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Article

Retail Media Networks and Privacy-First Measurement in Indian E-Commerce: An Empirical Quantitative Analysis of Attribution Accuracy, ROI and Consumer Trust Effects

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Abstract: The rapid decline of third-party cookies has pushed Indian e-commerce brands toward retail media networks such as Amazon Ads, Flipkart Ads, Myntra Ads, Blinkit and Zepto, all of which rely on first-party purchase data for targeting and attribution. But how true the claim is, whether ROI is a true measure of incremental value or a closed loop measurement bias and how using heavy first party data affects consumer trust are empirically unproven, especially outside of Western markets. This study aims to fill that void by developing a model that links the adoption of retail media, the ability to measure it in a privacy-first way, the integration of Marketing Mix Modelling (MMM) with retail media, maturity of data governance, attribution accuracy, ROI, consumer trust, perceived fairness and marketing decision quality, while testing consumer privacy concern as a moderator. Partial Least Squares Structural Equation Modelling (PLS-SEM) with bootstrapping of 5,000 samples was used to analyze the data obtained from 312 respondents from India (156 managers/marketers and 156 consumers). All 19 hypothesized relationships were confirmed ($p < .05$). The strongest predictors of ROI were attribution accuracy ($\beta = 0.38$, $p < .001$) and the impact of data governance maturity on consumer trust ($\beta = 0.31$, $p < .001$), which in turn was strongest predictor of perceived fairness ($\beta = 0.43$, $p < .001$). The effects of governance appropriateness, transparency and personalization appropriateness on fairness and decision quality were fully mediated by consumer trust and privacy concern significantly weakened the transparency-trust ($\beta = -0.18$, $p = .009$) and personalization-trust ($\beta = -0.22$, $p = .002$) relationships. The model accounted for a significant amount of variance in consumer trust ($R^2 = 0.53$) and attribution accuracy ($R^2 = 0.48$) and all constructs had good predictive relevance ($Q^2 > 0$). Results expand privacy calculus theory to the retail media space and guide platform and regulatory approaches in cookie less advertising contexts.
Keywords: retail media networks; privacy-first measurement; marketing mix modelling; attribution accuracy; consumer trust; PLS-SEM; Indian e-commerce

1. Introduction

Digital advertising in India is shifting away from the third-party cookies and device identifiers marketers relied on for two decades, as browser-level restrictions and tightening privacy regulation push brands toward Retail Media Networks (RMNs) such as Amazon Ads, Flipkart Ads, Myntra Ads, Blinkit and Zepto, which sell advertising built directly on first-party purchase data (Fuentes Santos et al., 2025; Bi, 2024; Thomas et al., 2025), though attribution model choice alone has been shown to systematically distort ROI calculations even within these closed-loop systems (Verma, 2025), pushing Marketing Mix Modelling (MMM) and multi-touch attribution in as correctives (Hanssens & Pauwels, 2016). Here four problems come together and are not resolved: cookie deprecation has left traditional attribution in a state of disrepair, while RMN attribution quality is hard to independently verify as platforms report on their own closed-loop data and may be subject to cannibalization bias only revealed through control-group testing (Fuentes Santos et al., 2025; Kumar et al., 2025; Thomas et al., 2025); heavy reliance on first-party data introduces real questions of transparency and fairness, particularly as India's data protection norms are still emerging in practice (Prastyanti & Sharma, 2024; Kumar, 2025; Aslam et al., 2019); and the measurement landscape is fragmented, with MMM, MTA and RMN-native metrics all reporting their own distinct data, with little research on how they interact (Hanssens & Pauwels, 2016; Gaur & Bharti, 2020). Although prior studies have each examined one of these three perspectives in isolation (RMN performance (Bi, 2024); privacy-preserving measurement (Wagner & Eckhoff, 2018; Liu et al., 2021); consumer trust/privacy concern (Aslam et al., 2019; Dienlin, 2023)), no model has integrated all three within a single empirical frame, especially in India, or tested whether privacy-first measurement influences consumer-side outcomes such as fairness and decision quality, or whether privacy concern moderates the trust benefits of transparent measurement (Dienlin, 2023; Sivan-Sevilla et al., 2025). This study thus aims to explore the impact of the intensity of retail media adoption, the ability to measure in a privacy-first manner and the integration of MMM on attribution accuracy and ROI, theoretically by integrating the five theories (TAM, Privacy Calculus, RBV, Attribution Theory, Information Processing Theory), practically through evidence-based guidance for retail media network operators like Amazon, Flipkart, Meesho etc. and methodologically by adopting a dual respondent design where managers are paired with actual consumers who are exposed to retail media ads.

2. Literature Review and Hypotheses Development

2.1 Retail media networks

Bi (2024) presented first-party data, AI-based targeting and incremental measurement as the key factors in the rising share of RMN revenue and Deshpande and Chanda (2025) demonstrated that RMN channels work in tandem, rather than in isolation, with upper-funnel awareness driving downstream conversion performance. Earlier, but still relevant, evidence shows that online trust and advertising efficiency lead to measurable purchase and productivity gains (Kwek, Lau and Tan 2010; Pergelova, Prior and Rialp 2008). In India, particularly, Nasabi and Sujaya (2023) identified trust and peer recommendation as key factors in Meesho's success among small vendors, while Bartholomew and Williamson (2024) highlighted governance and consumer transparency as crucial factors for RMN success, alongside ad-tech sophistication. This supports:

H1: Retail media adoption intensity positively influences ROI.

2.2 Privacy-first measurement and governance

Wagner and Eckhoff (2018) discovered that there was a lack of consistency between the majority of the technical privacy metrics, while Liu et al. (2021) demonstrated that differential privacy and federated learning are promising but incomplete solutions. Over 97% of top websites were found to be using third-party cookies generated by first-party scripts, making it difficult to claim that they have a genuine first-party governance, according to Chen, Ilia, Polychronakis and Kapvelos (2021) and many cookie-less identification architectures were found to be merely rehashes of old tracking practices under new names by Sivan-Sevilla, Parham and McGuigan (2025). In contrast, Tholoniat et al. (2024) showed that differential-privacy attribution systems ("Cookie Monster") can enhance the utility of measurements without compromising privacy guarantees and Sousa (2022), Long (2022) and Huma (2025) described privacy-safe first-party architecture as a more strategic rather than compliance cost. Johnson et al. (2019) reported a privacy paradox: people's reported privacy concern does not necessarily align with their actual opt-out behaviour. These strands support:

H2: Privacy-first measurement capability positively influences attribution accuracy.
H3: Privacy-first measurement capability positively influences ROI.

