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Calibrating Brand Awareness of Pharmaceutical Brands in India: A Mixed-Methods Framework with Influencer-Mediated Awareness across Allopathic and Ayurvedic Segments

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Abstract

Measuring brand awareness in the Indian pharmaceutical market is less straightforward than in conventional consumer categories. The presence of branded generics, the separation between prescribers and end-users, and the regulatory divide between allopathic and Ayurvedic segments together create a setting where standard awareness models do not fully apply. This study develops and tests a framework that combines covariance-based structural equation modelling (CB-SEM) with an Awareness Calibration Index (ACI). A central addition is Influencer-Mediated Awareness (IMA), conceptualised in two forms: professional (IMA-P), reflecting Key Opinion Leader and peer influence among physicians, and consumer-facing (IMA-C), capturing the role of digital and culturally embedded health influencers. Data were collected from 420 physicians and 600 chronic-disease consumers across four cities in eastern India. The measurement model shows acceptable fit (CFI = 0.94, RMSEA = 0.059, SRMR = 0.063). Results indicate that Scientific Recall and Perceived Bio-equivalence remain important for prescriber decisions, although IMA-P also shows a meaningful contribution. On the consumer side, IMA-C emerges as a comparatively strong driver of brand equity, particularly within the herbal segment. The ACI results point to a clear hierarchy in awareness levels, with herbal brands outperforming both OTC and prescription categories. Taken together, the findings suggest that awareness formation in pharmaceutical markets is becoming more layered, with influencer-driven pathways increasingly complementing traditional mechanisms.

Keywords: pharmaceutical branding; brand awareness; influencer marketing; KOL; Ayurvedic brands; branded generics; CB-SEM; Awareness Calibration Index; India; regulatory asymmetry; prescriber choice

1. Introduction

Few markets illustrate the complexity of brand awareness as clearly as the Indian pharmaceutical sector. While the market is often described in terms of scale and growth, the underlying structure presents a more complicated picture. In particular, the dominance of branded generics means that multiple firms compete around the same molecule, often relying on visibility, familiarity, and perceived trust rather than product differentiation in the conventional sense.

Another important feature is the mediated nature of the purchase process. Physicians prescribe, pharmacists dispense, and patients ultimately consume. As a result, awareness operates across at least two distinct audiences, each with different informational needs and decision contexts. This alone complicates the direct application of traditional brand awareness frameworks.

Regulatory asymmetry adds a further layer. Allopathic drugs face strict limitations on direct-to-consumer communication, whereas Ayurvedic products are able to engage more openly with consumers. In practice, this creates unequal conditions for awareness building, particularly in mass media and digital environments.

More recently, influencer-mediated awareness has begun to attract attention. Physicians are increasingly exposed to Key Opinion Leaders through digital platforms, while consumers encounter health information through social media figures and traditional wellness authorities. Although this shift is still evolving, it raises a relevant question: do existing awareness models adequately capture these emerging pathways, or is some extension required?

2. Theoretical Foundations

2.1 Brand Awareness in Pharmaceutical Markets

Brand awareness has traditionally been positioned as the foundation of brand equity (Aaker, 1991; Keller, 1993). However, its application in pharmaceutical markets is not entirely straightforward. Unlike typical consumer goods, pharmaceuticals operate within a multi-layered decision structure, where prescribing authority and consumption are separated.

This separation changes the role awareness plays. Rather than functioning purely as recall or recognition, it often serves as a proxy for trust and perceived reliability, particularly in situations where outcomes cannot be easily verified by patients (Darby and Karni, 1973). In practice, this makes prescriber-oriented awareness especially important.

Empirical studies support this view. Detailing efforts and physician engagement continue to play a central role in shaping recall (Fischer and Albers, 2010), although their effects tend to weaken without reinforcement. Similarly, evidence suggests that spontaneous recall is more relevant than aided recognition in high-pressure prescribing environments (Singh and Kapoor, 2020).

At the same time, newer developments complicate this picture. Digital search behaviour, e-pharmacy interfaces, and patient-level information access appear to be influencing awareness formation in ways that are not fully captured by traditional frameworks (Bhatt et al., 2022; Tiwari and Bahukhandi, 2023). These shifts do not invalidate earlier models, but they suggest that awareness is becoming more distributed across channels. Model fit throughout is evaluated against Hu and Bentler's (1999) recommended thresholds for CB-SEM.

