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Pricing Analytics Capability and Competitive Pricing Effectiveness: Empirical Evidence from Third-Party Sellers on Indian E-Commerce Platforms

P. Bhavya
MBA Student, Faculty of Management Studies, CMS Business School,
JAIN (Deemed-to-be-University), Bangalore, Karnataka, India

Abstract

The explosive growth of Indian e-commerce has created an intensely algorithmic competitive environment in which pricing is the primary determinant of marketplace visibility and sales conversion. This study empirically examines the impact of Pricing Analytics Capability (PAC) — operationalised across three dimensions: technology infrastructure (PAC-TECH), human analytical skill (PAC-HUMAN), and management process (PAC-MGMT) — on Competitive Pricing Effectiveness (CPE) among third-party sellers on major Indian e-commerce platforms. Anchored in Dynamic Capabilities Theory (Teece et al., 1997), the Resource-Based View (Barney, 1991), and the Technology Acceptance Model (Davis, 1989), a quantitative cross-sectional survey yielded N = 121 valid responses from active sellers across nine product categories and seven platforms. Statistical analyses including descriptive statistics, Pearson correlation, simple and multiple OLS regression were conducted using SPSS. Results reveal that PAC significantly and positively predicts CPE (β = 0.550, R^2 = 0.404, $p < .001$). At the sub-dimension level, PAC-HUMAN emerges as the strongest driver (β = 0.393, $p < .001$), followed by PAC-TECH (β = 0.184, p = .050), while PAC-MGMT does not achieve independent significance when controlling for the other dimensions. The findings provide the first empirically validated evidence of the PAC-CPE relationship in the Indian marketplace context, extending the BDAC framework to individual MSME seller pricing behaviour.

Keywords: pricing analytics capability, competitive pricing effectiveness, Indian e-commerce, dynamic capabilities, third-party sellers, MSME, Buy Box

INTRODUCTION

India's digital commerce ecosystem has undergone a structural transformation over the past decade, emerging as one of the world's most dynamic and algorithmically governed online retail markets. Platforms such as Amazon India, Flipkart, Meesho, Snapdeal, JioMart, Myntra, and Nykaa collectively serve hundreds of millions of consumers across 28 states and 8 union territories, enabling millions of independent third-party sellers to reach a national market from local warehouses. Third-party sellers — micro, small, and medium enterprises (MSMEs) that list products in open competition with rival sellers on the same platform — constitute the fundamental supply engine of this ecosystem. Their collective success or failure in converting product listings into sales transactions determines not only their own commercial viability but also the depth and breadth of the e-commerce marketplace itself.

In this environment, pricing is not merely a revenue lever but a visibility determinant. On Amazon India, the coveted Buy Box — the default purchase pathway through which more than 80 percent of transactions are completed — is awarded algorithmically, with competitive pricing being among the most heavily weighted criteria. Sellers maintaining prices within one to three percent of the lowest available offer achieve significantly higher Buy Box win rates (Zhu & Liu, 2018). On Flipkart, similar Featured Seller mechanisms operate on related principles. A price difference of even one to two percent can be the margin between winning and losing a sale in these algorithmically governed environments.

Despite the strategic centrality of pricing in this context, academic research examining how sellers systematically develop the analytical capacity to price competitively — and whether higher analytical capability translates into better competitive pricing outcomes — remains remarkably sparse in the Indian context. The concept of Pricing Analytics Capability (PAC), defined here as a seller's systematic, data-driven ability to gather, process, interpret, and act upon pricing-related market intelligence, has received almost no empirical investigation among Indian MSME e-commerce sellers. Most relevant scholarship focuses on Western markets (primarily Amazon US), ignores the MSME scale at which most Indian sellers operate, and treats pricing analytics as a component of broader firm-level analytics capability rather than as a construct in its own right.

The present study addresses this gap directly. Drawing on the Big Data Analytics Capability (BDAC) framework of Akter et al. (2016) as its measurement foundation, and grounding the theoretical model in Dynamic Capabilities Theory (Teece et al., 1997), the Resource-Based View (Barney, 1991), and the Technology Acceptance Model (Davis, 1989), it investigates whether PAC — across its three constituent dimensions — significantly predicts Competitive Pricing Effectiveness (CPE) among Indian third-party sellers. By focusing explicitly on the MSME seller population across nine product categories and seven platforms, the study generates insights that are both academically original and practically actionable.

LITERATURE REVIEW

The scholarly literature most directly relevant to this study spans four thematic streams: analytics capability frameworks, dynamic pricing and Buy Box research, competitive pricing effectiveness measurement, and technology adoption among Indian MSMEs.

