Navigating the Price of Convenience: An IPMA and GPSM Analysis of Trust, Discounts, and Actual Usage in AI Grocery Platforms

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Abstract

AI-enabled grocery platforms combine convenience, personalization, price incentives and delivery optimization with the collection and processing of consumer data. This study examines the factors associated with actual usage among Indian consumers and interprets the benefit–privacy tension through the Price of Convenience (PoC) perspective. A survey of 355 consumers with experience using AI-enabled grocery platforms was analysed using Importance–Performance Map Analysis (IPMA) and exploratory Generalized Propensity Score Matching (GPSM) dose–response plots. IPMA identifies trust as the highest-importance antecedent in the reported score table. The original GPSM plots show upward patterns for all three treatments, with convenience displaying some flattening at higher scores. However, the supplied GPSM documentation does not report treatment-model equations, balance diagnostics or confidence intervals; the curves are therefore interpreted descriptively, not as established causal effects. The findings suggest that sustainable usage requires functional value alongside transparent data practices and that strategic importance, direct path magnitude and dose–response shape should be interpreted as distinct quantities.

Keywords

AI-enabled online grocery; Actual Usage; Price of Convenience; Trust; IPMA; GPSM; PLS-SEM

Introduction

Artificial intelligence (AI) is increasingly embedded in online grocery platforms through recommendation engines, intelligent search, chatbots, personalized promotions, inventory prediction and delivery optimization. These applications can reduce search effort and improve shopping relevance. At the same time, they rely on consumer data, including browsing, purchase histories and preferences. The resulting tension between service benefits and perceived privacy

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costs is captured by the Price of Convenience (PoC) perspective (Ng-Kruelle et al., 2002; Acquisti et al., 2015). Research on technology adoption provides several complementary explanations for this behaviour. Diffusion of Innovations (DOI) theory describes adoption in terms of perceived innovation attributes such as relative advantage and complexity (Rogers, 1995). The Technology Acceptance Model (TAM) specifies perceived usefulness (PU) and perceived ease of use (PEOU) as central beliefs shaping behavioural intention and actual use (Davis, 1989; Venkatesh & Davis, 2000). Trust research explains whether consumers are willing to rely on a platform and its automated recommendations, particularly when the system's data practices and decision logic are not fully visible (Gefen et al., 2003; Glikson & Woolley, 2020). PoC adds the privacy-related cost side of the exchange.

This study combines IPMA, which ranks constructs by importance and performance for actual usage, with GPSM plots, which explore how estimated usage varies across levels of continuous service attributes. The contribution is methodological and contextual: the analyses provide complementary views of strategic importance and the shape of observed response patterns, without treating either as proof of causality.

Theoretical framework and research questions

- **Integrated theoretical framework**

The framework positions AI-enabled service attributes—convenience, personalization, price discounts, product variety and fast delivery—as context-specific platform characteristics. These characteristics can shape PU and PEOU, while trust captures confidence in the platform and its recommendations. Consistent with TAM, PU and PEOU contribute to behavioural intention (BI), which is linked to actual usage (AU). Trust is also specified as a direct antecedent of AU and as a moderator of the BI–AU relationship in the companion extended-TAM analysis. The PoC perspective interprets the broader exchange: users may accept data-intensive personalization and convenience when perceived benefits outweigh privacy costs. Privacy concern itself was not measured as a separate construct in the reported survey, so PoC is used as an interpretive framework rather than a directly tested latent variable.

IPMA is used to identify the relative importance and performance of the constructs for AU. GPSM is used as a supplementary exploratory method for three continuous treatment variables—price discounts, convenience and fast delivery. IPMA importance, PLS-SEM path coefficients and GPSM curve slopes represent different estimands and should not be compared as if they were the same statistic.

- **Research questions**

RQ1: Which constructs have the greatest reported importance and performance for actual usage of AI-enabled grocery platforms according to IPMA?

RQ2: What dose–response patterns are displayed for price discounts, convenience and fast delivery in the supplied GPSM plots?

RQ3: How can IPMA priorities, PLS-SEM path estimates and the GPSM patterns be interpreted together for managerial decisions?