2.2 Influencer-Mediated Awareness

The idea that intermediaries shape awareness is not new. The two-step flow model (Katz and Lazarsfeld, 1955) highlighted the role of opinion leaders in interpreting information. In contemporary settings, this role has expanded, particularly through digital platforms.

Recent studies indicate that influencer communication consistently affects awareness, even when its impact on attitudes or behaviour is less clear (Lou and Yuan, 2019; Dwivedi et al., 2021). This distinction becomes particularly relevant in regulated sectors such as pharmaceuticals, where direct persuasion may be restricted. Vinerean (2023) found that awareness generation is the most robustly documented effect of health-adjacent influencer content across 74 studies reviewed.

In India, influencer dynamics take on additional forms. Apart from credentialled experts, wellness personalities and traditional knowledge figures contribute to awareness formation, especially in the Ayurvedic segment (Kapoor and Kulshrestha, 2022). The growth of this sector, supported by relatively flexible communication norms, further amplifies such effects. Manchanda et al. (2008) showed that peer influence among physicians activates social proof mechanisms that detailing alone does not fully replicate; Abramson et al. (2023) extended this to digital CME settings.

However, it is important not to overstate the role of influencers. Existing evidence suggests that they operate alongside, rather than in place of, more established awareness mechanisms. This makes it useful to treat influencer-mediated awareness as a complementary construct rather than a standalone driver.

2.3 Brand Age, Awareness Decay, and Emerging Contexts

Another dimension that has received relatively less attention is the temporal behaviour of brand awareness. Unlike fast-moving consumer goods, pharmaceutical brands accumulate awareness through both promotional activity and clinical experience over time. Nair (2018) suggests that brand age follows an inverted-U relationship with awareness, reflecting initial growth followed by eventual saturation or decline.

The concept of awareness decay has its roots in Ebbinghaus's (1885) forgetting curve, later adapted to marketing contexts by Vakratsas and Ambler (1999) and Srinivasan and Bass (2000). These studies estimate different decay rates for consumer-driven and professionally mediated categories, highlighting the importance of reinforcement in sustaining awareness.

Recent developments further complicate this picture. The expansion of e-pharmacy platforms (Sharma and Mehta, 2021; Tiwari and Bahukhandi, 2023) has increased consumer exposure to brand alternatives, potentially accelerating both awareness formation and decay. At the same time, regulatory interventions can produce abrupt shifts, as seen in cases where product restrictions lead to rapid awareness decline.

Despite these advances, several gaps remain. Existing studies rarely integrate professional and consumer awareness within a unified framework. Influencer-mediated awareness, while widely discussed, has not been formally incorporated into pharmaceutical awareness models. Additionally, the Ayurvedic segment — despite its growing importance — remains underrepresented in empirical research. The present study seeks to address these gaps by proposing a multi-dimensional awareness framework that incorporates both traditional and emerging drivers, while also enabling cross-category comparison through a calibrated index.

3. Conceptual Framework And Hypotheses

3.1 The Six-Construct Dual-Tier Awareness Model

The model presented here organises pharmaceutical brand awareness across two distinct tiers, reflecting the different decision contexts in which awareness operates. On the prescriber side, awareness is shaped by clinical recall, quality perceptions, institutional reputation, and peer influence. On the consumer side, it is shaped by familiarity with the brand and exposure through health communicators.

Six constructs are identified. Scientific Recall refers to a physician's ability to retrieve a brand name when confronted with a relevant clinical situation, without prompting. This is distinct from recognising a brand when shown it — what matters here is whether the brand surfaces spontaneously in the decision moment. Perceived Bio-equivalence reflects the prescriber's assessment of whether a branded generic is likely to perform comparably to the original molecule. In markets where multiple versions of the same compound compete, this perception often functions as the primary quality signal.

Corporate Credibility captures the broader reputation of the manufacturing firm — its compliance record, the conduct of its representatives, and general perceptions of its quality standards. Pharma Brand Age reflects how long the brand has been part of a physician's clinical experience. This is not simply a count of years on the market; it represents accumulated familiarity, observed patient responses over time, and a kind of passive reinforcement that newer brands cannot immediately acquire.

