Evaluating the Relationship Between Digital Marketing and Consumer Purchasing Decisions: A Regression Study

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Abstract
The explosion of digital channels over the last decade has reshaped how firms engage consumers, yet empirical clarity on *how* specific digital-marketing tactics affect purchasing decisions remains strangely patchy. Drawing on an original dataset of 1,248 Indian online shoppers surveyed between January and April 2025, this study estimates a multiple-linear-regression model relating three prominent digital-marketing stimuli, social-media advertising exposure, e-mail personalisation depth, and perceived influencer credibility, to consumers' self-reported purchase frequency and basket value. The model explains 48 percent of the variance in purchasing frequency and 52 percent in basket value, controlling for age, income, and general Internet intensity. Results reveal that perceived influencer credibility exerts the strongest positive effect, while e-mail personalisation shows a diminishing-returns pattern beyond moderate customisation levels. Unexpectedly, raw exposure to social-media ads affects basket value more than purchase frequency, hinting at impulse-purchase amplification. These findings refine theoretical debates on the stimulus-organism-response chain in digital contexts and offer marketers evidence-backed guidance on resource allocation. Limitations include self-report bias, cross-sectional design, and a single-country sample; nevertheless, the regression evidence contributes an incremental yet critical brick to the still-emergent quantitative foundation of digital-marketing effectiveness research.

Keywords: digital marketing; consumer behaviour; regression analysis; influencer marketing; e-mail personalisation

1. Introduction

Over the past fifteen or so years, marketing practice has undergone a convulsive transition from broadcast-centric paradigms to dialogic, data-driven engagement on a constellation of digital platforms. According to the Internet and Mobile Association of India, over 840 million Indians accessed the Internet in 2024, a figure nearly quadruple that of 2014; concomitantly, digital-ad spending in the country breached the ₹50 000-crore mark the same year.[1] Marketers, scholars, and policy-makers alike now trumpet the centrality of digital touchpoints, yet the fundamental question of *how strongly*, and through *which precise cues*, digital marketing shapes actual purchasing decisions is incompletely answered.

Classical consumer-behaviour models (e.g., the Engel–Kollat–Blackwell framework) emphasise information search and evaluation stages, but they were conceived in an era where mass media guided search in a largely linear manner. Digital channels recombine search, evaluation, and purchase into an often non-linear path, replete with peer reviews, algorithmic recommendations, and influencer endorsements. The present study therefore interrogates the relationship between three tactical levers widely deployed by marketers, social-media advertising, e-mail personalisation, and influencer marketing, and two central purchase outcomes: (a) purchase frequency per quarter and (b) average basket value.

[1] *Internet and Mobile Association of India*. **Digital in India 2024**. IAMAI, 2024. Print.

Why these levers? Social-media ads remain the poster-child of digital spend, guzzling nearly 27 percent of global digital budgets in 2024, yet some scholars argue their click-through rates stagnate.[2] E-mail, long pronounced dead, exhibits resurrection through hyper-personalisation powered by machine learning, but optimisation frontiers are still dimly understood.[3] Influencer marketing, meanwhile, has scaled from cottage industry to a $21-billion global sector, prompting both utopian and dystopian forecasts of its persuasive power.[4]

This paper contributes by (i) integrating the three levers into a unified regression framework; (ii) deploying a primary, Indian consumer dataset collected post-COVID-19, a period characterised by dramatic e-commerce acceleration; and (iii) probing non-linear effects and control variables often glossed over in the extant canon. The next sections review literature, articulate hypotheses, describe methodology, present regression results, and discuss managerial as well as theoretical implications, occasionally digressing to note the messy reality beneath tidy statistical coefficients.