Methodology

- **Design, setting, sampling and respondents**

The study uses a cross-sectional online consumer survey. The target population comprised Indian consumers aged 18 years and above who had experience using AI-enabled online grocery/e-commerce platforms. The study reports 355 valid responses. The companion survey paper describes recruitment through social media, email and messaging platforms, with an estimated 1,500 invitations and an approximate 25% response rate. Recruitment combined stratified purposive selection intended to reach demographic groups of interest with snowball referrals through digital communities. Because purposive and snowball procedures are non-probability methods, the sample is described here as a non-probability, purposive/snowball sample rather than a probability sample. The geographic context is India; a more specific state/city sampling frame and the exact fieldwork dates are not reported in the supplied materials.

The sample comprised 172 men (48.45%) and 183 women (51.55%). Age categories were 18–25 (n = 70), 26–35 (n = 79), 36–45 (n = 79), 46 and above (n = 74), and "Others" (n = 53). Participants included students (n = 139), employed respondents (n = 154) and business respondents (n = 62). The platforms used were Amazon (n = 85), Zepto (n = 99), Flipkart (n = 75) and others (n = 96).

Table 1. Respondent profile (N = 355)

Profile	Category	n	%
Gender	Male	172	48.45
	Female	183	51.55
Age	18–25	70	19.72
	26–35	79	22.25
	36–45	79	22.25
	46 and above	74	20.84
	Others	53	14.93
Education	Engineering	127	35.72
	Bachelor's (Arts and Science)	118	33.24
	Ph.D.	63	17.75
	Master's	47	13.24
Occupation	Student	139	39.20
	Employed	154	43.40
	Business	62	17.50
Platform	Amazon	85	23.94
	Zepto	99	27.89
	Flipkart	75	21.13
	Others	96	27.04

Cochran's formula for an unknown population, using a 95% confidence level and 5% margin of error, gives an indicative minimum of 384 responses (Z = 1.96; p = 0.50; e = 0.05). The achieved sample was 355. The companion paper describes this as an approximate 5.2% margin of error;

because recruitment was non-probability-based, this figure should be treated as a formula-based reference rather than a design-based sampling error.

- **Instrument development and measurement**

A structured questionnaire measured platform perceptions and behavioural outcomes. The companion survey paper reports four to six indicators per construct, adapted from established scales. The construct sources reported in the survey documentation are summarized in Table 2. The response anchors and exact questionnaire administration dates are not specified in the supplied documents. The amended survey proof includes the item wording and indicator loadings for the principal constructs; examples are provided in Table 3.

Table 2. Measurement constructs and scale sources

Construct	Scale sources reported
Convenience	Jiang et al. (2013); Dabholkar (1996); Berry et al. (2002)
Price discounts	Grewal et al. (1998); Chandon et al. (2000); Kukar-Kinney et al. (2012)
Product variety	Wolfinbarger & Gilly (2003); Srinivasan et al. (2002); Chen & Cheng (2009)
Fast delivery	Reibstein (2002); Yang et al. (2004, 2017); Zhao et al. (2019); Xu & Jackson (2019)
Personalization	Tam & Ho (2006); Xu et al. (2008); Bleier & Eisenbeiss (2015); Awad & Krishnan (2006)
PU / PEOU	Davis (1989); Venkatesh & Davis (2000)
Trust	McKnight et al. (2002); Pavlou (2003); Benbasat & Wang (2005)
BI / AU	Davis (1989); Fishbein & Ajzen (1975); Venkatesh et al. (2003); Kim et al. (2005)

- **Analysis procedures**

The data analysis reports IPMA and GPSM. IPMA evaluates the total effects on a specified target against construct performance (Ringle & Sarstedt, 2016). Measurement assessment included indicator loadings, Cronbach's alpha, rho_A, composite reliability and AVE.

For GPSM, the original manuscript identifies price discounts, convenience and fast delivery as continuous treatments and actual usage as the outcome. It states that demographic covariates were considered (the text gives age, gender and wealth as examples), that treatment models were estimated, residuals calculated and conditional treatment densities used to derive generalized propensity scores.