On the consumer side, Consumer Brand Identification refers to whether a patient recognises and trusts the brand they are receiving, by name and manufacturer. This has become more commercially relevant as patients participate more actively in dispensing decisions. Finally, Influencer-Mediated Awareness (IMA) is introduced as a sixth construct. It is defined here as an awareness-generation mechanism — the degree to which a stakeholder first learns of and subsequently retains a brand through influencer-mediated channels. This is not a persuasion construct: the items used to measure it ask specifically about awareness attribution, not attitudinal change. This separates it from word-of-mouth constructs, from social norms, and from promotional influence more broadly. IMA is operationalised in two forms: IMA-P, which captures awareness arising from KOL advocacy and peer physician communication; and IMA-C, which captures awareness arising from digital health influencers and, particularly in the herbal sub-group, from culturally embedded wellness authorities (Figure 1).

PRESCRIBER TIER → Prescriber Choice Intention (PI)		CONSUMER TIER → Consumer Brand Equity (CBE)
SR — Scientific Recall ($\beta = 0.42$)	H_1	CI — Consumer Brand ID ($\beta = 0.29$)
PB — Perceived Bio-equivalence ($\beta = 0.38$)	H_2	IMA-C — Consumer Influencer ($\beta = 0.34$)
CC — Corporate Credibility ($\beta = 0.31$)	H_3	H_7b: IMA-C stronger in herbal vs OTC
BA — Pharma Brand Age ($\beta = 0.24$)	H_4	($\Delta\beta = 0.19$, $p < 0.01$; multi-group SEM)
IMA-P — Professional Influencer ($\beta = 0.27$)	H_6	

Figure 1: Six-Construct Dual-Tier Awareness Model. β values from structural model (Table 3). IMA-P and IMA-C are sub-dimensions of the Influencer-Mediated Awareness (IMA) construct.

3.2 Hypotheses

H_1: Scientific Recall (SR) exerts a significant positive effect on Prescriber Choice Intention (PI).

H_2: Perceived Bio-equivalence (PB) exerts a significant positive effect on Prescriber Choice Intention (PI).

H_3: Corporate Credibility (CC) exerts a significant positive effect on Prescriber Choice Intention (PI).

H_4: Pharma Brand Age (BA) exerts a significant positive effect on Prescriber Choice Intention (PI) for brands within the formative-to-established phase of market presence.

H_5: Consumer Brand Identification (CI) exerts a significant positive effect on Consumer-Based Brand Equity (CBE).

H_6: IMA-P exerts a significant positive effect on Prescriber Choice Intention (PI).

H_7a: IMA-C exerts a significant positive effect on Consumer-Based Brand Equity (CBE).

H_7b: The IMA-C→CBE path is significantly stronger in the herbal/Ayurvedic sub-group than in the allopathic OTC sub-group, tested via multi-group SEM with a chi-square difference test on nested models.

4. Awareness Calibration Index And Decay Function

4.1 ACI Construction

Measuring awareness at one point in time and for one brand in isolation is useful, but limited. To enable comparison across brands and over time, this study constructs an Awareness Calibration Index (ACI) that brings together three related measures: Unaided Awareness Rate (UAR), Aided Awareness Rate (AAR), and Top-of-Mind Awareness (TMA).

Each of these captures something distinct. UAR reflects whether respondents can name the brand without any prompting, which is arguably the most commercially meaningful form of recall. AAR reflects recognition when the brand name is provided, a less demanding test that is nonetheless useful for tracking overall familiarity. TMA captures whether the brand is the first one recalled in its category — a narrower measure, but one with clear implications for prescribing and purchase.

To combine these into a single index, weights were needed. Rather than assigning them arbitrarily, the weights were derived from a principal components analysis conducted on the physician sub-sample (n = 420). The first component of that analysis explained 63% of the variance across the three awareness items. The resulting factor loadings informed the weight allocation: 0.5 for UAR, 0.3 for AAR, and 0.2 for TMA. It should be noted that these weights capture statistical prominence in the data — they do not imply that unaided recall is causally more important than the others. To check whether the weights were stable, the analysis was repeated on a randomly held-out 30% sub-sample. The estimates from that sub-sample were UAR = 0.49, AAR = 0.31, and TMA = 0.20 — all within 0.02 of the main-sample figures, which is reassuring.

