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Comparative Technology Acceptance in B2C Automotive E-Commerce Platforms Using an Extended TAM

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Abstract

Background: Indonesia's digital used-car market has expanded substantially, with used-car sales reaching 1.8 million units in 2024 and financing totaling IDR 117 trillion in 2025.
Objective: This research compares technology acceptance across two B2C used-car platforms with different brand histories: OLX Mobbi, which inherits an established brand, and Caroline.id, introduced as a newer brand in 2022. The analysis extends the Technology Acceptance Model (TAM) by incorporating Information Quality (IQ), Trust, and Perceived Transaction Risk (PTR) as a moderating variable.
Methods: A quantitative survey was conducted with 200 respondents selected through purposive sampling, with 100 users representing each platform. The model was evaluated using Partial Least Squares Structural Equation Modeling (PLS-SEM) in SmartPLS 4, followed by Henseler's bootstrap-based Multi-Group Analysis (MGA).
Results: Information Quality and the Behavioral Intention-to-Actual Use path were significant for both platforms, whereas Perceived Usefulness and the PTR × PU moderation effect were not significant. Perceived Ease of Use and Trust predicted Behavioral Intention only for OLX Mobbi. MGA indicated no significant between-group differences for seven of the eight paths; the only significant difference was observed in the path from PTR to Behavioral Intention ($p = 0.041$), with coefficients in opposite directions (OLX Mobbi: $\beta = 0.099$; Caroline.id: $\beta = -0.108$).
Conclusion: Overall, the two platforms exhibit broadly comparable technology acceptance structures. Information Quality is consistently important, whereas Perceived Ease of Use and Trust play a stronger role for OLX Mobbi. Nevertheless, the between-group findings should be interpreted cautiously because of limitations related to measurement invariance and discriminant validity.

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INTRODUCTION

Indonesia's automotive market, especially the used-car segment, is undergoing a structural shift as digital technologies become increasingly embedded in consumer decision-making. Mobile devices, social media, and data-supported tools now allow buyers to assess alternatives, compare prices, and progress further through the purchase process online rather than relying primarily on dealership visits (Brewis et al., 2023; Hakim et al., 2023).

Market data illustrate the scale of this change. Annual used-car sales increased from approximately 517,000 units in 2013 to 1.8 million units in 2024. In 2025, used-car financing reached IDR 117 trillion, representing 15.56% year-on-year growth and exceeding the growth rate of new-car financing (UI, 2026). As a result, digital intermediaries increasingly connect sellers and buyers and function as an important component of the transaction infrastructure for Indonesia's used-vehicle market.

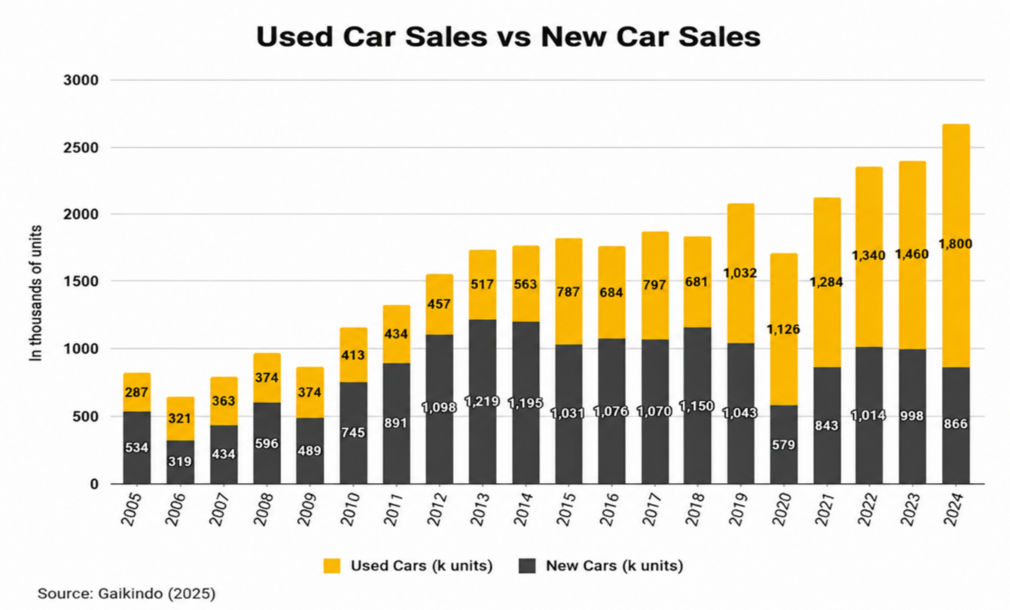

Figure 1. Used Car Sales vs. New Car Sales

Acceptance of a digital automotive marketplace, however, cannot be treated in the same way as acceptance of conventional mass e-commerce. Online used-car purchases involve large financial commitments, limited opportunities to inspect the vehicle physically before purchase, and substantial information asymmetry between buyers and platforms (Engelmann et al., 2022). Consequently, adoption decisions depend on more than system functionality and perceived convenience.

Caroline.id and OLX Mobbi provide two relevant B2C cases. Caroline.id is operated by PT Autopedia Sukses Lestari Tbk (ASLC), which has been listed on the Indonesia Stock Exchange since 2022; the platform operates 16 showrooms across four regions and applies a 150-point vehicle inspection process. OLX Mobbi was established on March 18, 2024, through the integration of mobil88, mobbi, and OLX Autos under PT Astra Digital Mobil (Astra Group), and operates more than 30 stores and inspection centers in 10 cities. Both platforms offer comparable core services, including standardized inspections, warranties, fixed pricing, and financing facilities managed by the platform rather than by individual sellers.