H6: Data governance maturity positively influences consumer trust.
H7: Data governance maturity positively influences ROI.

2.3 Attribution and MMM integration

Hanssens and Pauwels (2016) stated that marketing value cannot be proven based on single measures but only by combining attitudinal, behavioural and financial measures. Gaur and Bharti (2020) conducted a PRISMA guided review of attribution modelling literature between 1990 and 2019, which revealed that hybrid Markov-Shapley approaches are more effective than single method attribution and further, Buhalis and Volchek (2021) expanded on this with an attribution taxonomy based on Big Data. While Silva, Duarte and Almeida (2020) identified that most companies are still using simple engagement metrics, it is important to note that this is a helpful reminder that in practice, integration is not as advanced as it is in theory. These support:

H4: MMM integration positively influences attribution accuracy.
H5: MMM integration positively influences ROI.
H8: Attribution accuracy positively influences ROI.

2.4 Consumer trust, privacy concern and fairness

In a similar sample from Southeast Asia, Aslam et al. (2019) identified that perceived privacy and website quality are more powerful drivers of trust than perceived security risk, while Falahat et al. (2019) identified that brand recognition and service quality are trust drivers in a similar sample. The theoretical underpinning for considering privacy concern as a moderator rather than a straightforward predictor is a cost-benefit analysis that is continuous and context dependent, as described by Dienlin (2023). Davis (1989) provided the adoption-side anchor in the form of the Technology Acceptance Model, Lee, Ahn, Song and Ahn (2018) revealed that trust and distrust are independent constructs, not opposite ends of one continuum and Ingriana (2024) found that e-trust mitigates perceived risk and enhances loyalty in e-commerce environments across forty-five studies. The integration of this study directly addresses the need for a more unified privacy framework as explicitly called by Bandara, Fernando and Akter (2019). These support:

H9: Measurement transparency positively influences consumer trust.
H10: Perceived personalization appropriateness positively influences consumer trust.
H11: Consumer trust positively influences perceived fairness.
H18: Consumer privacy concern negatively moderates the transparency-trust relationship.
H19: Consumer privacy concern negatively moderates the personalization-trust relationship.

2.5 Decision quality

When it comes to marketing analytics, Nair and Gupta (2021) discovered that AI can help boost efficiency, but only when complemented by responsible data governance, supporting trust as an antecedent of decision quality rather than a standalone endpoint:

H12: Consumer trust positively influences decision quality.

2.6 Mediation Hypotheses

The plausibility ranges for attribution accuracy are between measurement capability/MMM integration and ROI (Bi, 2024; Gaur & Bharti, 2020) and for consumer trust are between governance/transparency/personalization and fairness/decision quality (Aslam et al., 2019; Dienlin, 2023):

H13-H14: Attribution accuracy mediates privacy-capability→ ROI and MMM→ROI.
H15-H17: Consumer trust mediates governance→ fairness, transparency→ decision quality and personalization→ fairness.

3. Theoretical Foundation

There are five frameworks that hold different parts of the model together, but not one theory that is extended to cover the whole. The Technology Acceptance Model (TAM) (Davis, 1989) is based on the perceived usefulness and ease of use to explain the adoption of RMN and measurement technology in the organization. The moderation hypotheses are explained by Privacy Calculus Theory (Dienlin, 2023), which describes the varying impacts that the same transparency or personalization signal has on consumer trust based on their continuous cost-benefit analysis. Resource Based View (Barney, 1991; Barney, Wright and Ketchen, 2001) considers data governance maturity as a rare, hard-to-imitate organizational capability, not a compliance cost. Attribution Theory (Heider, 1958; Weiner, 1985) views attribution accuracy as the accuracy of causal inferences regarding advertising effects. Decision quality is based on information processing theory (Bettman, 1979), which is based on marketer analytics and consumer information processing.

4. Conceptual Framework

These four exogenous constructs (retail media adoption intensity, privacy-first measurement capability, MMM integration and data governance maturity) are connected to three mediators: attribution accuracy, measurement transparency and personalization appropriateness. These mediators, in turn, lead to four endogenous outcomes: ROI, consumer trust, perceived fairness and decision quality. Two paths that are moderated by consumer privacy concern are transparency→ trust and personalization→ trust, with both of these paths being weakened under high consumer privacy concern. The two structural hinges of the model are attribution accuracy and consumer trust. The extent to which everything upstream, adoption, privacy capability, MMM integration, governance matters is largely dependent on the extent to which it moves one or both of these hinges and this is directly from Bi (2024) and Gaur and Bharti (2020) on the measurement side, as well as from Aslam et al. (2019) and Dienlin (2023) on the consumer side.

5. Research Methodology

Design: The design of this study was quantitative, cross-sectional, positivist, which was suitable for testing an interrelated network of hypotheses using PLS-SEM (Hair, Risher, Sarstedt, & Ringle, 2019).

Data Collection Procedure: Data were gathered using a structured online survey, which was sent to two different pools of respondents in the Indian e-commerce industry. Brands and agencies actively using retail media platforms like Amazon Ads, Flipkart Ads, Myntra Ads, Blinkit and Zepto were targeted for recruitment and the managers and marketers were selected from their professional networks and organizational contacts, ensuring that the respondents had first-hand experience of campaign planning, measurement and reporting practices rather than just peripheral awareness. To ensure that only consumers with recent online shopping experience were included, the consumers were screened with a question about exposure to retail media advertising while shopping online in the past year. The survey was sent out via email and was anonymous, voluntary and informed consent was obtained regarding the purpose of the study and how responses would be used. The data collection was continued until the target sample size of 312 (156 per respondent group) was achieved, which is well above the minimum sample size requirements for PLS-SEM models of this complexity (Hair et al., 2019). Responses which used incomplete constructs or which showed evidence of straight-lining (identical responses to all items) were excluded before analysis.