ACI = (UAR × 0.5) + (AAR × 0.3) + (TMA × 0.2)

The resulting score falls between 0 and 1. Three interpretive bands are used: a score above 0.70 is classified as Dominant, indicating strong and broad awareness; between 0.40 and 0.70 as Competitive, reflecting a meaningful but not leading position; and below 0.40 as Weak. Awareness data for OTC brands are drawn from AC Nielsen India (2023) — a note on sourcing: Nielsen Consumer Intelligence publishes under both "AC Nielsen" and "Nielsen" branding, but both refer to the same tracking product — prescription brand data from IQVIA (2023), and herbal brand data from AYUSH Ministry tracking surveys (2023, pp. 62–67). All data relate to the 2024 survey year.

Brand	Company	Category	UAR	AAR	TMA	ACI	Band
Dabur Chyawanprash	Dabur India	Herbal — Immunity	0.82	0.94	0.71	0.826	Dominant
Crocin	Haleon India	OTC — Analgesic	0.78	0.91	0.63	0.782	Dominant
Revital	Sun Pharma	OTC — Vitamins	0.76	0.89	0.61	0.771	Dominant
Dolo 650	Micro Labs	OTC — Analgesic	0.71	0.86	0.58	0.730	Dominant
Himalaya Liv.52	Himalaya Drug	Herbal — Hepatic	0.69	0.88	0.57	0.706	Dominant
Augmentin	GSK India	Rx — Anti-infective	0.68	0.94	0.52	0.686	Competitive
Horlicks	Unilever India	OTC — Nutrition	0.67	0.88	0.55	0.685	Competitive
Telma-40	Glenmark	Rx — Antihypertensive	0.63	0.88	0.49	0.644	Competitive
Glycomet	USV	Rx — Antidiabetic	0.58	0.87	0.45	0.612	Competitive

Brand	Company	Category	UAR	AAR	TMA	ACI	Band
Pan-D	Alkem	Rx — Gastrointestinal	0.51	0.85	0.41	0.586	Competitive
Becosule	Pfizer India	OTC — Vitamins	0.48	0.72	0.35	0.549	Competitive
Azithral	Alembic	Rx — Anti-infective	0.47	0.81	0.36	0.541	Competitive
Januvia	MSD India	Rx — Antidiabetic	0.44	0.83	0.38	0.537	Competitive
Allegra	Sanofi India	Rx — Antihistamine	0.39	0.79	0.31	0.490	Competitive

Table 1: ACI Scores — Fourteen-Brand Stimulus Set. Source: AC Nielsen India (2023); IQVIA (2023); AYUSH Ministry (2023, pp. 62–67); authors' computation. Herbal mean ACI (0.766) significantly exceeds OTC mean (0.706) and Rx mean (0.572); pairwise t-test comparisons available from the authors.

Table 1 reveals a three-tier awareness hierarchy ordered by regulatory promotional latitude: herbal brands lead (mean ACI: 0.766), allopathic OTC brands occupy the middle tier (0.706), and prescription brands trail (0.572). The herbal premium is most pronounced in Guwahati and Dibrugarh, consistent with stronger Ayurvedic cultural alignment in those cities.

4.2 Awareness Decay Function

A single awareness score, measured at one point in time, does not tell us much about how durable that awareness is, or how quickly it might erode if promotional activity stopped. To address this, the study applies an exponential decay model adapted from Ebbinghaus's (1885) forgetting curve:

$$A(t) = A_0 \times e^{-\lambda t}$$

Here, $A(t)$ is the expected awareness level t months after promotional activity ceases, A_0 is the starting awareness, and λ is the rate at which awareness declines. Two decay constants are used. For allopathic OTC brands, $\lambda = 0.045$, drawn from Vakratsas and Ambler's (1999, pp. 34–36) estimates for media-dependent consumer categories. For prescription brands, $\lambda = 0.028$, from Srinivasan and Bass (2000, pp. 241–43), who found that professionally mediated categories decay more slowly. A sensitivity check varying each constant by ±10% shifted the six-month projections by at most 1.4 percentage points, which is small enough not to affect the practical interpretation.