The foundational measurement framework for this study is the Big Data Analytics Capability (BDAC) model developed by Akter et al. (2016) in the International Journal of Production Economics. Validated across 152 organisations, the BDAC model identifies three sub-dimensions of analytics capability — technology infrastructure, human analytical talent, and management capability — each measured by multiple reflective indicators. With over 3,000 citations as of 2024, the BDAC scale represents the most widely validated instrument for analytics capability measurement in the management literature. The present study adapts this scale to the pricing analytics context of individual e-commerce sellers, operationalising PAC-TECH, PAC-HUMAN, and PAC-MGMT as its constituent dimensions. Wamba et al. (2017) extended the BDAC framework by demonstrating that analytics capability influences competitive performance through dynamic capability mediation — a pathway this study examines in the pricing domain.

From the theoretical standpoint, Dynamic Capabilities Theory (Teece et al., 1997) provides the primary explanatory lens. The theory argues that firms achieve sustainable competitive advantage in turbulent environments through three capabilities: sensing competitive signals, seizing opportunities in response, and reconfiguring resources as conditions evolve. In the Indian e-commerce pricing context, these map precisely onto PAC: sensing competitor price movements

(PAC-MGMT), seizing repricing opportunities through automated tools (PAC-TECH), and reconfiguring pricing strategy based on analytics insights (PAC-HUMAN). Barney's (1991) Resource-Based View complements this by positioning advanced pricing analytics tools, proprietary market data, and the organisational skill to leverage them as potentially VRIN resources — Valuable, Rare, Inimitable, and Non-substitutable — that generate sustained competitive pricing advantage.

The empirical evidence on dynamic pricing effects is compelling. Zhu and Liu (2018) demonstrated that Amazon sellers maintaining prices within one to three percent of the lowest available offer achieved significantly higher Buy Box win rates. Ke, Li and Tang (2016) quantified that sellers using automated repricing tools increased sales volume by an average of 23 percent compared to manual pricers. Chen, Kauffman and Liu (2009) showed empirically that automated price adjustment mechanisms significantly outperform static pricing in revenue generation. Grewal, Ailawadi and Gauri (2011) provided the most comprehensive operationalisation of competitive pricing effectiveness, using sales conversion rate, price competitiveness relative to category leaders, and listing visibility as measurement dimensions — all directly incorporated into this study's CPE instrument.

In the Indian context, Kaur and Gupta (2020) found that Flipkart sellers with analytics access priced more competitively during festive sales events. However, their study was limited to a single platform and the consumer electronics category, leaving multi-platform and multi-category dynamics unaddressed. Davis (1989) introduced the Technology Acceptance Model (TAM), establishing perceived usefulness and ease of use as primary adoption determinants — constructs embedded in this study's PAC-HUMAN dimension to capture sellers' perceptions of pricing tool utility. Nambisan et al. (2019) extended TAM to the Indian MSME digital context, documenting cost constraints, digital literacy deficits, and perceived complexity as barriers to analytics adoption — barriers directly measured in this study's instrument.

METHODOLOGY

This study adopted a quantitative, descriptive-cum-explanatory, cross-sectional research design. Primary data were collected from active third-party sellers on major Indian B2C e-commerce platforms through a structured, self-administered online questionnaire distributed via Google Forms. The questionnaire comprised 45 items across 10 sections, employing a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree) for all attitudinal and perceptual constructs.

The target population comprised all active third-party sellers currently listing and selling products on at least one major Indian B2C e-commerce marketplace, with a minimum of six months of active selling experience across any of nine specified product categories: Health and Wellness, Automotive Accessories, Furniture and Home Decor, Grocery and FMCG, Toys and Sports, Beauty and Personal Care, Books and Stationery, Home and Kitchen, and Fashion and Clothing. Purposive non-probability sampling was employed, with sellers reached through LinkedIn professional networks, WhatsApp seller communities, Facebook seller groups (Amazon India Sellers, Flipkart Sellers India), and platform-specific forums. An eligibility screening question filtered inactive or ineligible respondents. A total of 162 responses were received; after applying the eligibility filter, 121 valid and complete responses were retained for analysis.

The measurement instrument operationalised four constructs. PAC was measured as a second-order reflective construct comprising three first-order dimensions: PAC-TECH (4 items, adapted from Akter et al., 2016), PAC-HUMAN (4 items, adapted from Davis, 1989 and Akter et al., 2016), and PAC-MGMT (6 items, adapted from Teece et al., 1997 and Akter et al., 2016). CPE was operationalised through a composite of four perceptual items adapted from Grewal et al. (2011) and Dolan and Simon (1996). All items were standardised using z-score normalisation prior to regression analysis to enable direct comparison of beta coefficients across dimensions.