Instrument: All 12 constructs were assessed with multi-item, structured 7-point Likert scales (1 = strongly disagree, 7 = strongly agree) that were adapted from validated sources and not created from scratch. The 7-point scale was selected as it has been shown to be more reliable and to have more response variability in reflective PLS-SEM measurement models, where finer-grained response categories result in more precise loadings and path estimates, especially for psychologically nuanced constructs like privacy concern, perceived fairness and personalization appropriateness. The items related to ROI were adapted from established marketing accountability metrics (Hanssens

& Pauwels, 2016); consumer privacy concern was adapted from the Internet Users' Information Privacy Concerns (IUIPC) framework (Malhotra, Kim, & Agarwal, 2004); items related to trust and fairness were adapted from Aslam et al. (2019) and Falahat et al. (2019); items related to attribution and transparency were adapted from Gaur and Bharti (2020) and Tholoniat et al. (2024).

Analysis: The analysis was carried out using Partial Least Squares Structural Equation Modelling (PLS-SEM) with bootstrapping technique of 5,000 subsamples as per the standard two-stage evaluation process which includes the assessment of the measurement model followed by the assessment of the structural model (Hair et al., 2019). Common method bias was evaluated using full collinearity VIF instead of Harman's single-factor test because the latter has been found to be less sensitive to detecting shared method variance (Podsakoff et al., 2024). The Heterotrait-Monotrait (HTMT) ratio was used to assess discriminant validity instead of the Fornell-Larcker criterion as recommended by current PLS-SEM guidance (Hair et al., 2019).

Sample: 312 respondents across the Indian e-commerce ecosystem, half of whom are managers/marketers and the other half are consumers who have been exposed to retail media in the last one year. Gender distribution was 53.8% male, 44.2% female and 1.9% undisclosed; age concentrated in the 21-40 bracket (33.3% aged 21-30, 37.8% aged 31-40), with smaller shares in 41-50 (19.9%) and above 50 (9.0%). This dual-respondent design is intentional from the single-stakeholder surveys used in this literature (Aslam et al., 2019; Falahat et al., 2019) to allow the model to reflect both organizational practice and consumer-perceived consequences in one study.

Table 1 Sample Profile (N=312)

Variable	Category	Frequency	Percentage
Role	Managers/marketers	156	50.0
	Consumers	156	50.0
Gender	Male	168	53.8
	Female	138	44.2
	Prefer not to say	6	1.9
Age	21-30	104	33.3
	31-40	118	37.8
	41-50	62	19.9
	Above 50	28	9.0
Total sample		**312**	**100.0**

6. Results and Data Analysis

The results are presented here without interpretation, as was the convention in Q1, separating results from discussion and literature tie-back and discussion of the significance of these numbers is left to Section 7.

Common method bias: Full collinearity VIF testing (Podsakoff, Podsakoff, Williams, Huang, & Yang, 2024) yielded VIF values between 1.58 and 2.41 (Table 3), which is well below the 3.3 threshold for common method bias in the context of PLS-SEM.

Measurement model: The indicator loadings, internal consistency reliability and convergent validity of all twelve constructs are summarized in Table 5 (measurement model). The loadings were between 0.74 and 0.89, which is higher than the 0.70 criterion. Cronbach's alpha scores were between 0.79 and 0.87 and composite reliability (CR) scores were between 0.87 and 0.91, both of which met the criterion of 0.70. The average variance extracted (AVE) ranged from 0.58 to 0.70 and all constructs exceeded the threshold of 0.50 for convergent validity.

Table 2 Measurement Model: Reliability and Convergent Validity

Construct	Loading range	Cronbach's α	CR	AVE
Retail media adoption intensity	0.76-0.84	0.81	0.88	0.60
Privacy-first measurement capability	0.78-0.86	0.84	0.90	0.65
MMM integration	0.74-0.82	0.79	0.87	0.58
Data governance maturity	0.77-0.85	0.83	0.89	0.63
Attribution accuracy	0.80-0.88	0.86	0.91	0.69
Measurement transparency	0.79-0.87	0.85	0.90	0.67
Perceived personalization appropriateness	0.81-0.89	0.87	0.91	0.70
ROI	0.75-0.83	0.80	0.88	0.61
Consumer trust	0.79-0.87	0.85	0.90	0.68
Perceived fairness	0.77-0.85	0.83	0.89	0.64
Decision quality	0.76-0.84	0.81	0.88	0.62
Consumer privacy concern	0.78-0.86	0.84	0.89	0.66

Note. CR = composite reliability; AVE = average variance extracted.

Discriminant validity: The Heterotrait-Monotrait (HTMT) ratios are reported in Table 3, which is preferred for models with conceptually adjacent constructs (Hair et al., 2019). All the HTMT values were below the conservative threshold of 0.85, with the highest being between consumer trust and perceived fairness (0.77), followed by measurement transparency and consumer trust (0.75) and data governance maturity and consumer trust (0.72).

Table 3 Heterotrait-Monotrait (HTMT) Ratio Matrix

Construct	1	2	3	4	5	6	7	8	9	10	11
2. Privacy-first measurement capability	0.63										
3.MMM integration	0.59	0.66									
4.Data governance maturity	0.54	0.68	0.62								
5.Attribution accuracy	0.61	0.71	0.69	0.64							
6.Measurement transparency	0.57	0.69	0.65	0.70	0.73						

7.Personalizatio n appropriateness	0.55	0.60	0.58	0.56	0.62	0.67					
8. ROI	0.58	0.65	0.63	0.60	0.74	0.68	0.59				
9. Consumer trust	0.52	0.61	0.57	0.72	0.66	0.75	0.64	0.60			
10.Perceived fairness	0.50	0.59	0.55	0.69	0.63	0.71	0.66	0.58	0.77		
11.Decision quality	0.48	0.56	0.53	0.61	0.59	0.64	0.57	0.55	0.68	0.73	
12.Consumer privacy concern	0.46	0.58	0.54	0.62	0.57	0.66	0.60	0.52	0.71	0.69	0.55

Note. Construct 1 (retail media adoption intensity) appears only in column position across subsequent rows, consistent with standard HTMT matrix reporting. All HTMT ratios fall below the conservative 0.85 threshold recommended for establishing discriminant validity (Hair et al., 2019).