Their principal contextual difference lies in brand history. Caroline.id has developed its automotive identity as a newer standalone brand, whereas OLX Mobbi retains the "OLX" name, which has been present in Indonesia since 2014 and traces its local history to Tokobagus, founded in 2005. Although OLX Mobbi itself emerged only after the 2024 merger, the inherited OLX name has long been associated with categories such as vehicles, property, and job listings. This distinction may matter for the present model in two ways. A familiar brand can create institutional trust before direct platform experience occurs (Yuan, 2023), and an established reputation can signal accountability, potentially reducing perceived transaction risk because reputational losses are more salient for a well-known firm. Accordingly, the comparison is not merely between two applications but between two B2C platforms with different levels of brand heritage.

The analysis is anchored in the Technology Acceptance Model (TAM) introduced by Davis et al. (1989); Marikyan (2026). TAM proposes that Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) shape Behavioral Intention to Use, which subsequently influences Actual Use. For high-value automotive transactions, however, the original formulation does not fully capture uncertainty arising from unverifiable physical condition, asymmetric information, and variation in used-vehicle quality (Engelmann et al., 2022). The model is therefore extended by treating Trust (Gefen et al., 2003; Lai et al., 2025) and Information Quality (DeLone & McLean, 2003; Syah et al., 2026) as direct antecedents of Behavioral Intention and by testing Perceived Transaction

Risk (PTR) as a moderator of the relationship between Perceived Usefulness and Behavioral Intention (Khan et al., 2025; Pavlou, 2003).

Platform trust may develop not only from personal use but also from confidence in the company behind the service. Such institutional confidence can be particularly relevant when consumers consider a high-value purchase without first verifying the vehicle's physical condition (Yuan, 2023). Mayayise (2024) similarly reported that trust is especially important in marketplaces for used goods. Information quality is also central because online buyers rely on photographs, specifications, inspection reports, and vehicle histories instead of direct physical assessment; the usefulness of these inputs depends on their accuracy and completeness (DeLone & McLean, 2003; Song et al., 2023). Risk remains another concern: even when a platform appears useful, intention to use it may be constrained by anticipated financial loss or a mismatch between the advertised and actual vehicle condition (Mutahar et al., 2022).

Against this background, the study evaluates Information Quality, Trust, and Perceived Transaction Risk within an extended TAM for Caroline.id and OLX Mobbi. The purpose is to determine how these factors relate to the acceptance and use of B2C digital used-car platforms and whether the two platform groups exhibit different structural patterns in a context of unequal brand heritage. Existing e-commerce TAM extensions have commonly focused on a single platform or product setting (e.g., (Purwianti et al., 2024; Sari et al., 2024; Song et al., 2023). Comparative evidence involving two B2C automotive platforms differentiated specifically by brand history remains limited, particularly for transactions characterized by high value and uncertainty. This study addresses that empirical gap.

Three objectives guide the analysis. First, the study tests an extended TAM in which Perceived Usefulness, Perceived Ease of Use, Information Quality, and Trust explain Behavioral Intention and Actual Use of digital used-car platforms. Second, it evaluates whether Perceived Transaction Risk moderates the strength of the relationship between Perceived Usefulness and Behavioral Intention. Third, it compares the structural paths for Caroline.id and OLX Mobbi through multi-group analysis. Brand heritage is used as contextual background for interpreting the group comparison rather than as a directly measured causal variable.

Within TAM, Perceived Usefulness and Perceived Ease of Use are expected to contribute to Behavioral Intention, which in turn precedes Actual Use (Davis et al., 1989; Marikyan et al., 2026). In online transaction settings, perceived usefulness and trust have repeatedly been associated with consumers' willingness to transact when face-to-face interaction is absent (Gefen et al., 2003; Lai et al., 2025). In a used-car marketplace, usefulness includes not only technical performance but also the ability to search efficiently, compare prices transparently, and access transaction features that support faster decision-making.

Information Quality extends this logic by representing how users judge the accuracy, completeness, relevance, and dependability of information supplied by the system (DeLone & McLean, 2003; Syah et al., 2026). For used vehicles, this includes condition descriptions, maintenance histories, and inspection results. Trust captures confidence in the intermediary and is particularly relevant when transactions are costly and buyers cannot independently verify product condition before purchase (Gefen et al., 2003; Lai et al., 2025; Mayer et al., 1995). Perceived Transaction Risk reflects concerns about financial loss or discrepancies in vehicle condition and may, in some contexts, reduce the extent to which perceived usefulness translates into intention (Mutahar et al., 2022; Pavlou, 2003).

Table 1 condenses the prior empirical and methodological evidence used to formulate the hypotheses, including research on extended TAM models, information quality, perceived-risk moderation, and multi-group procedures in PLS-SEM.

Table 1
Prior Evidence Supporting Hypothesis Development

No	Study	Method	Key Finding
1	Purwianti et al. (2024)	PLS-SEM; purposive sample, n = 349	PU, social influence, and IQ were significant antecedents of attitude; attitude mediated purchase intention, while PEOU was non-significant.

No	Study	Method	Key Finding
2	Sari et al. (2024)	Linear regression/path analysis; n = 100	PU, PEOU, Trust, and perceived risk were associated with online-shopping attitude; perceived risk showed a significant negative effect.
3	Liu, Guo, & Hsu (2023)	Two-stage scale development: EFA n = 111; CFA/SEM n = 251	IQ was validated as a higher-order construct covering content validity, scope, presentation, and hedonic quality; each dimension was related to behavioral intention.
4	Song et al. (2023)	Survey, n = 418; expanded IS Success Model and TAM	PU, PEOU, service quality, Trust, and expectation confirmation contributed significantly to satisfaction and continuance intention.
5	Mutahar et al. (2022)	PLS-SEM; n = 428	PU and PEOU significantly predicted intention (R^2 = 77%); perceived risk weakened the PU→intention relationship but did not moderate PEOU→intention.
6	Cheah, Amaro, & Roldán (2023)	Systematic review of 378 studies plus a three-group empirical illustration	MICOM was used in only 31.34% of reviewed multi-group studies; the authors recommend a sequence of MICOM, omnibus/permutation testing, and Henseler's MGA with multiplicity correction.
7	Bungkang (2020); Arsy (2026)	Explanatory quantitative design; multiple regression; n = 100	Perceived risk and Trust were both significant positive predictors of Behavioral Intention to Use.

