplinary Academic Business Studies*, *2*(4), 239-255. https://doi.org/10.35912/ijamis.v3i1.3252

Rai, A. (2020). Explainable AI: From black box to glass box. *Journal of the academy of marketing science*, *48*(1), 137-141. https://doi.org/10.1007/s11747-019-00710-5

Shin, D. (2021). The effects of explainability and causability on perception, trust, and acceptance: Implications for explainable AI. *International journal of human-computer studies, 146, 102551. doi:*. https://doi.org/10.1016/j.ijhcs.2020.102551

Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J.-H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: Guidelines for using PLSpredict. *European Journal of Marketing*, *53*(11), 2322-2347. https://doi.org/10.1108/ejm-02-2019-0189

Tamilmani, K., Rana, N. P., Wamba, S. F., & Dwivedi, R. (2021). The extended Unified Theory of Acceptance and Use of Technology (UTAUT2): A systematic literature review and theory evaluation. *International journal of information management, 57, 102269. doi:*. https://doi.org/10.1016/j.ijinfomgt.2020.102269

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management science*, *46*(2), 186-204. https://doi.org/10.1287/mnsc.46.2.186.11926

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view1. *MIS quarterly*, *27*(3), 425-478. https://doi.org/10.2307/30036540

Wahyuningtyastuti, I., & Ariyanti, M. (2025). Understanding continued BNPL usage behavior in e-commerce: Extended UTAUT2 with usage intention mediation. *International Journal of Accounting and Management Information Systems*, *3*(1), 49-69. https://doi.org/10.35912/ijamis.v3i1.3254

Zerine, I., Biswas, Y. A., Doha, M. Z., Meghla, H. M., & Polas, M. R. H. (2025). Adoption of Artificial Intelligence in retail: Examining the impact of technological and organizational factors on customer retention and loyalty. *Annals of Management and Organization Research (AMOR)*, *6*(3), 287-302. https://doi.org/10.35912/amor.v6i3.2548