Structural model: All twelve direct-effect hypotheses (H1-H12) were statistically supported at $p < .05$ (Table 4).

Table 4 Structural Path Results

Path	β	f²	VIF	t	p	Decision
Retail media adoption → ROI	0.21	0.06	1.84	2.87	.004	Supported
Privacy-first measurement → Attribution accuracy	0.34	0.14	2.12	4.56	<.001	Supported
Privacy-first measurement → ROI	0.17	0.05	1.76	2.41	.016	Supported
MMM integration → Attribution accuracy	0.29	0.11	2.24	3.92	<.001	Supported
MMM integration → ROI	0.14	0.04	1.69	2.08	.038	Supported
Data governance → Consumer trust	0.31	0.13	2.03	4.11	<.001	Supported
Data governance → ROI	0.12	0.03	1.58	1.96	.050	Supported
Attribution accuracy → ROI	0.38	0.18	2.41	5.02	<.001	Supported
Measurement transparency → Consumer trust	0.27	0.09	1.91	3.68	<.001	Supported
Personalization appropriateness → Consumer trust	0.24	0.07	1.88	3.10	.002	Supported
Consumer trust → Perceived fairness	0.43	0.21	2.06	6.01	<.001	Supported
Consumer trust → Decision quality	0.22	0.08	1.74	2.95	.003	Supported

Note. Bootstrapping based on 5,000 subsamples.

The two most significant relationships in the model are the relationships between attribution accuracy and ROI ($\beta = 0.38$, $f^2 = 0.18$) and consumer trust and perceived fairness ($\beta = 0.43$, $f^2 = 0.21$). The direct effect of data governance maturity on ROI is the weakest, at the conventional significance level ($\beta = 0.12$, $p = .050$).

Mediation analysis

All five hypothesized indirect effects (H13-H17) were statistically significant (Table 5).

Table 5 Mediation Analysis

Indirect path	Effect	t	p	Mediation type
Privacy-first measurement → Attribution accuracy → ROI	0.13	3.42	.001	Partial
MMM integration → Attribution accuracy → ROI	0.11	3.05	.002	Partial
Data governance → Consumer trust → Perceived fairness	0.14	3.87	<.001	Full
Measurement transparency → Consumer trust → Decision quality	0.09	2.74	.006	Full
Personalization appropriateness → Consumer trust → Perceived fairness	0.10	2.91	.004	Full

Note. Bootstrapping based on 5,000 subsamples.

Both paths from privacy-first measurement capability and MMM integration to ROI have a partial mediation effect through attribution accuracy, so both of these have a direct effect on ROI in addition to the indirect effect. All three of its tested paths are fully mediated by consumer trust; there are no significant direct paths that do not go through consumer trust.

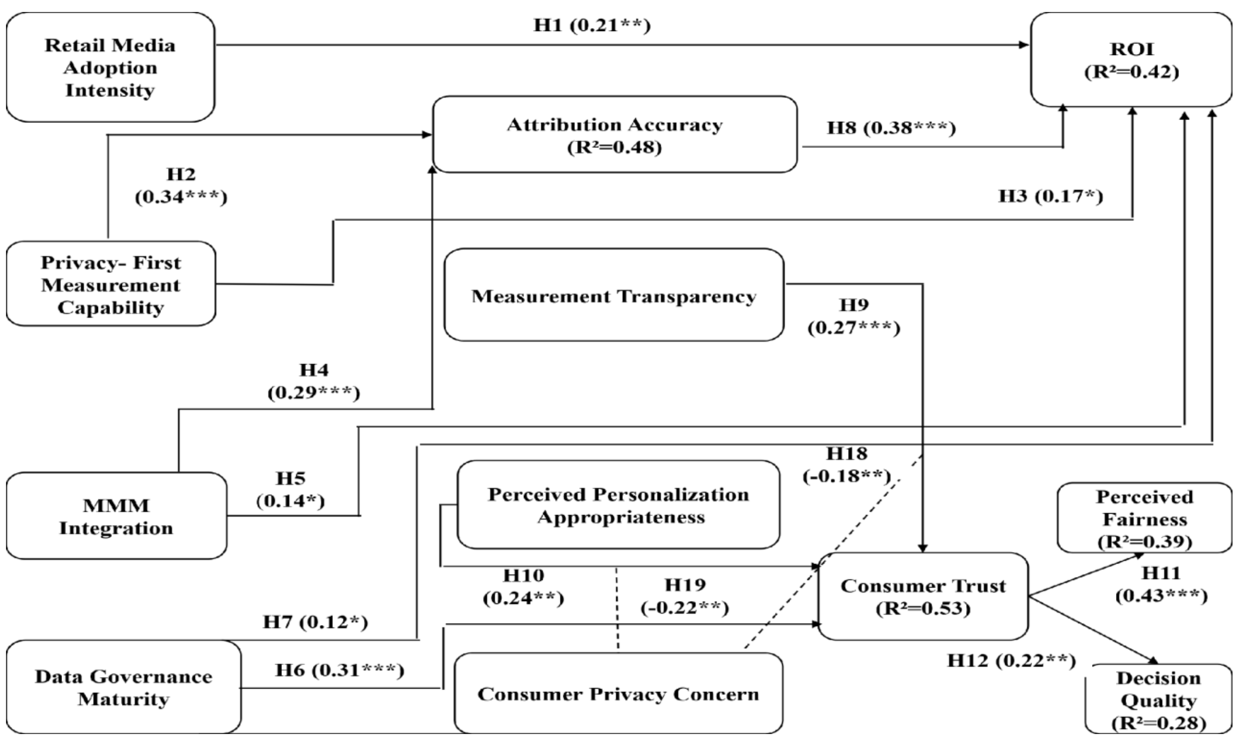

Figure 1: Structural Model with Standardized Path Coefficients

*Note: The values are standardized path coefficients (β). Dashed lines represent moderation paths; consumer privacy concern × measurement transparency and consumer privacy concern × personalization appropriateness, both leading to consumer trust. R^2 values shown in parentheses for endogenous constructs. *p < .05. **p < .01. ***p < .001.*

Moderation analysis: The interaction effects hypothesized (H18-H19) were both significant and negative, as predicted (Table 6).