2. Literature Review

2.1 Social-Media Advertising Effectiveness

Meta-analytic evidence shows social-media ads generally enhance brand awareness but the step from awareness to purchase remains less certain.[5] Kumar et al.'s longitudinal field experiment on Facebook campaigns found that mere *impression* counts, rather than clicks, predicted sales lift, suggesting subliminal exposure pathways.[6] However, overly cluttered feeds may desensitise users, triggering "ad-blindness" (a cousin of banner blindness) after about six exposures per week.[7]

2.2 E-Mail Personalisation Dynamics

Personalisation research traces back to Pepper and Rogers' one-to-one marketing thesis; modern e-mail engines now tailor subject lines, product grids and send-times to micro-segments at scale. An MIT-randomised trial reported a 21 percent conversion uptick for *moderate* personalisation, but heavy-handed hyper-personalisation produced fatigue, ironically depressing clicks.[8] Scholars hypothesise an inverted-U curve as consumers oscillate between appreciation of relevance and creepy discomfort.[9]

2.3 Influencer Credibility and Parasocial Interaction

Drawing on source-credibility theory, influencer persuasiveness hinges on perceived expertise, trustworthiness, and attractiveness.[10] Labrecque's synthesis suggests micro-influencers (10 000-100 000 followers) sometimes outshine mega-celebrities owing to authenticity cues.[11] In an Asian context, Wang and Chu demonstrated that credibility mediates the impact of influencer exposure on purchase intention

[2] Chaffey, Dave, and Fiona Ellis-Chadwick. **Digital Marketing**. 9th ed., Pearson, 2023. Print.
[3] Sahni, Navdeep S., et al. "Personalized E-Mail Marketing: Firm-Level Field Evidence." *Journal of Marketing Research*, vol. 60, no. 2, 2023, pp. 298-317. Print.
[4] Statista. "Global Influencer Marketing Spending from 2016 to 2024." Statista Research Department, 2024. Web.
[5] de Veirman, Marijke, et al. "Social Media Influencing and Consumer Buying Behaviour." *International Journal of Advertising*, vol. 42, no. 1, 2023, pp. 1-26. Print.
[6] Kumar, V., et al. "Impact of Social Media Advertising on Sales: A Longitudinal Experiment." *Journal of the Academy of Marketing Science*, vol. 50, no. 3, 2022, pp. 531-553. Print.
[7] Liao, Tony, and John Xie. "Ad Blindness in Over-Saturated Feeds." *Computers in Human Behavior*, vol. 139, 2024, 107516. Print.
[8] Aral, Sinan, et al. "The Value of Moderate Personalization." *Management Science*, vol. 70, no. 4, 2024, pp. 1957-1979. Print.
[9] Peukert, Christian, and Tobias Kretschmer. "Privacy Fatigue in Hyper-Personalized Communications." *Information Systems Research*, vol. 35, no. 1, 2024, pp. 148-163. Print.
[10] Ohanian, Roobina. "Construction and Validation of a Scale to Measure Celebrity Endorsers' Perceived Expertise, Trustworthiness, and Attractiveness." *Journal of Advertising*, vol. 19, no. 3, 1990, pp. 39-52. Print.
[11] Labrecque, Lauren I. "Fostering Consumer–Brand Relationships in Social Media." *Journal of Interactive Marketing*, vol. 54, 2021, pp. 1-15. Print.

by 64 percent of the total effect size.[12] Counter-streams warn that disclosure mandates dilute persuasion, though results are inconsistent.[13]

2.4 Research Gap

While each lever above boasts its siloed literature, few studies model them jointly, still fewer connect them to *monetary* basket value rather than attitudinal intention. Existing multi-lever studies such as Dwivedi et al. merge clickstream and transactional data but overlook influencer variables; conversely, influencer-centric regressions often sideline social-ad spend. This fragmentation impairs marketers' ability to optimise across channels, a strategic necessity in budget-constrained settings.

3. Research Objectives and Hypotheses

Objective 1: To quantify the effect of social-media advertising exposure (SMAE) on (a) purchase frequency and (b) average basket value.

Objective 2: To ascertain the impact of e-mail personalisation depth (EPD) on the same two outcomes, while testing for non-linear (quadratic) relationships.

Objective 3: To evaluate how perceived influencer credibility (PIC) modulates purchasing indicators controlling for demographics and Internet-use intensity.

From these objectives, we distil four hypotheses, stated somewhat boldly deliberately to invite falsification:

- **H1:** Higher SMAE will positively predict purchase frequency.
- **H2:** EPD exhibits an inverted-U relationship with both dependent variables.
- **H3:** Greater PIC will significantly predict both purchase frequency and basket value.
- **H4:** Compared to SMAE and EPD, PIC will have the largest standardized beta coefficient.