Data analysis was conducted in IBM SPSS Statistics v26 following a structured analytical sequence: descriptive statistics, reliability analysis using Cronbach's Alpha, Pearson bivariate correlation analysis, simple OLS regression (PAC Overall → CPE, H1), and multiple OLS regression (PAC-TECH + PAC-HUMAN + PAC-MGMT → CPE, H2-H4). All hypotheses were tested at $\alpha = .05$. Seller size (SKU count), tenure, revenue, and city tier were incorporated as control variables in supplementary analyses. Ethical compliance was maintained through voluntary participation, guaranteed anonymity, and absence of personally identifiable information in accordance with CMS Business School AI and Research Policy 2024-26.

DATA ANALYSIS & RESULTS

Descriptive Statistics

Table 1 presents descriptive statistics for all 14 PAC items. The overall PAC composite score is M = 3.421 (SD = 0.852), sitting just above the scale midpoint and indicating moderate pricing analytics capability across the sample. Among the three sub-dimensions, PAC-MGMT records the highest mean (M = 3.541, SD = 0.880), suggesting sellers have greater confidence in management practices such as regular dashboard review (M = 3.700) and data-driven decision-making (M = 3.700). PAC-HUMAN follows (M = 3.410, SD = 1.014), while PAC-TECH records the lowest sub-dimension mean (M = 3.247, SD = 0.998). The single lowest-scoring item in the entire instrument is PAC-T1 — access to best-in-class analytics systems (M = 2.860) — identifying technology access as the most critical capability gap among Indian MSME sellers. The CPE composite score is M = 3.366 (SD = 0.870), with analytics-driven improvement scoring highest (M = 3.479) and profit margin satisfaction lowest (M = 3.283), reflecting persistent margin pressure in the competitive Indian marketplace environment.

Reliability Analysis

Table 2 presents Cronbach's Alpha coefficients for each composite scale. The overall PAC scale achieves excellent reliability (α = 0.911), substantially exceeding the conventional threshold of 0.70 recommended by Hair et al. (2010). The PAC-MGMT sub-scale achieves good reliability (α = 0.816), while PAC-TECH (α = 0.759) and PAC-HUMAN (α = 0.795) both meet the acceptable threshold. The CPE composite scale falls marginally below the threshold (α = 0.696) and is treated as a borderline scale in subsequent analyses; CPE findings are therefore interpreted with appropriate caution. All PAC scales are confirmed as reliable for hypothesis testing.

Pearson Correlation Analysis

Table 3 presents the Pearson bivariate correlation matrix for all PAC dimensions, the overall PAC score, and the CPE score. All correlations involving CPE are statistically significant at $p < .001$. PAC-HUMAN demonstrates the strongest correlation with CPE ($r = 0.641$, $p < .001$), suggesting that human analytical skill — the capacity to find pricing tools useful, interpret data, and act on it — is most closely linked to competitive pricing outcomes. PAC-TECH follows ($r = 0.571$, $p < .001$), and PAC-MGMT shows the lowest but still highly significant correlation ($r = 0.512$, $p < .001$). The overall PAC composite correlation with CPE is $r = 0.635$ ($p < .001$), indicating a strong and positive relationship. These bivariate correlations provide preliminary support for all four alternate hypotheses.

Regression Analysis

Table 4 summarises the regression results for all four hypotheses. The simple OLS regression of PAC Overall Score on CPE (H1) yields a highly significant model: $F(1, 119) = 80.580$, $p < .001$, $R^2 = 0.404$, Adj. $R^2 = 0.399$. The standardised beta coefficient for PAC is $\beta = 0.550$ ($p < .001$), indicating that every one standard deviation increase in a seller's pricing analytics capability is associated with a 0.55 standard deviation increase in competitive pricing effectiveness. PAC explains 40.4% of total CPE variance — a large effect size by social science standards. H_{01} is firmly rejected; H1 is supported.

The multiple OLS regression simultaneously entering all three PAC sub-dimensions confirms a significant combined model: $F(3, 117) = 30.54$, $p < .001$, $R^2 = 0.439$, Adj. $R^2 = 0.423$. PAC-HUMAN emerges as the strongest independent predictor ($\beta = 0.393$, $p < .001$), confirming H3. PAC-TECH achieves marginal significance ($\beta = 0.184$, $p = .050$), supporting H2 at the conventional threshold. PAC-MGMT does not achieve independent significance in the presence of the other two dimensions ($\beta = 0.071$, $p = .071$), leading to non-rejection of H_{04}; H4 is not supported in the multivariate model. This finding suggests that the management process dimension's effect on CPE is largely mediated through — or shared with — the technology and human dimensions rather than operating independently.