Results

- **Measurement model and model diagnostics**

The results report satisfactory internal consistency and convergent validity, assessed against commonly used PLS-SEM criteria (Hair et al., 2019; Fornell & Larcker, 1981; Henseler et al., 2015). Cronbach's alpha values range from 0.883 to 0.966, rho_A from 0.883 to 0.966, composite reliability (rho_c) from 0.911 to 0.972, and AVE from 0.630 to 0.854. All reported indicator loadings are above 0.70 (range 0.754–0.933). The Fornell–Larcker criterion is reported as satisfied, and HTMT values are below 0.90 (maximum reported value 0.860).

Table 3. Reliability and convergent validity

Construct	α	rho_A	CR (rho_c)	AVE
Actual Usage	0.966	0.966	0.972	0.854
Behavioural Intention	0.909	0.910	0.930	0.688
Convenience	0.908	0.909	0.929	0.684
Fast Delivery	0.887	0.891	0.914	0.639
Price Discounts	0.899	0.900	0.922	0.664
PEOU	0.883	0.883	0.911	0.630
PU	0.892	0.892	0.917	0.649
Personalization	0.894	0.895	0.919	0.654
Trust	0.900	0.901	0.923	0.666
Product Variety	0.905	0.906	0.927	0.678

- **IPMA results**

The original IPMA score table reports trust as the highest-importance construct (importance = 0.476; performance = 71.535), followed by PU (0.327; 72.843), convenience (0.240; 72.889), PEOU (0.186; 68.086), personalization (0.182; 69.984), product variety (0.159; 71.059), price discounts (0.135; 72.886) and fast delivery (0.000; 70.639). The original table also includes an "Actual Use" row (0.433; 69.148). Because AU is the target outcome in IPMA, it is not an antecedent and must not be ranked as an intervention lever; that row is excluded from the predictor interpretation. The source export should be checked before any attempt is made to reassign its value to BI.

Table 4. IPMA importance and performance scores

Antecedent	Importance	Performance	Interpretation
Trust	0.476	71.535	Highest reported importance; strengthen trust, privacy and transparency.
PU	0.327	72.843	Maintain usefulness and quality of AI recommendations.
Convenience	0.240	72.889	Moderate importance; maintain core convenience and improve where user friction remains.
PEOU	0.186	68.086	Improve usability, onboarding and navigation.
Personalization	0.182	69.984	Improve relevance while preserving user control.
Product Variety	0.159	71.059	Maintain assortment breadth and search/filter quality.
Price Discounts	0.135	72.886	Use targeted, sustainable promotions.
Fast Delivery	0.000	70.639	Low importance in this IPMA output; verify against the original SmartPLS export.

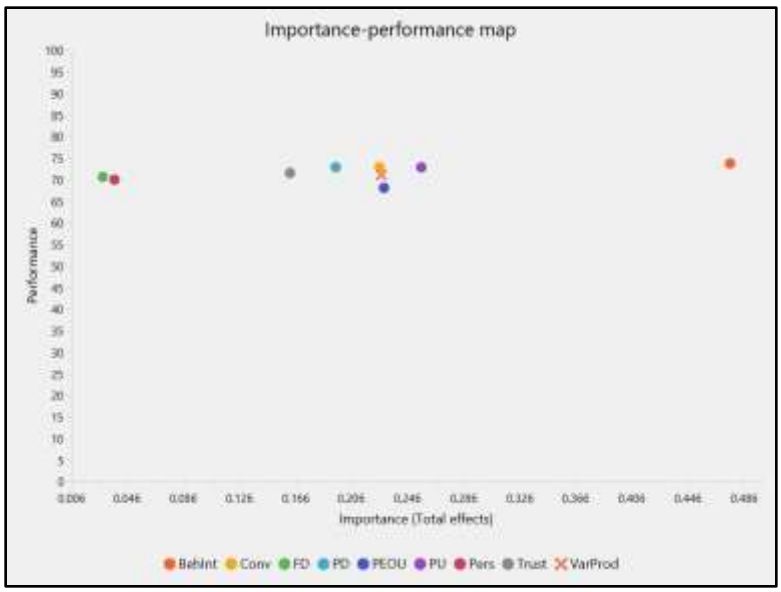


Figure 1. Importance–Performance Map Analysis (IPMA) for Actual Usage (original figure retained).