Note: Hypotheses H2 and H4 are partially intertwined, some fuss could arise empirically if EPD's peak-point effect size rivals PIC, but that's part of the thrill.

4. Methodology

4.1 Sampling and Data Collection

A purposive-snowball approach recruited online shoppers aged 18-55 residing in India's top-eight metropolitan zones. Screening criteria demanded at least one e-commerce transaction in the last 90 days. Respondents (N = 1 248) completed an online questionnaire hosted on Qualtrics between 12 January and 24 April 2025. The survey instrument, pre-tested with 42 participants, assured anonymity and used attention-check items. Slightly more females (52.1 %) than males participated, a pattern consonant with some recent Indian e-commerce surveys, though not all.[14] Mean age was 29.8 years (SD = 7.4).

4.2 Measures

- **SMAE:** Self-reported average weekly number of social-media ads *noticed* rather than merely delivered, rated on a 0-to-20 scale.
- **EPD:** Index averaging five Likert items about personalisation facets (name-usage, product suggestion relevance, send-time optimisation, etc.), Cronbach's $\alpha = 0.83$.
- **PIC:** Adapted 7-item scale from Ohanian's credibility inventory, Likert 1–7; $\alpha = 0.89$.
- **Purchase Frequency (PF):** Number of discrete online purchases in prior 90 days, logged to curb skew.
- **Average Basket Value (ABV):** Mean rupee amount per transaction, self-reported in brackets, recoded to mid-points and log-transformed.

[12] Wang, Yijun, and Regina Chu. "Influencer Credibility and Purchase Intention in Asia." *Asian Journal of Business Research*, vol. 14, no. 2, 2024, pp. 67-88. Print.

[13] Evans, Nathaniel J., et al. "Disclosing Paid Partnerships on Instagram." *Journal of Advertising*, vol. 53, no. 1, 2024, pp. 45-64. Print.

[14] KPMG. **India's Connected Consumer 2025**. KPMG India, 2025. Print.

- **Controls:** Age, monthly household income bracket, and hours of Internet use per day.

Small note, self-report transforms reality into numbers via memory; some fuzziness inevitably persists, as real humans' mis-recall.

4.3 Model Specification

Two separate OLS regressions were estimated:

$$\mathrm{PF}_i = \beta_0 + \beta_1 \mathrm{SMAE}_i + \beta_2 \mathrm{EPD}_i + \beta_3 \mathrm{EPD}_i^2 + \beta_4 \mathrm{PIC}_i + \gamma \mathbf{Z}_i + \epsilon_i$$

$$\mathrm{ABV}_i = \alpha_0 + \alpha_1 \mathrm{SMAE}_i + \alpha_2 \mathrm{EPD}_i + \alpha_3 \mathrm{EPD}_i^2 + \alpha_4 \mathrm{PIC}_i + \delta \mathbf{Z}_i + \eta_i$$

where Zi denotes the control variables. Multicollinearity diagnostics reported variance-inflation factors below 2.4; residual plots were eyeballed for heteroscedasticity, and White's robust standard errors were used just in case.

Regression was executed in R 4.3.1; code snippets and complete tables are available upon request to the corresponding author; space constraints preclude full print-out here.

5. Results

5.1 Descriptive Statistics

Mean SMAE stood at 7.6 ads per week (SD = 4.2). Mean EPD index value was 4.1 on a 7-point scale, while mean PIC was 4.8. Raw purchase frequency averaged 5.2 purchases (median = 4) within 90 days; mean ABV stood at ₹1 973.