Seven hypotheses were derived from the theoretical framework. Hypotheses H1–H4 are evaluated separately for the two platforms so that potential group-specific patterns can be observed in the context of differing brand heritage:

1) H1a/H1b: Perceived Usefulness is expected to have a positive and statistically significant relationship with Behavioral Intention to Use for Caroline.id (H1a) and OLX Mobbi (H1b).
2) H2a/H2b: Perceived Ease of Use is expected to positively and significantly predict Behavioral Intention to Use for Caroline.id (H2a) and OLX Mobbi (H2b).
3) H3a/H3b: Higher Information Quality is expected to be associated with stronger Behavioral Intention to Use among Caroline.id (H3a) and OLX Mobbi (H3b) users.
4) H4a/H4b: Trust is expected to show a positive and statistically significant association with Behavioral Intention to Use for Caroline.id (H4a) and OLX Mobbi (H4b).
5) H5: Perceived Transaction Risk is expected to significantly moderate the relationship between Perceived Usefulness and Behavioral Intention to Use.
6) H6: Behavioral Intention to Use is expected to positively and significantly predict Actual Use for users of both Caroline.id and OLX Mobbi.
7) H7: The structural coefficients in the TAM-based model are expected to differ significantly between Caroline.id and OLX Mobbi users, indicating platform-group differences in information-system acceptance patterns in the context of unequal brand heritage.

The proposed model connects Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Information Quality (IQ), and Trust (TR) with Behavioral Intention to Use (BI), which then predicts Actual Use (AU). Perceived Transaction Risk (PTR) is specified as a moderator of the PU-to-BI relationship. The same structural model is estimated for Caroline.id and OLX Mobbi, after which multi-group analysis is used to determine whether the path coefficients differ across the two B2C platform groups.

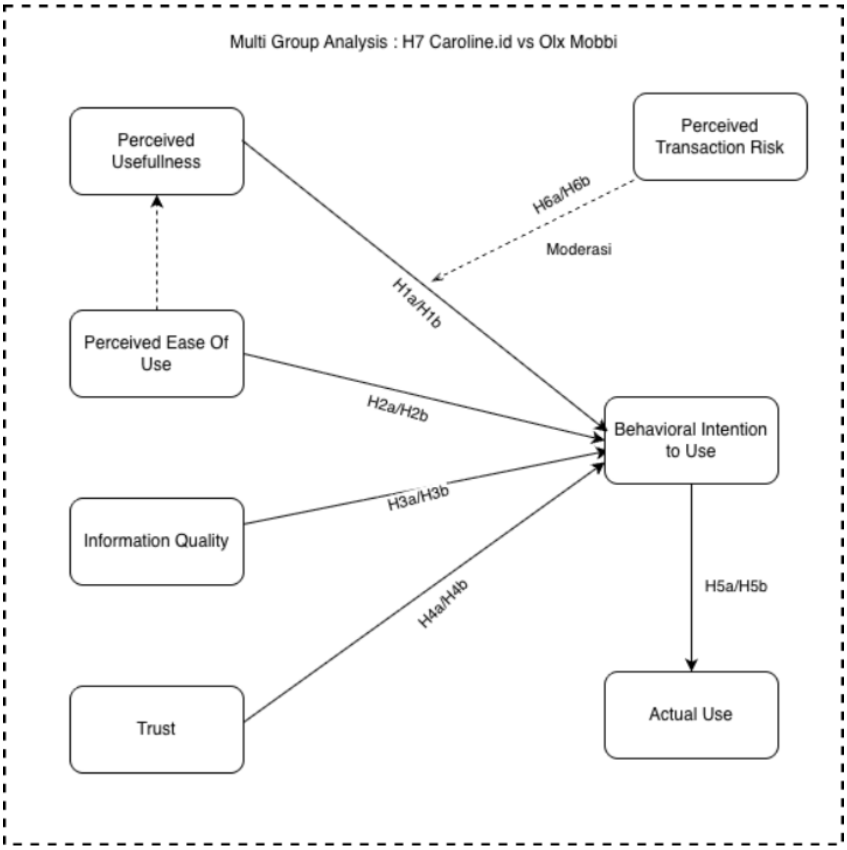

Figure 2. Research Model

METHOD

A quantitative explanatory design was adopted to evaluate the proposed relationships through hypothesis testing, consistent with established quantitative research guidance (Creswell & Creswell, 2018; Hair et al., 2019, 2021; Sekaran & Bougie, 2020). Primary data were obtained using a five-point Likert-scale questionnaire administered to Caroline.id and OLX Mobbi users. The structural model and between-group differences were examined using SmartPLS 4 with Partial Least Squares Structural Equation Modeling (PLS-SEM) and Multi-Group Analysis (MGA).

Caroline.id, operated by PT Autopedia Sukses Lestari Tbk, supports the sale, purchase, and trade-in of used cars and lists more than 600 warrantied vehicles through 16 branches in Jabodetabek and Bandung. Its "7G+" program provides one-year coverage for the engine, transmission, air conditioning, brakes, electrical system, drivetrain, and steering, together with a buyback guarantee. OLX Mobbi operates under PT Astra Digital Mobil (Astra Group) following the March 18, 2024, merger of mobil88, mobbi, and OLX Autos, with more than 30 stores and inspection centers distributed across 10 cities.

The study population comprised Indonesian residents who had used either Caroline.id or OLX Mobbi to search for, compare, or transact used four-wheeled vehicles online. The total number of active users was not publicly reported; consequently, the population size could not be specified precisely. Purposive sampling was therefore used. Eligible respondents had to reside in Indonesia, have interacted with at least one of the two platforms, be at least 17 years old, and be able to understand the Indonesian-language questionnaire.

Because the overall population size was unknown, the required sample size was calculated using the Lemeshow formula:

$$n = Z^2\, p(1-p) / d^2$$

Using a 95% confidence level ($Z = 1.96$), a 10% margin of error ($d = 0.1$), and the conservative maximum proportion of 0.50 ($p = 0.5$), the calculation yielded $n = (1.96)^2 \times 0.5 \times 0.5 / (0.1)^2 = 96.04$. This value was rounded up to 100 respondents for each platform, producing a total target sample of 200 respondents.