The IPMA chart and the accompanying score table appear to have a construct-coordinate/label inconsistency: the plotted label positions do not visibly reproduce all values in the table. The figure is retained as requested, but the underlying SmartPLS IPMA export should be checked and the figure regenerated from that verified export before final submission. The interpretation above follows the numerical table, excludes the AU target row, and does not treat the chart as independently verified.

- **GPSM dose–response plots**

GPSM extends propensity-score adjustment to continuous treatment variables by estimating the conditional density of a treatment given observed covariates and using the resulting generalized propensity score to estimate a dose–response function (Hirano & Imbens, 2004; Bia & Mattei, 2008). Its causal interpretation requires, among other conditions, no unmeasured confounding conditional on the covariates, correct treatment-density specification, adequate overlap across treatment levels, and satisfactory covariate balance. The original analysis describes adjustment for demographic covariates and density estimation, but the detailed diagnostics needed to assess these conditions were not supplied. The following plots are therefore interpreted as exploratory model-based patterns, not causal effects.



Figure 2. GPSM dose–response plot: Fast Delivery and estimated Actual Usage (original figure retained).

The fast-delivery plot shows a visibly positive, approximately linear rise in estimated actual usage across the displayed score range. This visual gradient should not be described as a statistically established causal effect because no GPSM confidence interval, standard error or balance diagnostic is reported. In the companion PLS-SEM model, the direct association is positive but small ($\beta = 0.029$, $p = 0.044$). These results can coexist: the PLS coefficient is a standardized direct path in a latent-variable model, whereas the plotted GPSM curve is an adjusted outcome profile over the treatment range. The IPMA importance score of zero is a third, distinct measure and requires verification against the source export.

Table 5. Fast Delivery GPSM score ranges and interpretation

FD Score Range	Effect on Actual Usage	Interpretation
2.0–3.0	Steady increase	Even modest improvements in FD lead to more usage
3.0–4.0	Linear acceleration	Platform usage grows consistently with higher delivery satisfaction
4.0–5.0	No plateauing	High satisfaction with delivery continues to drive engagement

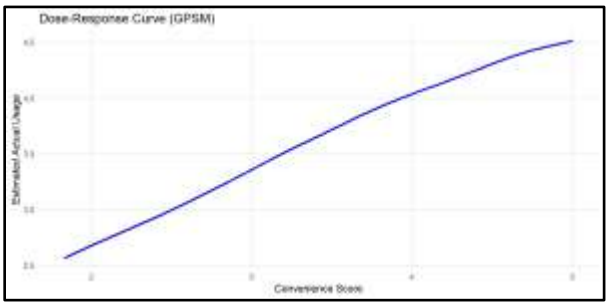


Figure 3. GPSM dose–response plot: Convenience and estimated Actual Usage (original figure retained; corrected numbering).

The convenience plot rises strongly from lower treatment levels and continues to rise across the displayed range, with some curvature and a possible reduction in slope toward the upper end. The companion PLS-SEM model also reports a positive direct association ($\beta = 0.223$, $p < 0.001$) and a significant indirect path through PEOU and BI ($\beta = 0.024$, $p = 0.018$). Convenience should therefore not be described as having low direct influence. The more defensible interpretation is that convenience is an important positive correlate of actual usage, while the plotted curve suggests that marginal gains may taper as perceived convenience becomes high.