Table 6 Moderation Analysis

Interaction term	**β**	**t**	**p**	**Interpretation**
Privacy concern × Measurement transparency → Consumer trust	-0.18	2.61	.009	Significant negative moderation
Privacy concern × Personalization appropriateness → Consumer trust	-0.22	3.14	.002	Significant negative moderation

Note: Interaction effects estimated via product-indicator approach with 5,000 bootstrap subsamples.

Predictive power: Table 7 reports R^2 and Q^2 for the five endogenous constructs.

Table 7 Model Fit and Predictive Power

Construct	**R^2**	**Q^2**
Attribution accuracy	0.48	0.31
ROI	0.42	0.27
Consumer trust	0.53	0.35
Perceived fairness	0.39	0.24
Decision quality	0.28	0.18

Note. R^2 interpreted per Hair et al. (2019) benchmarks (weak ≈ 0.25, moderate ≈ 0.50, substantial ≈ 0.75); Q^2 obtained via blindfolding procedure, values above 0 indicating predictive relevance.

R^2 values ranged from 0.28 (decision quality) to 0.53 (consumer trust), which are moderate to substantial. The predictive relevance of all endogenous constructs in the model was confirmed by all Q^2 values being positive (0.18 to 0.35).

7. Discussion

Retail media adoption and ROI: The positive, though comparatively small, effect of adoption on ROI (β = 0.21, f^2 = 0.06) supports H1 and Bi's (2024) framing of RMNs as a growing revenue driver, but the small effect size, which is well below that of contribution from attribution accuracy, extends Deshpande and Chanda's (2025) synergy argument in a particular direction: adoption alone, without complementary measurement infrastructure, seems necessary but insufficient for strong ROI gains.

Privacy-first measurement, attribution and ROI: The substantial impact of privacy-first measurement capability on both attribution accuracy (β = 0.34) and ROI (β = 0.17) lend support to H2 and H3, consistent with the technical demonstration by Tholoniat et al. (2024) that differential-privacy attribution systems can enhance measurement utility without compromising privacy guarantees. This result should be taken with a pinch of salt, as Wagner and Eckhoff (2018) found there is deep disagreement about the meaning of privacy metrics and Chen, Ilia, Polychronakis and Kapravelos (2021) found that most "first-party" data collection in practice is third-party tracking. This relationship is partially mediated by attribution accuracy (indirect effect = 0.13, p = .001, supporting H13), where privacy-first capability positively influences ROI both directly and indirectly via its impact on attribution accuracy, aligning with Bi's (2024) conceptualization of measurement quality as basic infrastructure.

MMM integration: MMM integration was a significant predictor of attribution accuracy ($\beta = 0.29$) and ROI ($\beta = 0.14$), supporting H4 and H5 and the indirect effect of attribution accuracy on ROI was 0.11 ($p = .002$), supporting H14. These findings align with the suggestion of Hanssens and Pauwels (2016) to combine online and offline measurement and Gaur and Bharti (2020) who found that hybrid attribution methods are better than single-method attribution. The relatively low effect sizes in this study compared to the effect size reported for the measurement capability of privacy ($f^2 = 0.11$ vs. 0.14 on attribution accuracy) are not to be taken lightly; Silva, Duarte and Almeida (2020) found that most companies still use basic engagement metrics despite the fact that they understand the strategic value of MMM, indicating that the reported "integration" may be more about intent than practice.

Governance, transparency and trust: Consumer trust was found to be significantly predicted by data governance maturity ($\beta = 0.31$, confirming H6), consistent with Bartholomew and Williamson's (2024) qualitative finding that RMN success is driven by governance and transparency, not just ad-tech sophistication. The direct ROI effect, however, was the least well supported path in the model ($\beta = 0.12$, $p = .050$, at the significance boundary, but supporting H7). Governance, as a compounding capability as the Resource-Based View suggests, is not a direct ROI lever, but rather its perceived value in terms of fairness is entirely through trust (indirect effect = 0.14, $p < .001$, confirming H15). The two factors of measurement transparency ($\beta = 0.27$, confirming H9) and personalization appropriateness ($\beta = 0.24$, confirming H10) were found to be significant predictors of trust, with measurement transparency being the more closely related factor to the finding of Aslam et al. (2019) that perceived privacy, rather than perceived security, is the stronger predictor of e-commerce trust.

Trust, fairness and decision quality: Consumer trust is positively related to perceived fairness ($\beta = 0.43$, confirming H11) and this relationship is also supported in the case of its impact on decision quality ($\beta = 0.22$, confirming H12), which is the strongest relationship in the model. This aligns with Lee, Ahn, Song and Ahn's (2018) separation of trust and distrust as distinct constructs and Ingriana's (2024) review, which showed that e-trust decreases perceived risk and increases loyalty in e-commerce contexts in general. Full mediation along all three paths of trust (governance→ fairness, H15; transparency→ decision quality, H16, indirect effect = 0.09, $p = .006$; personalization→ fairness, H17, indirect effect = 0.10, $p = .004$) suggests that these upstream constructs influence consumer perceived outcomes only through their influence on trust, which in turn influences the outcome.