All seven constructs were specified as reflective and measured using four indicators adapted from established information-systems scales, following Hair et al. (2019); Zhang (2026). Responses were recorded using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The instrument included four profile questions covering age, gender, usage frequency, and usage purpose, followed by 28 measurement statements for PU, PEOU, IQ, TR, PTR, BI, and AU. Two equivalent questionnaire versions were administered; the item content was identical except for the platform name referenced in each version.

Table 2

Construct Definitions and Example Measurement Items

Construct	Operational Definition	Sample Indicator
Perceived Usefulness (PU)	Extent to which a user perceives the platform as making used-vehicle search and evaluation more effective.	The platform is useful overall in the process of searching for and evaluating vehicles.
Perceived Ease of Use (PEOU)	Extent to which interacting with the platform is perceived as requiring little effort.	Overall, the platform is easy to use.
Information Quality (IQ)	User judgment of whether vehicle information is accurate, complete, relevant, and consistent.	Vehicle information on the platform is accurate and matches the vehicle's actual condition.
Trust (TR)	Confidence that the platform acts honestly, competently, and accountably when facilitating a transaction.	Overall, I trust the platform as a reliable intermediary for used-vehicle transactions.
Perceived Transaction Risk (PTR)	Perceived possibility of financial loss or a discrepancy between expected and actual vehicle condition in an online transaction.	Overall, I perceive a considerable degree of risk in transacting a vehicle through the platform.
Behavioral Intention to Use (BI)	Readiness or intention to keep using the platform in future vehicle-search activities.	I intend to continue using the platform as my primary reference for finding a used vehicle.
Actual Use (AU)	Observed level of platform use for searching for and assessing used vehicles.	I have used the platform in the past month to search for or evaluate used vehicles.

SmartPLS 4 was used to estimate the PLS-SEM model because the analysis involved latent constructs, a moderation term, and two groups of moderate size ($n = 100$ each). The procedure consisted of four stages. First, the measurement model was assessed using outer loadings and average variance extracted (AVE) for convergent validity, Cronbach's alpha and composite reliability for internal consistency, and the heterotrait–monotrait ratio (HTMT) for discriminant validity. Second, the structural model was evaluated using variance inflation factor (VIF), R^2, and bootstrapped path coefficients based on 5,000 subsamples. Third, moderation was tested using the PU × PTR interaction term to predict Behavioral Intention. Fourth, between-group analysis employed the Measurement Invariance of Composite Models (MICOM) procedure, followed by Henseler's MGA (Cheah et al., 2023; Henseler et al., 2015). A two-tailed permutation result was considered significant when $p < 0.05$ or $p > 0.95$.

RESULTS AND DISCUSSION

Result

Respondent Profile

Table 3 presents the respondent characteristics for the two platform groups. Respondents aged 20–25 years constituted the largest age category in both samples, and women accounted for a slightly larger share of each group; the proportions were 49% aged 20–25 and 51% female for Caroline.id, compared with 54% and 57%, respectively, for OLX Mobbi. Usage frequency was also comparable, as most respondents accessed the platforms one to three times per month (63% for Caroline.id and 66% for OLX Mobbi), which was consistent with the occasional nature of vehicle-purchase decisions. A clearer difference appeared in usage purpose. Caroline.id had more respondents who were primarily browsing prices or options (55% versus 37%), whereas OLX Mobbi had larger shares who compared vehicles before deciding (40% versus 32%) or had already completed a transaction (7% versus 3%). Descriptively, OLX Mobbi respondents therefore appeared to be further along in the purchase process.

Table 3
Comparative Respondent Profile

Category	Group	Caroline.id (n=100)	OLX Mobbi (n=100)
Gender	Male	49%	43%
	Female	51%	57%
Age	20–25 years	49%	54%
	26–30 years	27%	20%
	31–35 years	14%	16%
	36–40 years	4%	3%
	> 40 years	6%	7%
Usage frequency	< 1 time/month	18%	9%
	1–3 times/month	63%	66%
	4–7 times/month	13%	17%
	> 7 times/month	6%	8%
Purpose of use	Browsing prices/options	55%	37%
	Comparing before deciding	32%	40%
	Seriously searching, intends to buy soon	10%	16%
	Has already transacted	3%	7%

Source: underlying thesis (Tables 4, 11, and 17)

Measurement Model Assessment

Measurement quality was evaluated independently for the Caroline.id and OLX Mobbi samples. For Caroline.id, most outer loadings were above 0.70 (Hair et al., 2019; Zhang et al., 2026). Four items fell between 0.40 and 0.70 (AU_4 = 0.625, BI_3 = 0.685, PU_2 = 0.659, and TR_1 = 0.647) and were retained because their respective constructs still satisfied the requirements for average variance extracted (AVE) and composite reliability. In the OLX Mobbi group, only PEOU_2 (0.664) was below 0.70 and was retained for the same reason.

Table 4
Construct Reliability and Validity (Summary)

Construct	Cronbach's Alpha (Caroline.id)	Composite Reliability rho_c (Caroline.id)	AVE (Caroline.id)	Cronbach's Alpha (OLX Mobbi)	Composite Reliability rho_c (OLX Mobbi)	AVE (OLX Mobbi)
AU	0.723	0.822	0.538	0.768	0.852	0.591
BI	0.750	0.842	0.572	0.812	0.876	0.640
IQ	0.736	0.834	0.558	0.777	0.856	0.599
PEOU	0.780	0.857	0.601	0.722	0.828	0.547
PTR	0.887	0.910	0.718	0.897	0.912	0.722
PU	0.812	0.876	0.642	0.761	0.848	0.584
TR	0.744	0.837	0.563	0.768	0.852	0.590

Source: underlying thesis, Tables 6 and 13. Each construct satisfies the Hair et al. (2019); Zhang (2026) criteria of at least 0.70 for reliability and at least 0.50 for AVE.