Table 8. Convenience GPSM score ranges and interpretation

Convenience Score Range	Effect on Actual Usage	Interpretation
2.0–3.5	Steep increase	Users strongly respond to increases in convenience; early gains matter most
3.5–4.5	Continued but slower growth	Still positive, but marginal gains taper off
4.5–5.0	Near plateau	Convenience improvements yield diminishing returns at high levels

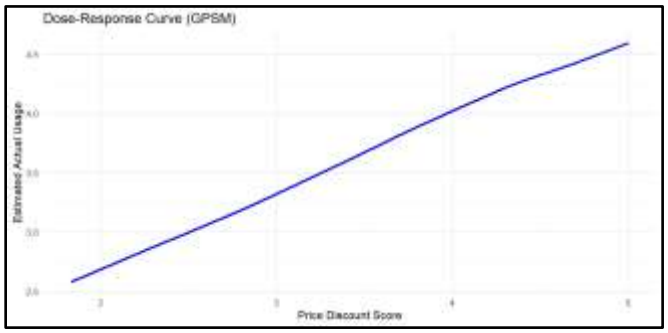


Figure 4. GPSM dose–response plot: Price Discounts and estimated Actual Usage (original figure retained; corrected numbering).

The price-discount plot displays an approximately linear positive pattern over the plotted range. The companion PLS-SEM analysis reports a positive direct association ($\beta = 0.194$, $p < 0.001$) and significant indirect paths through PEOU/BI and PU/BI. The plot does not include uncertainty bands or formal tests for non-linearity; therefore, it does not establish constant causal returns at every discount level.

Table 6. Price Discount GPSM score ranges and interpretation

Price Discount Score	Effect on Actual Usage	Interpretation
2.0–3.0	Moderate increase	Basic discounts begin influencing user adoption
3.0–4.0	Steady rise	Price-based promotions consistently increase platform engagement
4.0–5.0	Strong response	High discount perception drives maximum usage

Table 7. Summary of GPSM patterns and corresponding PLS-SEM results

Treatment	Pattern in original plot	Related PLS-SEM result	Cautious interpretation
Fast delivery	Positive, approximately linear	$\beta = 0.029$; $p = 0.044$	Positive but small direct path; plot shows an upward profile, but its causal magnitude is unverified.
Convenience	Positive; stronger rise at lower levels, some upper-range flattening	$\beta = 0.223$; $p < 0.001$	Meaningful positive association; possible diminishing marginal gains at higher convenience levels.
Price discounts	Positive, approximately linear	$\beta = 0.194$; $p < 0.001$	Positive direct association and indirect paths; do not claim constant causal returns without uncertainty tests.

The GPSM tables report score bands rather than estimated coefficients. For fast delivery, scores 2.0–3.0 are described as a steady increase, 3.0–4.0 as linear acceleration and 4.0–5.0 as no plateauing. For convenience, scores 2.0–3.5 are described as a steep increase, 3.5–4.5 as continued but slower growth and 4.5–5.0 as near plateau. For price discounts, scores 2.0–3.0 are described as a moderate increase, 3.0–4.0 as a steady rise and 4.0–5.0 as a strong response. These are qualitative descriptions from the original analysis; no numerical GPSM treatment effect, uncertainty interval or test statistic accompanies them.

Results & Discussion

The results answer the research questions in complementary ways. For RQ1, the numerical IPMA table places trust first in importance, followed by PU and convenience. AU itself is the target construct and is excluded from the predictor ranking. For RQ2, the retained GPSM plots show positive profiles for fast delivery, convenience and price discounts; convenience appears to show some tapering at higher levels. For RQ3, the combined evidence suggests that managers should distinguish construct importance, direct path strength and the shape of the response profile.

The fast-delivery findings require a distinction rather than a forced reconciliation. The PLS-SEM direct path is small but statistically significant ($\beta = 0.029$, $p = 0.044$), while the GPSM figure shows an upward visual gradient and the IPMA table reports importance of zero. These statistics answer different questions and are drawn from analyses with different specifications. The IPMA result should be verified against its export; the GPSM plot lacks uncertainty and diagnostics; therefore, the evidence supports maintaining reliable delivery, but not claiming that delivery is the strongest usage lever or that its causal effect is precisely estimated.