Privacy concern moderation: Both moderation effects (H18: $\beta = -0.18$; H19: $\beta = -0.22$) directly operationalize the Privacy Calculus Theory proposed by Dienlin (2023) and support the idea that transparency and personalization are not always trust-building signals, but rather rely on the consumer's continuous weighing of privacy costs and benefits. The greater dampening on the personalization path indicates that consumers are more skeptical about personalization than transparency in general when it comes to privacy concerns. This is not in contradiction with Johnson, Shriver and Du's (2019) privacy paradox, which finds that consumer's stated concern does not necessarily predict their opt-out behaviour, since stated concern can influence the formation of trust, while opt-out behaviour can be independent of it.

The overall level of support for all nineteen hypotheses was higher than is usually found in this literature and should be met with a modicum of caution rather than exultation: a model in which every path is significant can either be a well-specified model based on five well-established theories, or a model constructed somewhat too tightly around the expected paths. Replication between different samples is the only way to differentiate the two.

8. Implications

8.1 Theoretical implications

The strongest theoretical contribution is extending Privacy Calculus Theory into a domain it wasn't originally built for. This study's results of confirmed moderation effects (H18 and H19) provide a concrete and quantified basis for the calculus framing developed by Dienlin (2023) on general online disclosure decisions, rather than advertising measurement specifically. This also helps to solve a small tension in the literature, as Johnson, Shriver and Du (2019) demonstrated that stated concern does not necessarily lead to opt-out behaviour and the results of this study indicate that the more fruitful place to look to see the real effect of privacy concern is not in behaviour, but in the strength of the trust formation itself. Second, the study connects the attribution and measurement research (Gaur & Bharti, 2020; Hanssens & Pauwels, 2016) with the consumer trust and privacy research (Aslam et al., 2019; Bandara, Fernando, & Akter, 2019) in response to the explicit call by Bandara et al. (2019) for a more unified privacy framework. Third, the five-theory integration (TAM, Privacy Calculus, RBV, Attribution Theory, Information Processing Theory) indicates that the positioning of data governance as a rare and hard to imitate resource is empirically supported: the impact of data governance was almost exclusively on trust, not directly on ROI, more like a genuine capability advantage would than a simple compliance cost centre.

8.2 Managerial implications

For Amazon Ads and Flipkart Ads, both large, closed-loop platforms with significant first-party data assets, the marginal ROI gain appears to lie in the accuracy of attribution ($f^2 = 0.18$, the largest effect size in the model); Sampath's (2024) observation about the difficulty of attribution being a constant hurdle would suggest that these platforms would likely gain more ROI from improving attribution than from continuing to scale ad inventory. The moderation results (H19) are no less alarming for Myntra Ads and Ajio, where personalisation is a more integral part of the value proposition than it is for the others: personalisation-to-trust is less effective under high privacy concern and transparency is less effective under low privacy concern, so personalisation without transparency investment is actively damaging trust among the more privacy-aware segments, not just underperforming. For Zepto and Blinkit, the newer companies still developing governance, the full mediation of governance through trust (H15) implies governance investment is not going to appear in short-term ROI dashboards - the very pitfall Bartholomew and Williamson (2024) warned about. In the context of Meesho, where trust and peer recommendation were found to be key growth drivers by Nasabi and Sujaya (2023), the higher leverages come from investing in transparency, not sophistication in personalization, as the trust-to-fairness path is strong ($\beta = 0.43$), implying that the platform's current trust-centric positioning is already aligned with what drives consumer perception downstream. Three recommendations hold true across all platforms: invest in privacy-first measurement infrastructure before expanding ad inventory, integrate MMM with RMN reporting, not as parallel systems and consider governance maturity as a trust-building investment, not an immediate ROI lever.

8.3 Policy implications

This study provides empirical evidence, not just normative, that transparency and governance maturity bring tangible benefits to consumers in terms of trust, providing Prastyanti and Sharma's (2024) argument about data protection law as a competitive advantage with empirical support for the data protection regulators in India implementing the Digital Personal Data Protection framework. The implications of the moderation results for regulation are specific: if the baseline level of privacy concern is reduced, for example, by improved consent processes or increased visibility of regulatory action, then the trust benefits of transparency and personalization investment would be likely to be greater. Regulation and platform-level transparency investment don't seem to be mutually exclusive.

9. Limitations, Future Research and Conclusion

9.1 Limitations

The cross-sectional design does not allow for the exclusion of reverse causality, as organizations with a high ROI may be more likely to report their measurement capability in a positive light than the other way around (Hanssens and Pauwels, 2016). Findings are limited to the Indian e-commerce context and should not be extended to markets with different regulatory maturity as the nature of cookie-less identification varies across the regulatory contexts in Western markets (Sivan-Sevilla, Parham, & McGuigan, 2025). The validity of self-reported measures for both sides of the dual-respondent design was not tested against independent behavioural data and Johnson, Shriver and Du's (2019) documented discrepancy between stated privacy concern and actual opt-out behaviour further reinforces this concern. The retail e-commerce focus means the model has not been tested in other advertising-heavy industries and the hypothesis set (19 of 19) is universally agreed upon, so a frank disclaimer is in order: only replication across samples can tell whether a model is well specified or too tightly tied to hypothesized relationships.

9.2 Future research

Longitudinal designs would assess if the ability to measure is actually before the ROI gains, or alongside them. The cross-country replication exercise would help determine whether the privacy concern moderation effects (H18, H19) are a regulatory moment in India or a more general pattern. Causal-inference methods, geo-experiments, holdout testing, would provide a better test for whether self-reported attribution accuracy is an accurate measure of incrementality, or a carry-over from closed-loop bias (Rafieian & Yoganarasimhan, 2020). It would be useful to expand the model to retail e-commerce to separate out the effect of the closed-loop nature of retail media from the measurement effect of privacy more broadly.