For Caroline.id, discriminant validity based on the heterotrait–monotrait (HTMT) ratio was satisfactory: every interconstruct value was below 0.85 (Henseler et al., 2015). The largest values were IQ–BI = 0.831 and TR–IQ = 0.828, while PTR remained comparatively distinct from the other constructs. The OLX Mobbi results were less satisfactory because three construct pairs exceeded 0.85: PU–PEOU = 0.953, PU–IQ = 0.920, and TR–IQ = 0.898. These values indicate overlap among perceived usefulness, perceived ease of use, information quality, and trust in that group and therefore require caution when interpreting structural estimates involving these constructs.

Structural Model: Path Coefficients and Hypothesis Testing

The bootstrapped structural estimates and hypothesis decisions for both samples are reported in Table 5. The model accounted for a moderate to substantial proportion of the variance. For Caroline.id, R^2 was 0.474 for Behavioral Intention, 0.353 for Perceived Usefulness, and 0.346 for Actual Use. For OLX Mobbi, the corresponding values were 0.638, 0.508, and 0.425. The following paragraphs summarize the path results before the between-group test.

Table 5

Path Coefficients and Hypothesis Testing Results

Hyp.	Path	β (Caroline.id)	t (Caroline.id)	p (Caroline.id)	β (OLX Mobbi)	t (OLX Mobbi)	p (OLX Mobbi)	Decision
H1a/b	PU → BI	0.061	0.512	0.609	0.046	0.339	0.735	Rejected – both platforms
H2a/b	PEOU → BI	0.130	0.923	0.356	0.376	3.658	0.000	Partially supported – OLX Mobbi only
H3a/b	IQ → BI	0.377	2.974	0.003	0.268	2.075	0.038	Supported – both platforms
H4a/b	TR → BI	0.217	1.894	0.058	0.247	2.728	0.006	Partially supported – OLX Mobbi only (Caroline.id marginal at α = 0.10)
–	PEOU → PU	0.594	6.513	0.000	0.713	14.278	0.000	Significant – both platforms (core TAM path)
H5	PTR × PU → BI	-0.011	0.120	0.905	0.079	0.935	0.350	Rejected – both platforms
–	PTR → BI (direct)	-0.108	1.398	0.162	0.099	1.080	0.280	Not significant – both platforms
H6	BI → AU	0.588	10.189	0.000	0.652	10.584	0.000	Supported – both platforms

Source: underlying thesis, Tables 9, 10, 15, and 16 (bootstrapping, 5,000 subsamples)

The direct PU-to-BI path was not statistically significant for either platform (Caroline.id: β = 0.061, p = 0.609; OLX Mobbi: β = 0.046, p = 0.735). The PEOU-to-BI path was significant for OLX Mobbi (β = 0.376, p = 0.000) but not for Caroline.id (β = 0.130, p = 0.356). In contrast, PEOU strongly predicted PU in both samples (Caroline.id: β = 0.594, p = 0.000; OLX Mobbi: β = 0.713, p = 0.000).

IQ significantly predicted BI in both groups (Caroline.id: β = 0.377, p = 0.003; OLX Mobbi: β = 0.268, p = 0.038). Trust reached significance for OLX Mobbi (β = 0.247, p = 0.006) but not at the 0.05 level for Caroline.id (β = 0.217, p = 0.058). Thus, the within-group tests supported IQ on both platforms, whereas the PEOU and trust effects were supported only for OLX Mobbi.

Neither the direct PTR-to-BI coefficient nor the PU × PTR interaction was significant in either sample. The moderation hypothesis H5 was therefore not supported. By comparison, BI strongly predicted AU for both Caroline.id (β = 0.588, p = 0.000) and OLX Mobbi (β = 0.652, p = 0.000), providing support for H6.

Between-Group Comparison: MICOM and Multi-Group Analysis

For MICOM Step 3, the observed differences in composite means for AU (−0.073), BI (0.282), IQ (0.166), PEOU (0.033), PTR (0.007), PU (−0.100), and TR (0.163) all lay within their 2.5%–97.5% permutation intervals. The associated p-values ranged from 0.153 to 0.956, providing no evidence of unequal composite means across groups. MICOM Step 2 also supported compositional invariance: the original construct correlations ranged from 0.909 to 0.999 and exceeded their respective 5% permutation quantiles (p = 0.068–0.827). PU was the closest to the decision boundary, with p = 0.068.

Table 6

Henseler's Bootstrap Multi-Group Analysis (MGA)

Path	β (OLX Mobbi)	β (Caroline.id)	Difference	Permutation p-value	Result
BI → AU	0.652	0.588	0.064	0.500	Not significant
IQ → BI	0.268	0.377	-0.109	0.562	Not significant
PEOU → BI	0.376	0.130	0.246	0.178	Not significant
PEOU → PU	0.713	0.594	0.119	0.339	Not significant
PTR → BI	0.099	-0.108	0.207	0.041	Significant
PU → BI	0.046	0.061	-0.015	0.928	Not significant
TR → BI	0.247	0.217	0.030	0.853	Not significant
PTR × PU → BI	0.079	-0.011	0.090	0.391	Not significant

Source: underlying thesis, SmartPLS Multi-Group Analysis output. Following Chin & Dibbern (2010), a two-tailed permutation difference is treated as significant when p < 0.05 or p > 0.95.

MGA showed that seven of the eight estimated structural paths were statistically comparable across the two platform groups (permutation p = 0.178–0.928). Numerical differences such as PEOU-to-BI (0.376 for OLX Mobbi versus 0.130 for Caroline.id) therefore cannot be interpreted as confirmed between-group effects. PTR-to-BI was the sole exception (permutation p = 0.041). Its sign was positive for OLX Mobbi (β = 0.099) and negative for Caroline.id (β = −0.108), although each within-group coefficient was itself nonsignificant. The evidence therefore points to a platform-group difference in the direction of the risk–intention association, but not to broad structural divergence across the entire model.