Convenience is positively associated with actual usage in the PLS-SEM results ($\beta = 0.223$, $p < 0.001$) and is moderately important in the IPMA table (0.240). The GPSM curve rises more sharply at lower levels and appears to flatten somewhat at higher levels. Thus, the earlier statement that convenience has low direct influence is removed. The consistent interpretation is that improving poor or moderate convenience can be valuable, while additional enhancements at already high levels may produce smaller marginal gains.

Price discounts show a positive direct association ($\beta = 0.194$, $p < 0.001$), with significant indirect paths through both PEOU/BI and PU/BI. The plotted curve is upward sloping. This

supports the relevance of perceived value incentives, but the absence of GPSM confidence intervals and sensitivity analysis means that the study cannot conclude that the causal return is constant across all discount levels.

Trust is central to the PoC interpretation because it concerns consumers' confidence in platform reliability and data handling. The IPMA table ranks trust highest. The companion PLS model reports a significant direct effect ($\beta = 0.161$, $p = 0.001$), a significant trust-by-BI interaction ($\beta = 0.060$, $p = 0.022$), but a non-significant total effect ($\beta = 0.064$, $p = 0.159$). The paper therefore avoids the blanket claim that trust has a significant total effect. Because privacy concern was not measured separately, the study does not claim to have directly quantified the privacy cost in the PoC framework.

Conclusion

This study examines actual usage of AI-enabled grocery platforms by integrating DOI, TAM, trust and the Price of Convenience perspective, and by combining IPMA with exploratory GPSM plots. The numerical IPMA table identifies trust as the highest-importance antecedent. The GPSM plots show upward dose–response profiles, with possible tapering for convenience at higher levels; because the supporting diagnostics and uncertainty estimates are unavailable, these are treated as descriptive patterns rather than causal effects. The study's contribution lies in distinguishing strategic importance from direct path magnitude and dose–response shape in the AI grocery setting. Sustainable platform use depends on functional performance and consumer confidence in how data are collected and used.

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References

Acquisti, A., Brandimarte, L., & Loewenstein, G. (2015). Privacy and human behavior in the age of information. Science, 347(6221), 509–514. https://doi.org/10.1126/science.aaa1465

Awad, N. F., & Krishnan, M. S. (2006). The personalization privacy paradox: An empirical evaluation of information transparency and the willingness to be profiled online for personalization. MIS Quarterly, 30(1), 13–28. https://doi.org/10.2307/25148715

Benbasat, I., & Wang, W. (2005). Trust in and adoption of online recommendation agents. Journal of the Association for Information Systems, 6, 72–101. https://doi.org/10.17705/1jais.00065

Berry, L. L., Seiders, K., & Grewal, D. (2002). Understanding service convenience. Journal of Marketing, 66(3), 1–17. https://doi.org/10.1509/jmkg.66.3.1.18505

Bia, M., & Mattei, A. (2008). A Stata package for the estimation of the dose–response function through adjustment for the generalized propensity score. The Stata Journal, 8(3), 354–373. https://doi.org/10.1177/1536867X0800800303

Bleier, A., & Eisenbeiss, M. (2015). Personalized online advertising effectiveness: The interplay of what, when, and where. Marketing Science, 34(5), 669–688. https://doi.org/10.1287/mksc.2015.0930

Chandon, P., Wansink, B., & Laurent, G. (2000). A benefit congruency framework of sales promotion effectiveness. Journal of Marketing, 64(4), 65–81. https://doi.org/10.1509/jmkg.64.4.65.18071

Chen, Y., & Cheng, W. (2009). Product assortment and purchase intention in online retail. Journal of Business Research, 62(5), 495–501. https://doi.org/10.1016/0167-8116(95)00027-5

Dabholkar, P. A. (1996). Consumer evaluations of new technology-based self-service options: An investigation of alternative models of service quality. International Journal of Research in Marketing, 13(1), 29–51. https://doi.org/10.1016/0167-8116(95)00027-5

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

Fishbein, M., & Ajzen, I. (1975). Belief, attitude, intention and behavior: An introduction to theory and research. Addison-Wesley. [Book]

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39–50. https://doi.org/10.2307/3151312