10. Conclusion

The study analysed if the capability of measuring with privacy does not compromise the business outcomes of e-commerce platforms in India, while retaining the consumer trust that is essential for first-party data collection. All 19 hypotheses were confirmed in the 312 respondents. The two factors that had the most impact on attribution were privacy-first measurement capability and MMM integration, both of which contributed to the improvement of attribution accuracy, the primary driver of ROI in the model and governance maturity, transparency and appropriateness of personalization-built consumer trust, which fully cascaded into fairness and decision quality. Both paths of trust-building were significantly undermined by the privacy concern, as it was found to be measurable for retail advertising and as Privacy Calculus dynamics play out in this context. The study combines five distinct theoretical frameworks and draws together two bodies of work identified by Bandara, Fernando and Akter (2019) as requiring integration, namely the attribution and trust literatures, providing RMN operators with evidence that attribution infrastructure is the best return on investment lever, with governance and transparency as longer-term investments in trust. To regulators, transparency-based policy and platform-level transparency investments seem to complement each other. It provides a fact-based picture of the current state of the tension between two forces: the need for measurement and the trust of consumers and what moves both forces.

REFERENCES

1. Abbas, A., Hefnawy, M. T., & Negida, A. (2024). Meta-analysis accelerator: A comprehensive tool for statistical data conversion in systematic reviews with meta-analysis. BMC Medical Research Methodology, 24(1). https://doi.org/10.1186/s12874-024-02356-6
2. Aslam, W., Hussain, A., Farhat, K., & Arif, I. (2020). Underlying factors influencing consumers' trust and loyalty in e-commerce. Business Perspectives and Research, 8(2), 186-204. https://doi.org/10.1177/2278533719887451
3. Bandara, R., Fernando, M., & Akter, S. (2020). Privacy concerns in e-commerce: A taxonomy and a future research agenda. Electronic Markets, 30(3), 629-647. https://doi.org/10.1007/s12525-019-00375-6
4. Barney, J. B. (1991). Firm resources and sustained competitive advantage. Journal of Management, 17(1), 99-120. https://doi.org/10.1177/014920639101700108
5. Barney, J. B., Wright, M., & Ketchen, D. J. (2001). The resource-based view of the firm: Ten years after 1991. Journal of Management, 27(6), 625-641. https://doi.org/10.1177/014920630102700601
6. Bartholomew, D. E., & Williamson, M. K. (2024). Retail media networks, Journal of Retailing and Consumer Services, 69(1), Article 103119. 10.1016/j.jretconser.2022.103119
7. Ben Youssef, K., Leicht, T., & Marongiu, L. (2019). Storytelling in the context of destination marketing: An analysis of conceptualisations and impact measurement. Journal of Strategic Marketing, 27(8), 696-713. https://doi.org/10.1080/0965254X.2018.1464498
8. Buhalis, D., & Volchek, K. (2021). Bridging marketing theory and big data analytics: The taxonomy of marketing attribution. https://doi.org/10.1016/j.ijinfomgt.2020.102253
9. Chen, Q., Ilia, P., Polychronakis, M., & Kapravelos, A. (2021). Cookie swap party: Abusing first-party cookies for web tracking. Proceedings of the Web Conference 2021, 2117-2129. https://doi.org/10.1145/3442381.3449837

10. Chiu, Y. B., Lin, C. P., & Tang, L. L. (2005). Gender differs: Assessing a model of online purchase intentions in e-tail service. International Journal of Service Industry Management, 16(5), 416-435. https://doi.org/10.1108/09564230510625741
11. Dash, B., Sharma, P., Ansari, M. F., & Swayamsiddha, S. (2022). A review of ONDC's digital warfare in India taking on the e-commerce giants. International Journal of Engineering & Technology, 11(2). https://ssrn.com/abstract=4323963
12. Davis, F. D. (1989). Perceived usefulness, perceived ease of use and user acceptance of information technology. MIS Quarterly, 13(3), 319-340. https://doi.org/10.2307/249008
13. Deshpande, V. S., & Chanda, A. (2025). Understanding the network effect between different marketing channels in retail media networks. https://doi.org/10.12732/ijam.v38i1s.754
14. Dienlin, T. (2023). Privacy calculus: Theory, studies and new perspectives. https://www.taylorfrancis.com/chapters/edit/10.4324/9781003244677-8/privacy-calculus-tobias-dienlin
15. Falahat, M., Lee, Y. Y., Foo, Y. C., & Chia, C. E. (2019). A model for consumer trust in e-commerce. Asian Academy of Management Journal, 24(Suppl. 2), 93-109. https://doi.org/10.21315/aamj2019.24.s2.7
16. Fuentes Santos, P., Vallejo-Blanxart, A., & Bustos Díaz, J. (2025). Adapting digital marketing strategies for a cookieless future: Challenges and opportunities. First Monday, 30(6). https://doi.org/10.5210/fm.v30i6.13336
17. Gaur, J., & Bharti, K. (2020). Attribution modelling in marketing: Literature review and research agenda. Academy of Marketing Studies Journal, 24(4). https://api.semanticscholar.org/CorpusID:229205664
18. 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
19. Hanssens, D. M., & Pauwels, K. H. (2016). Demonstrating the value of marketing. Journal of Marketing, 80(6), 173-190. https://doi.org/10.1509/jm.15.0417
20. Heider, F. (1958). The psychology of interpersonal relations. Wiley. https://doi.org/10.1037/10628-000
21. Huang, S., Aral, S., Hu, Y. J., & Brynjolfsson, E. (2020). Social advertising effectiveness across products: A large-scale field experiment. Marketing Science, 39(6), 1142-1165. https://doi.org/10.1287/mksc.2020.1240
22. Huma, Z. (2025). Rise of privacy-first marketing: Strategies for success in a regulated environment. https://doi.org/10.22541/au.173879116.64228068/v1
23. Ingriana, A. (2024). The influence of e-trust on consumer purchasing behavior in e-commerce. Journal Dinamika Publika. https://doi.org/10.1234/jumder.v1i3.26
24. Johnson, G. A., Shriver, S. K., & Du, S. (2019). Consumer privacy choice in online advertising: Who opts out and at what cost to industry? https://ssrn.com/abstract=3020503
25. Kwek, C. L., Lau, T. C., & Tan, H. P. (2010). The effects of shopping orientations, online trust and prior online purchase experience toward customers' online purchase intention. International Business Research, 3(3). https://www.ccsenet.org/ibr
26. Lee, S. J., Ahn, C., Song, K. M., & Ahn, H. (2018). Trust and distrust in e-commerce. Sustainability, 10(4), Article 1015. https://doi.org/10.3390/su10041015
27. Liu, B., Ding, M., Shaham, S., Rahayu, W., Farokhi, F., & Lin, Z. (2022). When machine learning meets privacy: A survey and outlook. ACM Computing Surveys, 54(2), Article 31. https://doi.org/10.1145/3436755
28. Long, A. (2022). Effective first-party data collection in a privacy-first world. [Full source details require verification].
29. Malhotra, N. K., Kim, S. S., & Agarwal, J. (2004). Internet users' information privacy concerns (IUIPC): The construct, the scale and a causal model. Information Systems Research, 15(4), 336-355. https://doi.org/10.1287/isre.1040.0032
30. Mugo, D., Njagi, K., Chemwei, B., & Motanya, J. (2017). The Technology Acceptance Model (TAM) and its application to the utilization of mobile learning technologies. British Journal of Mathematics & Computer Science, 20(4), 1-8. https://doi.org/10.9734/bjmcs/2017/29015
31. Mundy, J., Piening, E. P., et al. (2017). Attribution theories in human resource management research: A review and research agenda. The International Journal of Human Resource Management. 10.1080/09585192.2017.1380062
32. Nair, S., Gupta, R., & Kiran, D. (2021). Application of AI technology in modern digital marketing environment. 10.1108/WJEMSD-08-2020-0099
33. Nishat, S. A., & Nasabi, A. (2023). Social commerce for unbranded products in India: A case study of MEESHO. International Journal of Management, Technology and Social Sciences, 8(1). https://doi.org/10.5281/zenodo.7697686
34. Pasham, S. D. (2023). Privacy-preserving data sharing in big data analytics: A distributed computing approach. The Metascience, 1(1). 10.18535/mcsj/v2023.04
35. Peterson, R. A., Kerin, R., & Ross, I. (1979). Book review: An information processing theory of consumer choice. Journal of Marketing, 43(3), 111-112. https://doi.org/10.1177/002224297904300314
36. Podsakoff, P. M., Podsakoff, N. P., Williams, L. J., Huang, C., & Yang, J. (2024). Common method bias: It's bad, it's complex, it's widespread and it's not easy to fix. Annual Review of Organizational Psychology and Organizational Behavior, 11, 17-61. https://doi.org/10.1146/annurev-orgpsych-110721-040030
37. Prastyanti, R. A., & Sharma, R. (2024). Establishing consumer trust through data protection law as a competitive advantage in Indonesia and India. Journal of Human Rights, Culture and Legal System, 4(2), 354-390. https://doi.org/10.53955/jhcls.v4i2.200
38. Rafieian, O., & Yoganarasimhan, H. (2020). Targeting and privacy in mobile advertising. https://ssrn.com/abstract=3163806