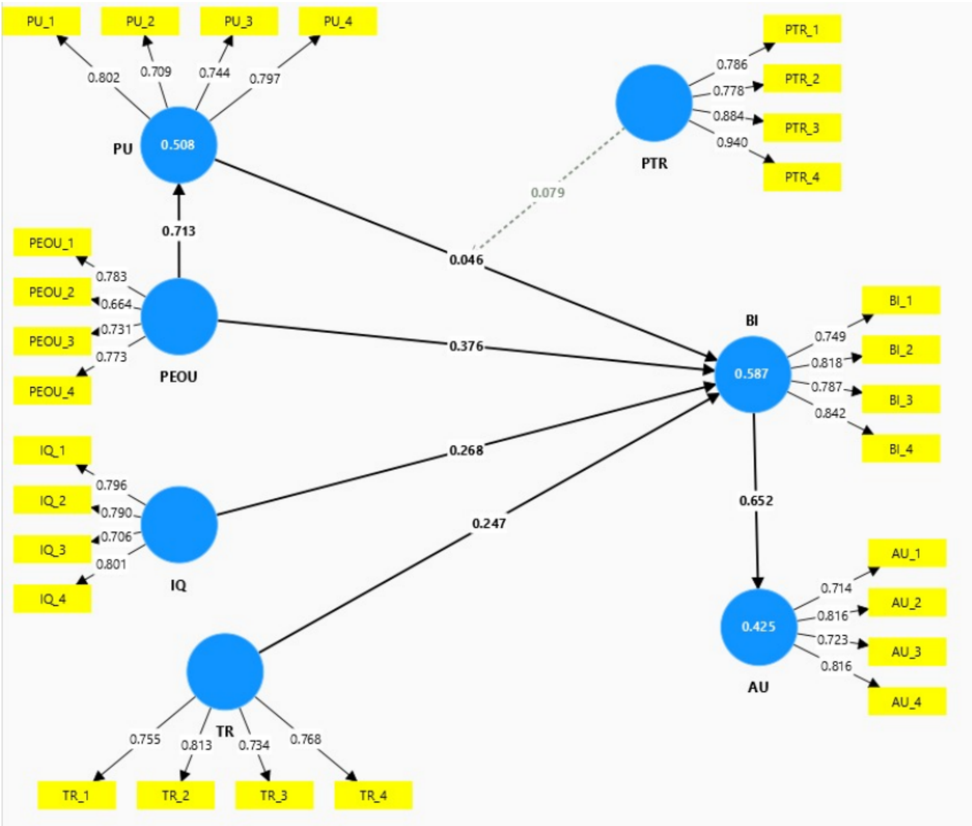

Figure 3. Multi-Group Evidence Relevant to H7

Discussion

The absence of a significant PU-to-BI effect on both platforms was the most consistent departure from the core TAM expectations in this study. PEOU, in contrast, was directly associated with BI for OLX Mobbi ($\beta = 0.376$, $p = 0.000$) but not for Caroline.id ($\beta = 0.130$, $p = 0.356$). PEOU nevertheless had a strong relationship with PU in both groups, which aligns with Davis's (1989); Marikyan (2026) proposition that ease of use may influence acceptance indirectly through perceived usefulness. Because PU itself did not predict BI here, that indirect mechanism provided little explanatory leverage for Caroline.id.

IQ emerged as the only exogenous predictor that was significant in both samples (Caroline.id: $\beta = 0.377$, $p = 0.003$; OLX Mobbi: $\beta = 0.268$, $p = 0.038$). This result is consistent with the role assigned to information quality by DeLone and McLean (2003) and Liu, Guo, and Hsu (2023). In a used-car setting, accurate and complete information can actively influence continued platform use because consumers often decide whether to proceed before they can conduct a physical inspection. Trust displayed a platform-specific pattern similar to PEOU: it was significant for OLX Mobbi ($\beta = 0.247$, $p = 0.006$) and marginal for Caroline.id ($\beta = 0.217$, $p = 0.058$; significant at $\alpha = 0.10$ but not at $\alpha = 0.05$).

PTR did not have a significant direct association with BI and did not significantly moderate the PU-to-BI relationship on either platform. The rejection of H5 differs from Mutahar et al. (2022), who observed that perceived risk weakened the usefulness–intention relationship in mobile banking. One plausible methodological explanation is the relatively limited statistical power available for detecting interaction effects with 100 respondents per group (Aguinis, 1995; Xu & Shiau, 2026). In contrast, BI was the most stable predictor of AU in both samples (Caroline.id: $\beta = 0.588$; OLX Mobbi: $\beta = 0.652$; both $p = 0.000$), which is consistent with the TAM expectation that intention precedes actual usage behavior (Davis et al., 1989; Marikyan et al., 2026; Nawaz et al., 2026).

These findings refine the interpretation of H7. The underlying thesis characterized the two platforms as having no significant difference in information-system acceptance patterns, yet the MGA results show a significant difference for one of eight paths. The evidence is therefore better summarized as partial support for H7: most structural relationships are comparable across

Caroline.id and OLX Mobbi, while the association between transaction risk and usage intention differs significantly in direction.

Limitations

Two methodological qualifications limit the strength of the between-group interpretation. First, the underlying analysis did not fully document MICOM Step 1 together with Steps 2 and 3, so complete measurement invariance cannot be claimed before structural differences are interpreted. Second, discriminant validity is problematic in the OLX Mobbi sample because HTMT exceeds 0.85 for PU–PEOU (0.953), PU–IQ (0.920), and TR–IQ (0.898). This is especially relevant because PU is also part of the PTR × PU interaction. The significant PTR-to-BI difference may therefore contain some influence from measurement nonequivalence rather than representing only a behavioral contrast between the two user groups. The H7 result should be interpreted in light of these limitations.