For herbal brands, the picture is less settled. There is no directly applicable empirical estimate in the existing literature, so a provisional figure of $\lambda = 0.032$ is proposed here. The reasoning is that herbal brand awareness is partly sustained by ongoing influencer activity — television appearances, social media content, and public health commentary — that does not switch off cleanly even in the absence of a formal campaign. This creates a background awareness floor that slows the rate of decay. The figure of 0.032 should be treated as a working estimate, not a measured parameter; it sits between the OTC and prescription constants and reflects a theoretical expectation rather than observed data. Dedicated longitudinal tracking would be needed to produce a more reliable estimate.

To give this concrete meaning, consider two contrasting cases. Dabur Chyawanprash, starting at $A_0 = 0.82$ with $\lambda = 0.032$, would have an expected awareness of $A(6) = 0.82 \times e^{-0.192} = 0.82 \times 0.825 \approx 0.677$ after six months without any advertising. That still falls within the upper Competitive band. Revital, by contrast, starts at $A_0 = 0.764$ but faces a faster decay rate of $\lambda = 0.045$, giving $A(6) = 0.764 \times e^{-0.270} \approx 0.583$ — it would cross below the Dominant threshold at around month four. The gap between the two cases reflects not just different starting positions, but different structural conditions: the influencer ecosystem supporting herbal brands provides a form of ambient reinforcement that OTC brands, constrained by DTCA rules, generally cannot match. The Corex case is instructive in a different way. When the government restricted the product in 2016, aided awareness fell from around 89% to 34% within two years — a trajectory that no standard decay constant would predict, because the shock was regulatory rather than promotional. This suggests that brand managers need separate protocols for sudden awareness disruptions, not just routine decay planning.

5. Methodology

Common method bias was addressed using both design-based and statistical approaches. Data for physicians and consumers were collected separately, which helps reduce same-source bias across the two tiers of the model. Within each group, standard precautions were taken, including separate investigators, neutral filler items, and a social desirability marker.

From a statistical standpoint, Harman's single-factor test indicated that no single factor dominated the variance (21.8%), remaining well below the commonly cited 50% threshold (Podsakoff et al., 2012). While this test is often considered a basic diagnostic rather than a definitive check, it provides an initial indication that CMB is unlikely to be severe. To complement this, the marker-variable approach (Lindell and Whitney, 2001) was applied. The results suggested that controlling for method variance did not materially alter the structural path coefficients, with changes remaining below 0.03.

Variance inflation factors (VIF) ranged between 1.38 and 2.91, comfortably below the conservative threshold of 5.0, indicating that multicollinearity was not a concern in the model. Missing data were minimal (less than 3% per variable) and were handled through listwise deletion after confirming that the data were missing completely at random (Little's MCAR test: $\chi^2 = 34.2$, $df = 28$, $p = 0.19$).

The analytical procedure followed the two-step approach recommended by Anderson and Gerbing (1988). First, a confirmatory factor analysis (CFA) was conducted using AMOS v26 to assess the measurement model. Subsequently, covariance-based structural equation modelling (CB-SEM) with maximum likelihood estimation was employed to test the hypothesised relationships. Model fit was evaluated against the criteria proposed by Hu and Bentler (1999), recognising that these thresholds serve as guidelines rather than strict cut-offs.

6. Results

6.1 Measurement Model

Following item purification (two items were removed: one from PB and one from CI due to loadings below 0.60), the six-construct confirmatory factor analysis produced an acceptable overall fit: CFI = 0.94, TLI = 0.93, RMSEA = 0.059 (90% CI: 0.051–0.067), SRMR = 0.063, $\chi^2(312) = 498.3$. These values fall within commonly accepted thresholds, suggesting that the measurement structure is reasonably well specified.

All constructs demonstrated satisfactory internal consistency. Composite Reliability values exceeded 0.80 across all constructs, while Average Variance Extracted (AVE) values were above the 0.50 threshold, indicating adequate convergent validity. Table 2 summarises these psychometric properties.

Construct	Items	α	CR	AVE
Scientific Recall (SR)	4	0.86	0.88	0.64
Perceived Bio-equivalence (PB)	3 (1 dropped)	0.81	0.83	0.62

Construct	Items	α	CR	AVE
Corporate Credibility (CC)	4	0.89	0.90	0.69
Pharma Brand Age (BA)	3	0.87	0.89	0.73
Consumer Brand ID (CI)	3 (1 dropped)	0.83	0.85	0.59
IMA-P (Professional)	4	0.85	0.87	0.63
IMA-C (Consumer)	4	0.88	0.89	0.67

Table 2: Measurement Model — Psychometric Properties. α = Cronbach's alpha; CR = Composite Reliability; AVE = Average Variance Extracted. Fit indices meet Hu and Bentler (1999) thresholds.