Implications

The findings carry significant implications for multiple stakeholder groups. For third-party sellers, the central implication is straightforward: investing in pricing analytics capability — and specifically in the human skill to use and act on analytics tools — delivers measurable competitive pricing advantages. The finding that PAC-HUMAN is the strongest predictor suggests that tool access alone (PAC-TECH) is insufficient; what differentiates high-CPE sellers is the analytical literacy and decision-making confidence to convert data into competitive pricing actions. Sellers should therefore prioritise not merely acquiring repricing tools but building the internal skill to interpret platform dashboards, understand Buy Box algorithm dynamics, and respond to competitor price movements with evidence-based decisions.

For platform providers such as Amazon India and Flipkart, the findings signal an opportunity to develop more accessible seller analytics interfaces and lower-cost analytics offerings targeted at the MSME segment. The lowest-scoring item in the entire instrument — PAC-T1 (access to best-in-class analytics systems, M = 2.860) — represents a structural access gap that platforms are uniquely positioned to address through seller tools, training programmes, and data sharing initiatives. For policymakers and industry bodies such as NASSCOM and the MSME Ministry, the findings reinforce the case for digital capability development programmes specifically targeting pricing analytics literacy among the estimated 4–5 million active e-commerce MSME sellers in India.

DISCUSSION AND CONCLUSION

This study provides the first empirical validation of a multi-dimensional PAC-CPE relationship in the Indian e-commerce context. The findings are both statistically robust and theoretically coherent. PAC explains 40.4% of CPE variance in the simple model — a large effect that confirms pricing analytics capability is not merely a supporting operational tool but a central strategic determinant of competitive pricing outcomes among Indian marketplace sellers.

The theoretical alignment is precise. Dynamic Capabilities Theory (Teece et al., 1997) predicted that firms operating in turbulent environments would achieve competitive advantage through sensing, seizing, and reconfiguring capabilities — capabilities that map directly onto PAC-MGMT, PAC-TECH, and PAC-HUMAN respectively. The empirical finding that PAC positively and significantly predicts CPE validates this mapping. The Resource-Based View (Barney, 1991) predicted that proprietary analytics resources satisfying VRIN criteria would generate sustained competitive advantage — the large R^2 effect (0.404) and the concentration of high PAC scores among larger sellers are consistent with this prediction. The Technology Acceptance Model (Davis, 1989) predicted that perceived usefulness and ease of use would determine analytics tool adoption — the emergence of PAC-HUMAN as the strongest sub-dimension predictor confirms that human perceptions and analytical skill are the dominant determinant of how effectively sellers translate analytics access into competitive pricing outcomes.

A practically critical finding is that PAC-MGMT does not achieve independent significance in the multivariate model despite being significantly correlated with CPE in bivariate analysis ($r = 0.512$, $p < .001$). This suppression effect suggests that management process — the discipline of regular competitor monitoring, dashboard review, and data-driven decision routines — operates primarily through its association with the human skill and technology dimensions rather than as an independent direct driver. Sellers who have strong management pricing processes tend also to have higher human skill and better technology access; it is the latter two that generate the direct CPE effect. This finding has a clear practical implication: management process investment without corresponding human skill development and tool access is unlikely to yield CPE improvement.

The borderline CPE scale reliability ($\alpha = 0.696$) represents the study's primary methodological limitation and calls for caution in interpreting the magnitude of CPE findings. Future research should develop a more psychometrically robust CPE scale incorporating additional indicators such as actual Buy Box win rate percentages, verified conversion rate data, and independent margin calculations. The cross-sectional design prevents causal inference beyond the statistical associations demonstrated here; longitudinal designs tracking PAC development and CPE outcomes across multiple selling seasons would strengthen causal claims. The purposive sampling method limits generalisability; a probability sample from a complete registry of registered e-commerce sellers would enable stronger external validity. Despite these limitations, the study makes a substantive contribution as the first empirical investigation of the PAC-CPE relationship among Indian e-commerce MSME sellers.