CONCLUSION

This study evaluated an extended Technology Acceptance Model (TAM) for digital used-car marketplaces by adding Trust and Information Quality and specifying Perceived Transaction Risk as a moderator. The analysis compared Caroline.id and OLX Mobbi, two B2C platforms that differ in inherited brand recognition. Partial Least Squares Structural Equation Modeling (PLS-SEM) and Henseler's (2015) bootstrap-based multigroup analysis (MGA) were applied to 200 responses (100 per platform). The principal conclusions are summarized by hypothesis below: (1) H1 – PU was not significantly related to BI on either platform (Caroline.id: $\beta = 0.061$, $p = 0.609$; OLX Mobbi: $\beta = 0.046$, $p = 0.735$). Functional usefulness therefore did not emerge as the principal driver of behavioral intention in this high-value transaction setting, where information quality and trust appear to be more salient. (2) H2 – PEOU significantly predicted BI for OLX Mobbi ($\beta = 0.376$, $p = 0.000$) but not for Caroline.id ($\beta = 0.130$, $p = 0.356$); thus, H2 receives partial support. This pattern is compatible with the possibility that familiarity with the OLX brand shapes users' expectations regarding ease of use, whereas Caroline.id offers a weaker inherited reference point. (3) H3 – IQ had a positive and significant effect on BI in both samples (Caroline.id: $\beta = 0.377$, $p = 0.003$; OLX Mobbi: $\beta = 0.268$, $p = 0.038$). H3 is therefore supported for both platforms, indicating that dependable vehicle information is a consistent determinant of behavioral intention rather than a platform-specific differentiator. (4) H4 – Trust significantly predicted BI for OLX Mobbi ($\beta = 0.247$, $p = 0.006$), whereas the Caroline.id coefficient did not reach the 0.05 significance level ($\beta = 0.217$, $p = 0.058$). H4 is thus only partially supported. This result is consistent with, but does not directly prove, an interpretation in which an inherited OLX reputation facilitates trust formation more quickly than on the newer Caroline.id platform. (5) H5 – The interaction between PTR and PU was not significant for Caroline.id ($\beta = -0.011$, $p = 0.905$) or OLX Mobbi ($\beta = 0.079$, $p = 0.350$). H5 is therefore rejected for both groups; the study provides no empirical evidence that PTR moderates the PU-to-BI relationship. (6) H6 – BI positively and significantly predicted AU for both Caroline.id ($\beta = 0.588$, $p = 0.000$) and OLX Mobbi ($\beta = 0.652$, $p = 0.000$). H6 is supported in both samples, and this relationship represents the strongest structural path in the model, consistent with the core TAM link between behavioral intention and actual use. (7) H7 – Seven of the eight MGA path comparisons were not significant (permutation $p = 0.178$–0.928): BI-to-AU, IQ-to-BI, PEOU-to-BI, PEOU-to-PU, PU-to-BI, TR-to-BI, and PTR × PU-to-BI. Only PTR-to-BI differed significantly between the groups ($p = 0.041$), and its coefficients had opposite signs (OLX Mobbi: $\beta = 0.099$; Caroline.id: $\beta = -0.108$), even though neither within-group effect was significant. H7 is therefore partially supported: the general acceptance structure is similar across the platforms, but the direction of the risk-to-intention relationship differs. The H7 conclusion remains provisional for two reasons. First, the MICOM procedure was not documented in full, so measurement invariance between the groups has not been completely established. Second, three OLX Mobbi construct pairs exceed the HTMT criterion (PU-PEOU = 0.953; PU-IQ = 0.920; TR-IQ = 0.898), and PU also appears in the PTR × PU interaction term. Consequently, some portion of the observed PTR-to-BI group difference may be attributable to measurement non-equivalence rather than exclusively to differences in user behavior.

Recommendations for future research; (1) Re-estimate the model with at least 200 respondents in each platform group to improve statistical power for MGA, particularly for the borderline Caroline.id TR-to-BI result ($p = 0.058$) and the apparent H2/H4 asymmetries, which have not yet been confirmed as statistically significant between-group differences. (2) Refine or re-test the

OLX Mobbi measurement indicators to address the HTMT concerns for PU-PEOU (0.953), PU-IQ (0.920), and TR-IQ (0.898). Better construct separation would reduce conceptual overlap in estimates involving PU, including the PTR × PU interaction used for H5. (3) Where access is possible, combine self-reported AU with objective platform-log measures. Behavioral records could reduce common-method bias and provide a stronger external validation of the H6 relationship. (4) Use a longitudinal design to assess whether the influence of PTR and Trust changes as users accumulate experience with a platform. Such a design could test whether trust in Caroline.id gradually approaches the level observed for OLX Mobbi, representing a possible brand-equity-transfer process that cannot be evaluated using cross-sectional data. (5) Broaden future models by considering constructs such as Perceived Value, After-Sales Service Quality, or Platform Governance as antecedents of Trust, and replicate the framework in other high-value digital marketplaces, including property or industrial equipment, to assess whether the findings extend beyond automotive transactions.

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AUTHOR CONTRIBUTION STATEMENT

Yulianti Masta Rotua Simatupang was responsible for conceptualization, methodology, data collection, formal analysis, and preparation of the initial manuscript. Sfenrianto provided supervision and validation and contributed to manuscript review and editing. Both authors reviewed and approved the final manuscript.

REFERENCES

Aguinis, H. (1995). Statistical power problems with moderated multiple regression in management research. *Journal of Management*, *21*(6), 1141–1158. https://doi.org/10.1016/0149-2063(95)90026-8

Arsy, K. M., & Iskamto, D. (2026). The Effect of Perceived Usefulness and Perceived Ease of Use on Intention to Use Shopee Paylater with Perceived Trust as a Mediating Variable among Generation Z in Bandung City. *Journal of Business, Social and Technology*, *7*(3), 777–796.

Brewis, C., Dibb, S., & Meadows, M. (2023). Leveraging big data for strategic marketing: A dynamic capabilities model for incumbent firms. *Technological Forecasting and Social Change*, *190*, 122402. https://doi.org/10.1016/j.techfore.2023.122402

Bungkang, R. D. (2020). The effect of perceived risk and trust toward behavioral intention to use: A study to Shopee application users in Surabaya. *Jurnal Ilmiah Mahasiswa FEB*, *8*(1).