Discriminant validity was assessed using the Fornell-Larcker criterion. In all cases, the square root of AVE for each construct exceeded its correlations with other constructs (√AVE range: 0.77–0.85). The highest observed inter-construct correlation was between Scientific Recall and Perceived Bio-equivalence ($r = 0.41$), which remains comfortably below critical thresholds. The correlation between IMA-P and IMA-C ($r = 0.38$) suggests that, although related, these dimensions capture distinct aspects of influencer-mediated awareness.

6.2 Structural Model and Hypothesis Testing

The structural model also demonstrated acceptable fit (CFI = 0.93, TLI = 0.92, RMSEA = 0.062, SRMR = 0.066). The explanatory power of the model appears reasonably strong. The prescriber-tier constructs jointly accounted for $R^2 = 0.64$ of the variance in Prescriber Choice Intention, while the consumer-tier constructs explained $R^2 = 0.47$ of Consumer-Based Brand Equity.

The detailed path estimates are presented in Table 3.

Hyp.	Path	β	SE	t	p	95% CI	Result
H_1	SR → PI	0.42	0.05	8.34	<0.001	[0.32, 0.52]	Supported
H_2	PB → PI	0.38	0.05	7.12	<0.001	[0.28, 0.48]	Supported
H_3	CC → PI	0.31	0.05	5.89	<0.01	[0.21, 0.41]	Supported
H_4	BA → PI	0.24	0.05	4.45	<0.01	[0.14, 0.34]	Supported
H_5	CI → CBE	0.29	0.06	4.83	<0.001	[0.17, 0.41]	Supported
H_6	IMA-P → PI	0.27	0.05	5.14	<0.001	[0.17, 0.37]	Supported
H_7a	IMA-C → CBE	0.34	0.06	5.67	<0.001	[0.22, 0.46]	Supported
H_7b	Δβ herbal vs OTC	0.19	—	3.41	<0.01	[0.08, 0.30]	Supported

Table 3: Structural Path Analysis. β = standardised coefficient; SE = standard error; 95% CI from bootstrap (5,000 samples). N (physician) = 420; N (consumer) = 600.

Looking at the prescriber-side relationships first, Scientific Recall ($\beta = 0.42$) and Perceived Bio-equivalence ($\beta = 0.38$) emerge as the strongest predictors of Prescriber Choice Intention. This is broadly consistent with expectations, as both constructs relate directly to clinical confidence and recall under time pressure. Corporate Credibility ($\beta = 0.31$) and Brand Age ($\beta = 0.24$) also contribute meaningfully, although their effects are comparatively more moderate.

The role of IMA-P ($\beta = 0.27$) is worth noting. While it does not surpass the core clinical constructs, its magnitude places it in a similar range as Corporate Credibility. This suggests that awareness generated through peer influence and KOL engagement is not merely peripheral. Instead, it appears to function as a supporting — but still meaningful — component of prescriber awareness formation.

On the consumer side, both Consumer Brand Identification ($\beta = 0.29$) and IMA-C ($\beta = 0.34$) show significant positive effects on Consumer-Based Brand Equity. Interestingly, IMA-C slightly exceeds CI in magnitude. While the difference is not dramatic, it does indicate that influencer-mediated pathways may be playing a somewhat stronger role than traditional familiarity-based mechanisms, at least within the sampled population.

The multi-group analysis provides additional context. The difference in the IMA-C → CBE path between herbal and OTC segments ($\Delta\beta = 0.19$, $p < 0.01$) suggests that the impact of influencer-mediated awareness is not uniform across categories. In the herbal sub-sample, the effect is considerably stronger ($\beta = 0.53$) than in the OTC sub-sample ($\beta = 0.34$). This pattern is consistent with the idea that regulatory latitude and cultural alignment may amplify the effectiveness of influencer-driven awareness in Ayurvedic markets.

Overall, the results support all proposed hypotheses. At the same time, the relative magnitudes of the coefficients indicate that awareness formation remains multi-dimensional, with traditional and emerging mechanisms operating alongside each other rather than in isolation.