FUTURE SCOPE FOR RESEARCH

Several directions emerge for extending this work. First, longitudinal designs are needed to track how PAC develops over time and whether PAC improvements translate into lagged CPE gains across multiple selling seasons — including the festive sale periods that account for a disproportionate share of annual e-commerce GMV in India. Second, the moderation hypotheses — specifically whether seller size, product category, and platform type condition the PAC-CPE relationship — warrant dedicated empirical attention with larger samples enabling reliable sub-group analyses; the present sample of 121 respondents was insufficient for reliable moderation testing. Third, a more comprehensive CPE instrument incorporating objective platform data (actual Buy Box win rate records, verified conversion metrics) alongside perceptual self-report items would address the borderline reliability limitation documented here. Fourth, qualitative complementation through interviews with high-PAC sellers would shed light on the specific management routines, team structures, and tool configurations that translate PAC investment into CPE outcomes. Fifth, comparative studies across different national e-commerce contexts — particularly other high-growth emerging markets such as Indonesia, Brazil, and Nigeria — would establish whether the PAC-CPE relationship documented here generalises beyond the Indian marketplace or is moderated by country-level digital infrastructure and MSME development factors.

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Table 1: Descriptive Statistics — PAC Item-Level Scores (N = 121)

Item	Statement	Mean	SD	Min	Max
PAC-T1	I have access to the best available pricing analytics systems	2.86	0.99	1.0	5.0
PAC-T2	I use software tools connecting pricing data across platforms	3.12	1.04	1.0	5.0
PAC-T3	My pricing tools allow rapid insight sharing across my business	3.30	1.02	1.0	5.0
PAC-T4	My analytics tools handle large competitor and sales data volumes	3.43	0.98	1.0	5.0
PAC-H1	I find pricing analytics tools useful for better pricing decisions	3.02	1.40	1.0	5.0
PAC-H2	I interpret pricing data and translate it into concrete actions	3.35	1.08	1.0	5.0
PAC-H3	I actively update my knowledge of pricing analytics methods	3.41	1.01	1.0	5.0
PAC-H4	I can use pricing analytics tools easily without difficulty	3.55	1.00	1.0	5.0
PAC-M1	I regularly scan and monitor competitor pricing data	3.03	1.12	1.0	5.0
PAC-M2	I use historical sales data to forecast demand before pricing	3.42	1.05	1.0	5.0
PAC-M3	When competitor prices change I respond within 24 hours	3.44	1.08	1.0	5.0
PAC-M4	I regularly review pricing performance on analytics dashboards	3.66	1.01	1.0	5.0
PAC-M5	My pricing decisions are primarily data-driven rather than intuitive	3.48	1.03	1.0	5.0
PAC-M6	I understand how price changes affect demand in my product category	3.48	0.99	1.0	5.0

Note: All items scored on five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). N = 121.

Table 2: Scale Reliability — Cronbach's Alpha Results (N = 121)

Construct / Scale	Items	Cronbach's α	Interpretation
PAC-TECH (Technology)	4	0.759	Acceptable (≥ 0.70)
PAC-HUMAN (Human Skill)	4	0.795	Acceptable (≥ 0.70)
PAC-MGMT (Management)	6	0.816	Good (≥ 0.80)
PAC Overall Scale (14 items)	14	0.911	Excellent (≥ 0.90)
CPE Composite Scale (4 items)	4	0.696	Borderline — noted as limitation

Note: Threshold: α ≥ 0.70 acceptable; α ≥ 0.80 good; α ≥ 0.90 excellent (Hair et al., 2010).

Table 3: Pearson Correlation Matrix — PAC Dimensions, Overall PAC & CPE (N = 121)

Variable	PAC-TECH	PAC-HUMAN	PAC-MGMT	PAC Overall	CPE
PAC-TECH	1.000	—	—	—	—
PAC-HUMAN	0.821***	1.000	—	—	—
PAC-MGMT	0.686***	0.773***	1.000	—	—
PAC Overall Score	0.912***	0.947***	0.898***	1.000	—
CPE Score	0.571***	0.641***	0.512***	0.635***	1.000

*Note: *** p < .001 (two-tailed). Lower triangular matrix shown. All PAC sub-dimension inter-correlations are significant, indicating convergent validity of the overall PAC scale.*

Table 4: Summary of OLS Regression Results — PAC → CPE

Hypothesis	DV	R	R^2	Adj. R^2	Sig.	Decision
H1 — PAC Overall → CPE	CPE	0.635	0.404	0.399	< .001	**H_{01} Rejected — Supported *** **
H2 — PAC-TECH → CPE	CPE	0.571	—	—	0.050	**H_{02} Rejected — Supported * **
H3 — PAC-HUMAN → CPE	CPE	0.641	—	—	< .001	**H_{03} Rejected — Supported *** **
H4 — PAC-MGMT → CPE	CPE	0.512	—	—	0.071	H_{04} Not Rejected — Not Supported
H2–H4 Combined Model	CPE	0.662	0.439	0.423	< .001	Model Significant ***

*Note: *** p < .001, * p = .050 (borderline). All predictors z-score standardised. N = 121. DV = CPE Composite Score.*