Cheah, J. H., Amaro, S., & Roldán, J. L. (2023). Multigroup analysis of more than two groups in PLS-SEM: A review, illustration, and recommendations. *Journal of Business Research*, *156*, 113539. https://doi.org/10.1016/j.jbusres.2022.113539

Creswell, J. W., & Creswell, J. D. (2018). *Research Design Qualitative, Quantitative, and Mixed Methods Approaches (Fifth Edition).*

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science*, *35*(8), 982–1003. https://doi.org/10.1287/mnsc.35.8.982

DeLone, W. H., & McLean, E. R. (2003). The DeLone and McLean model of information systems success: A ten-year update. *Journal of Management Information Systems*, *19*(4), 9–30. https://doi.org/10.1080/07421222.2003.11045748

Engelmann, A., Bauer, I., Dolata, M., Nadig, M., & Schwabe, G. (2022). Promoting less complex and more honest price negotiations in the online used car market with authenticated data. *Group Decision and Negotiation*, *31*(2), 419–451. https://doi.org/10.1007/s10726-021-09773-8

Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. *MIS Quarterly*, *27*(1), 51–90. https://doi.org/10.2307/30036519

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2019). *A primer on partial least squares structural equation modeling (PLS-SEM) (2nd ed.)*.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2021). *A primer on partial least squares structural equation modeling (PLS-SEM)*. SAGE Publications.

Hakim, I. M., Singgih, M. L., & Gunarta, I. K. (2023). Critical success factors for Internet of Things (IoT) implementation in automotive companies, Indonesia. *Sustainability*, *15*(4), 2909. https://doi.org/10.3390/su15042909

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Khan, S., Alam, S., & Arafat, M. Y. (2025). Effect of block-chain technology on purchase decision of organic food: Insights from extended technology adoption model. *Journal of Cleaner Production*, *513*, 145653.

Lai, Z. J., Leong, M. K., Khoo, K. L., & Sidhu, S. K. (2025). Integrating technology acceptance model and value-based adoption model to determine consumers' perception of value and intention to adopt AR in online shopping. *Asia Pacific Journal of Marketing and Logistics*, *37*(1), 1–19.

Liu, C.-T., Guo, Y. M., & Hsu, J. L. (2023). Creating and validating an information quality scale for e-commerce platforms. *Journal of Electronic Commerce in Organizations*, *21*(1), 1–28. https://doi.org/10.4018/JECO.327350

Marikyan, D., Papagiannidis, S., & Stewart, G. (2026). Technology acceptance research: Meta-analysis. *Journal of Information Science*, 01655515231191177.

Mayayise, T. O. (2024). Investigating factors influencing trust in C2C e-commerce environments: A systematic literature review. *Data and Information Management*, *8*(1), 100056. https://doi.org/10.1016/j.dim.2023.100056

Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An integrative model of organizational trust. *Academy of Management Review*, *20*(3), 709–734. https://doi.org/10.5465/AMR.1995.9508080335

Mutahar, A. M., Aldholay, A., Isaac, O., Jalal, A. N., & Kamaruddin, F. E. B. (2022). The moderating role of perceived risk in the technology acceptance model (TAM): The context of mobile banking in developing countries. In *Proceedings of International Conference on Emerging Technologies and Intelligent Systems* (Vol. 299, pp. 389–403). Springer. https://doi.org/10.1007/978-3-030-82616-1_34

Nawaz, N., Durst, S., Shaik, S. A., & Parayitam, S. (2026). Relationship between behavioral intention and actual use of artificial intelligence on knowledge management and job satisfaction: Evidence from India. *Knowledge and Process Management*, *33*(1), 66–86. https://doi.org/10.1002/kpm.70008

Pavlou, P. A. (2003). Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model. *International Journal of Electronic Commerce*, *7*(3), 101–134. https://doi.org/10.1080/10864415.2003.11044275

Purwianti, L., Nurjanah, L., Katherine, K., & Chen, R. (2024). The impact of TAM, social influence, and information quality on purchase intention in e-commerce. *Jurnal Organisasi Dan Manajemen*, *20*(2), 187–206. https://doi.org/10.33830/jom.v20i2.9123.2024

Sari, R. D., Hersusetiyati, Ekaputra, A. E., & Ihwani, N. (2024). Integrating TAM, trust and perceived risk factors on emerging-market consumers' attitude towards shopping for Muslim fashion online. *Sinergi International Journal of Management and Business*, *2*(3), 148–158. https://doi.org/10.61194/ijmb.v2i3.244

Sekaran, U., & Bougie, R. (2020). *Research methods for business: A skill-building approach*. Wiley.

Song, Y., Gui, L., Wang, H., & Yang, Y. (2023). Determinants of continuous usage intention in community group buying platform in China: Based on the information system success model and the expanded technology acceptance model. *Behavioral Sciences*, *13*(11), 941. https://doi.org/10.3390/bs13110941

Syah, R. M. H., Nurhayati, O. D., & Surarso, B. (2026). Evaluating the Success Factors of a Tourism Management Information System Using the DeLone and McLean Model: A User Perspective. *Journal of Information Technology and Computer Science*, *11*(1), 107–126.

UI, L. F. E. B. (2026). *Trend pergeseran new car to used car*. Institute for Economic and Social Research, Faculty of Economics and Business, Universitas Indonesia. https://www.instagram.com/p/DTh6JEUD3h0/?img_index=2

Xu, Y., & Shiau, W. L. (2026). Moderation analysis in business and management research: Common issues, solutions, and guidelines for future research. *International Journal of Information*

Management, *86*, 102995.
Yuan, L. (2023). *Company trust and platform adoption in online consumer markets*.
Zhang, Y., Adams, D., Cheah, J., Teeroovengadum, V., & Ramayah, T. (2026). An Assessment of the Use of Partial Least Squares Structural Equation Modelling (PLS-SEM) in Educational Leadership and Management Research. *European Journal of Education*, *61*(2), e70600.