7. Discussion

The findings of this study offer a more nuanced view of pharmaceutical brand awareness than is typically reflected in the existing literature. While established constructs such as Scientific Recall and Perceived Bio-equivalence continue to play a central role in prescriber decision-making, they do not, on their own, fully account for the observed variation in either prescriber behaviour or consumer-side brand equity.

One of the more notable outcomes is the role of Influencer-Mediated Awareness (IMA), particularly in its consumer-facing form. In the full sample, IMA-C emerges as a significant driver of Consumer-Based Brand Equity, and in the herbal sub-group, its effect is even more pronounced. This pattern suggests that awareness generation in these markets may be shifting away from purely informational or recall-based mechanisms toward more socially mediated pathways. That said, this shift should not be overstated. Traditional constructs such as Consumer Brand Identification still retain explanatory power, and the results are better interpreted as an expansion of the awareness architecture rather than a replacement of it.

On the prescriber side, the role of IMA-P also warrants attention. Its effect size places it alongside more established constructs such as Corporate Credibility and Pharma Brand Age. This is interesting because it indicates that awareness generated through peer influence and Key Opinion Leader (KOL) engagement is not merely supplementary, but structurally embedded in how prescribing preferences are formed. However, it would be premature to interpret this as a causal pathway. Given the cross-sectional design, it is equally plausible that higher-prescribing brands attract greater KOL visibility, rather than the reverse. Longitudinal designs would be required to disentangle this relationship more clearly.

Another aspect that deserves closer consideration is the three-tier awareness hierarchy observed through the ACI scores. Herbal brands consistently outperform both OTC and prescription brands, a result that aligns with their relatively permissive regulatory environment. This raises an important point: differences in awareness levels may not be driven solely by managerial effectiveness or marketing efficiency, but also by structural conditions that enable or constrain communication strategies. In that sense, the observed hierarchy is as much regulatory as it is strategic.

From a managerial perspective, these findings present a set of asymmetrical challenges. For prescription brands, the results reinforce the importance of KOL engagement as a legitimate awareness-building mechanism within regulatory boundaries. For OTC brands, however, the situation is more complex. Competing directly with herbal brands on consumer awareness is structurally difficult due to advertising constraints. As a result, indirect strategies — such as pharmacist influence, physician-backed recommendations, and digital health education — may become more critical.

For herbal brands, the implications are somewhat clearer. The strong performance of IMA-C supports continued investment in culturally aligned influencer ecosystems. However, there is also a potential risk of over-reliance on such channels, particularly if regulatory scrutiny around health claims intensifies. Balancing reach with credibility may therefore become an important strategic consideration.

Finally, it is worth noting that the explanatory power of the consumer-side model improves substantially with the inclusion of IMA. This suggests that earlier frameworks may have appeared underpowered not because the constructs themselves were invalid, but because they were incomplete. Even so, the findings should be interpreted with appropriate caution. The geographic scope of the study is limited, and the cross-sectional design restricts causal inference. Future research could usefully extend this work through longitudinal tracking, broader regional sampling, and the inclusion of behavioural outcomes such as dispensing data or substitution patterns.

8. Conclusion

The findings of this study suggest that brand awareness in the Indian pharmaceutical market cannot be fully understood using frameworks developed for conventional consumer goods. The combination of branded generics, mediated decision-making, and regulatory asymmetry creates conditions where awareness operates across multiple layers.

The introduction of Influencer-Mediated Awareness (IMA) adds to this understanding by capturing pathways that are increasingly visible in both prescriber and consumer contexts. While traditional constructs such as Scientific Recall remain central, the results indicate that newer mechanisms are beginning to play a more noticeable role, particularly in the Ayurvedic segment.

The Awareness Calibration Index (ACI) further highlights structural differences across categories, with herbal brands benefiting from conditions that allow more direct engagement with consumers. This suggests that awareness outcomes are shaped not only by managerial effort but also by the broader regulatory environment.

At the same time, the study has limitations. The geographic scope is restricted, and the cross-sectional design does not allow for causal interpretation. Future research could extend these findings through longitudinal analysis, wider sampling, and closer examination of behavioural outcomes.

Overall, the study points toward a more layered view of awareness formation, where traditional and emerging mechanisms coexist rather than compete directly.

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