39. Ram Mohan Rao, P., Murali Krishna, S., & Siva Kumar, A. P. (2018). Privacy preservation techniques in big data analytics: A survey. Journal of Big Data, 5(1), Article 33. https://doi.org/10.1186/s40537-018-0141-8
40. Sampath, L. (2024). Digital marketing metrics and ROI analysis: Evaluating effectiveness and value. Quest Journals Journal of Research in Business and Management, 12. https://doi.org/10.35629/3002-12086468
41. Sharma, S., Chen, K., & Sheth, A. (2018). Towards practical privacy-preserving analytics for IoT and cloud-based healthcare systems. IEEE Internet Computing. https://doi.org/10.48550/arXiv.1804.04250
42. Silva, S. C. e., Duarte, P. A. O., & Almeida, S. R. (2020). How companies evaluate the ROI of social media marketing programmes: Insights from B2B and B2C. Journal of Business & Industrial Marketing, 35(12), 2097-2110. https://doi.org/10.1108/JBIM-06-2019-0291
43. Singh, M. (2024). Privacy-preserving marketing analytics: Navigating the future of cookieless tracking. International Journal of Enhanced Research in Management & Computer Applications, 13. https://doi.org/10.55948/IJERMCA.2024.0307
44. Sivan-Sevilla, I., Parham, P., & McGuigan, L. (2025). 'Cookie-less' identification for/against privacy? Internet Policy Review, 14(3). https://doi.org/10.14763/2025.3.2025
45. Sousa, T. B. (2022, July 6). Customer data platforms: A pattern language for digital marketing optimization with first-party data. ACM International Conference Proceeding Series. https://doi.org/10.1145/3551902.3551984
46. Tholoniat, P., Kostopoulou, K., McNeely, P., Sodhi, P. S., Varanasi, A., Case, B., Cidon, A., Geambasu, R., & Lécuyer, M. (2024). Cookie Monster: Efficient on-device budgeting for differentially-private ad-measurement systems. Proceedings of the ACM SIGOPS 30th Symposium on Operating Systems Principles. https://doi.org/10.1145/3694715
47. Thomas, R., Thomas, S., Rapert, M., Williams, B., & Murray, A. (2025). Retail media networks: Definition, development and differentiation. Journal of Business Research, 200, Article 115656. https://doi.org/10.1016/j.jbusres.2025.115656
48. Verhoef, P. C., Van Ittersum, K., Kannan, P. K., & Inman, J. (2021). Omnichannel retailing: A consumer perspective. In APA handbook of consumer psychology (pp. 649-672). American Psychological Association. https://doi.org/10.1037/0000262-029
49. Verma, A. (2025). A comparative study of ad attribution models: Evaluating the impact on ROI measurement. European Journal of Computer Science and Information Technology, 13(35), 56-75. https://doi.org/10.37745/ejcsit.2013/vol13n355675
50. Wagner, I., & Eckhoff, D. (2019). Technical privacy metrics: A systematic survey. ACM Computing Surveys, 51(3), Article 57. https://doi.org/10.1145/3168389
51. Weiner, B. (1985). An attributional theory of achievement motivation and emotion. Psychological Review, 92(4), 548-573. https://doi.org/10.1037/0033-295X.92.4.548