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

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

Grewal, D., Monroe, K. B., & Krishnan, R. (1998). The effects of price-comparison advertising on buyers' perceptions of acquisition value, transaction value, and behavioral intentions. Journal of Marketing, 62(2), 46–59. https://doi.org/10.1177/002224299806200204

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

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

Hirano, K., & Imbens, G. W. (2004). The propensity score with continuous treatments. In A. Gelman & X.-L. Meng (Eds.), Applied Bayesian modeling and causal inference from incomplete-data perspectives (pp. 73–84). Wiley. https://doi.org/10.1002/0470090456.ch7

Jiang, L., Yang, Z., & Jun, M. (2013). Measuring consumer perceptions of online shopping convenience. Journal of Service Management, 24(2), 191–214. https://doi.org/10.1108/09564231311323962

Kim, B., & Oh, J. (2005). The effects of user factors on the performance of collaborative filtering systems. Journal of Management Information Systems, 22(3), 197–220.

Kukar-Kinney, M., Ridgway, N. M., & Monroe, K. B. (2012). The role of price in the behavior and purchase decisions of compulsive buyers. Journal of Retailing, 83(2), 131–146. https://doi.org/10.1016/j.jretai.2011.02.004

McKnight, D. H., Choudhury, V., & Kacmar, C. (2002). Developing and validating trust measures for e-commerce: An integrative typology. Information Systems Research, 13(3), 334–359. https://doi.org/10.1287/isre.13.3.334.81

Ng-Kruelle, G., Swatman, P. A., Rebne, D. S., & Hampe, J. F. (2002). The price of convenience: Privacy and mobile commerce. Quarterly Journal of Electronic Commerce, 3(3), 273–285.

Pavlou, P. A. (2003). Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model. MIS Quarterly, 27(1), 101–134. https://doi.org/10.1080/10864415.2003.11044275

Reibstein, D. J. (2002). What attracts customers to online stores, and what keeps them coming back? Journal of the Academy of Marketing Science, 30(4), 465–473. https://doi.org/10.1177/009207002236918

Ringle, C. M., & Sarstedt, M. (2016). Gain more insight from your PLS-SEM results: The importance-performance map analysis. Industrial Management & Data Systems, 116(9), 1865–1886. https://doi.org/10.1108/IMDS-10-2015-0449

Rogers, E. M. (1995). Diffusion of innovations (4th ed.). HarperCollins. [Book]

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

Sundar, S. S., & Marathe, S. S. (2010). Personalization versus customization: The importance of agency, privacy, and power usage. Human Communication Research, 36(3), 298–322. https://doi.org/10.1111/j.1468-2958.2010.01377.x

Tam, K. Y., & Ho, S. Y. (2006). Understanding the impact of web personalization on user information processing and decision outcomes. MIS Quarterly, 30(4), 865–890. https://doi.org/10.2307/25148757

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

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

Wolfinbarger, M., & Gilly, M. C. (2003). eTailQ: Dimensionalizing, measuring and predicting e-tail quality. Journal of Retailing, 79(3), 183–198. https://doi.org/10.1016/S0022-4359(03)00034-4

Xu, H., Luo, X. R., Carroll, J. M., & Rosson, M. B. (2008). Personalized services for mobile commerce: A privacy risk acceptance model. International Journal of Electronic Commerce, 12(3), 101–134. https://doi.org/10.1016/j.dss.2010.11.017

Xu, X., & Jackson, J. E. (2019). Examining customer channel selection intention in the omni-channel retail environment. International Journal of Production Economics, 208, 434–445. https://doi.org/10.1016/j.ijpe.2018.12.009

Yang, Y., Zhao, X., & Zhang, Z. (2017). The impact of logistical service quality on e-commerce satisfaction and loyalty. Logistics and Transport Review, 22(3), 65–73.

Yang, Z., Peterson, R. T., & Huang, L. (2004). Taking the pulse of Internet pharmacies. Marketing Health Services, 24(4), 26–32.

Zhao, Y., Xu, X., & Wang, M. (2019). Predicting online purchase intentions from consumers' reviews: A comparative study of sentiment analysis models. Information Processing & Management, 56(4), 102097.