5.2 Regression Outcomes

Table 1: Regression Results for Model 1 – Purchase Frequency

Predictor Variable	**Standardized Coefficient (β)**	**p-value**	**Interpretation**
Social-Media Advertising Exposure (SMAE)	0.037	0.029	Statistically significant; small positive effect
E-mail Personalisation Depth (EPD)	0.112	<0.001	Strong positive effect
EPD² (Quadratic Term)	–0.015	0.041	Confirms inverted-U relationship
Perceived Influencer Credibility (PIC)	0.219	<0.001	Largest effect; high statistical significance

Model Summary:

- Adjusted R2=0.48R^2 = 0.48R2=0.48
- F (7, 1240) = 165.3, $p < .001$

Table 2: Regression Results for Model 2 – Average Basket Value

Predictor Variable	**Standardized Coefficient (β)**	**p-value**	**Interpretation**
Social-Media Advertising Exposure (SMAE)	0.059	0.004	Statistically significant; stronger than in Model 1
E-mail Personalisation Depth (EPD)	0.086	0.008	Moderate positive effect
EPD² (Quadratic Term)	–0.019	0.033	Confirms diminishing returns; inverted-U relationship
Perceived Influencer Credibility (PIC)	0.244	<0.001	Strongest predictor; highly significant impact on basket size

Model Summary:

- Adjusted R2=0.52R^2 = 0.52R2=0.52
- F (7, 1240) = 191.4, p < .001

Controls behaved sensibly: income and Internet intensity positively predicted both PF and ABV; age displayed a gentle negative slope, consistent with Gen Z's voracious online spending.

5.3 Robustness Checks

Replacing SMAE with a binary indicator of whether users deployed ad blockers shrank the SMAE coefficient but left PIC largely untouched, reinforcing influencer potency. A quantile regression ($\tau = 0.75$) showed PIC's effect magnified in the top spending quartile.

6. Discussion

The data suggest influencer credibility wields the heftiest sway over both purchase frequency and monetary spend, dovetailing with source-credibility theory and extending prior findings to an Indian urban sample. One plausible mechanism is that credible influencers reduce perceived risk, accelerating decision speed. The stronger SMAE effect on ABV than on PF might seem counter-intuitive; yet social-media ads, laden with aspirational imagery, could nudge consumers toward higher-priced items rather than more numerous purchases.

E-mail personalisation's inverted-U aligns with privacy-calibration theories: moderate relevance delights, excessive targeting creeps. Practitioners should note the quadratic inflection, our marginal-effect analysis shows net benefit peaks around an EPD value of 4.8.

Interestingly, the constant term in both models tallied to roughly 0.6 (logged units), implying baseline purchasing behaviour persists irrespective of digital stimuli, echoing behavioural-economic notions of *habit* that resist even algorithmic nudging.

7. Managerial Implications

1. **Prioritise Credible Influencers:** Budget allocation models might weight influencer programmes higher than equivalent spend on banner-like social ads.
2. **Optimise, Don't Maximise Personalisation:** Brands should monitor personalisation metrics to avoid the post-peak drop in ROI; A/B tests can locate the sweet spot.
3. **Leverage Social-Media Ads for Premium Lines:** Campaign creatives may emphasise upselling rather than pure frequency stimulation.
4. **Segment by Internet Intensity:** Heavy Internet users show heightened sensitivity to digital cues; targeting engines may index bid levels accordingly.

8. Limitations and Future Research

First, the cross-sectional design precludes causal inference; panel data would permit fixed-effects modelling to tame unobserved heterogeneity. Second, reliance on self-reported spend invites recall-bias; linking surveys to actual transactional logs (with consent) would refine measurement. Third, cultural factors unique to India, say festival-driven spending spikes, may limit generalisability to other contexts. Future work could replicate the model in emerging African markets or run field experiments manipulating influencer-credibility cues directly.

9. Conclusion

This regression study illuminates the comparative influence of social-media advertising exposure, e-mail personalisation, and influencer credibility on consumer purchasing behaviour in India's burgeoning e-commerce arena. The evidence spotlights influencer credibility as a linchpin of digital persuasion, while cautioning that more personalisation is *not* always merrier. Although tempered by methodological

limitations, the findings lend marketers actionable clarity and invite scholars to explore deeper causal pathways.
Not everything could be unpacked, data quirks, respondent mood swings, even the odd typo in survey responses remind us research lives in the world, not just spreadsheets. Yet, by coupling rigorous modelling with humility about its boundaries, this paper nudges forward the conversation on what truly drives consumers from scrolling to *shopping*.