

From Brand Building to Enrolment: A Mixed-Methods Extension of the Digital Brand Building Index in Private Universities of Telangana

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ABSTRACT

Today, applicants decide mostly based on what they see online. A university's website, its social feeds, the reviews its students leave all make impressions long before any campus visit, and make them decisively. The Digital Brand Building Index provided a way for researchers to quantify that digital front end: seven dimensions, 24 items, validated on Telangana student samples with solid reliability and validity evidence (S & POGUL, 2025). What the index has yet to be shown to do is to predict anything downstream no enrolment intention, no application behaviour. This paper details the methodology for testing exactly that as a sequential explanatory mixed-methods design. In Phase 1, approximately 600 applicants for private universities in Telangana respond to the DBBI items along with brand equity, reputation and enrolment intention measures. The data is modelled using PLS-SEM with mediation through university brand equity and institutional reputation, moderation across program type and first-generation status and out-of-sample prediction is assessed through PLSpredict. Phase 2 involves interviewing survey respondents aged 18–24 at the extremes of the intention distribution about which touchpoints mattered and why, and thematically analyzing the transcripts. Integration follows the conventions of explanatory designs where statistical pathways and applicant stories are read against each other, joined and displayed. The methodology provides forecast-like diagnostics for university marketers that show not only the strength of an institution's digital brand building, but where that strength fails to convert into enrolment and why.

Keywords: Digital brand building, Higher education marketing, PLS-SEM, Sequential explanatory mixed methods, Enrolment intention, Telangana

INTRODUCTION

Not many of today's students will pick a university without seeing it on a screen first. Before any campus visit, before any call from counsellors, there are search results, Instagram reels, review sites and forwarded WhatsApp texts. In Telangana, where dozens of private universities are competing for the same pool of applicants, that digital front end has become the main battleground.

To measure this battleground, the Digital Brand Building Index was built with its seven dimensions assembled into a 24-item instrument validated on two samples of Telangana students ($n = 480$ for the EFA, $n = 512$ for the CFA) (S & POGUL, 2025). The seven dimensions are Content Quality, Social Engagement, Electronic Word of Mouth, Search Visibility, Website Experience, Paid Media Breadth, and Online Reputation. Reliability, convergent and discriminant validity and measurement invariance across gender and program type were all supported and the index performed as theory predicts: DBBI was positively related to university brand equity ($\beta = .64$, $R^2 = .42$) and institutional reputation ($\beta = .49$, $R^2 = .24$).

But a measurement instrument is not yet an explanation of behaviour. The original validation was cross-sectional, perception based, and on covariance-based factor analysis. It defines what digital brand building is; it doesn't define what it does. The authors themselves say as much, recommending longitudinal tracking,

linkage to admissions data, comparisons across contexts and qualitative input from students. We take that list as our agenda and that reduces to four questions. Do DBBI scores contribute beyond known antecedents to the explanation of enrolment intention and application behavior? Does brand equity and reputation have an effect? Does it vary by program type and first-generation versus other students? And what do the applicants themselves say about which touchpoints tipped the scales?

To answer these questions we have to change our method, not just get more data. Three moves characterize the contribution. DBBI is moved from a diagnostic construct to a predictor in a variance-based structural equation model and its out-of-sample predictive ability is tested. The survey is embedded in a sequential explanatory mixed-methods design, so the coefficients are explained through testimony rather than left to inference. And the outcomes are the enrolment behaviours that universities actually spend money to influence through marketing.

REVIEW OF LITERATURE AND HYPOTHESES

Digital marketing and student decision-making

There is broad agreement that digital activity guides students through the choice funnel. Institutions that run targeted campaigns, respond quickly to queries and post authentic content perform better at selection time, measurably better (R & Chandana, 2026). Data from surveys in tertiary education indicate high correlations—social media presence and retargeting campaigns at $r = .963$, mobile-friendly websites and apps at $r = .821$, video content at $r = .820$, and search-optimized pages at $r = .810$ (Labausa et al., 2023).

But the funnel isn't the same for everyone. Different channels earn their keep at different stages: awareness is mostly built through social media marketing, consideration happens on blogs, word of mouth and search, and websites with video content do the converting late in the process (Eum, 2025). Similar patterns are found in research on how digital marketing and university image create college interest and, through interest, final choice (Kurniawan et al., 2024), and in students' own accounts of always consulting university digital sources throughout their search (Kusumawati, 2019). Figure 1 shows the stage-mapping as a single funnel



Figure 1. Student digital decision funnel: touchpoints active at the awareness, consideration, and decision stages, terminating in enrolment intention and application behaviour.

From digital brand building to equity

The DBBI framework also views these touchpoint-level results as one coherent phenomenon rather than a bag of tricks. Digital activity accumulates into brand equity, dimension by dimension, and it is the accumulation that carries the weight (S & POGUL, 2025). The instrument structure is shown in Fig. 2. Elsewhere there is precedent for the mechanism - in UK universities the quality of social media interaction predicted recruitment performance and explained 45.4% of its variance (Rutter et al., 2016). The ultimate step, whether accumulated

digital brand perception, working through equity and reputation, transforms into enrollment behavior, has not yet been shown by any study in this line.



Figure 2. Digital Brand Building Index Structure: seven dimensions with four items each, of the higher-order construct validated in Telangana

PLS-SEM fits the prediction task

The estimator should follow the question. The parent study had a measurement-confirmation problem and covariance-based SEM was right for it. Ours is a prediction problem — a higher-order construct feeding two mediators, with applicant survey data nobody should assume are multivariate normal — and that is the standard domain of partial least squares SEM (Macha-Huamán et al., 2026; Shmueli et al., 2019). Predictive claims in PLS cannot be asserted; they must be demonstrated, which is why the protocol commits in advance to PLSpredict: case-level forecast errors on holdout samples, benchmarked against naive baselines. PLS-SEM is also no stranger to university branding research, where models of brand image, reputation, and value co-creation routinely clear the usual thresholds, α and CR above .80 and AVE above .50 (Foroudi et al., 2018).

Importance of mixed methods

Statistics answer how much; they stay quiet on why. The sequential explanatory design exists for exactly this gap — the quantitative strand runs first, the qualitative strand second, and the second exists to explain the first (Ivankova et al., 2005; Toyon, 2021). Integration is built in at two points: quantitative results dictate who gets interviewed and what they are asked, after which the two bodies of evidence are compared side by side to produce meta-inferences (McCrudden et al., 2025). The design is also one a single investigator can realistically execute, which matters for an extension project of this kind (Dawadi et al., 2021).

Hypotheses

H1: DBBI is positively associated with university brand equity.

H2: DBBI is positively associated with institutional reputation.

H3: University brand equity is positively associated with enrolment intention.

H4: Institutional reputation is positively associated with enrolment intention.

H5: University brand equity mediates the DBBI–enrolment intention relationship.

H6: Institutional reputation mediates the DBBI–enrolment intention relationship.

H7: The DBBI–enrolment intention relationship differs across student segments (program type, first-generation status).

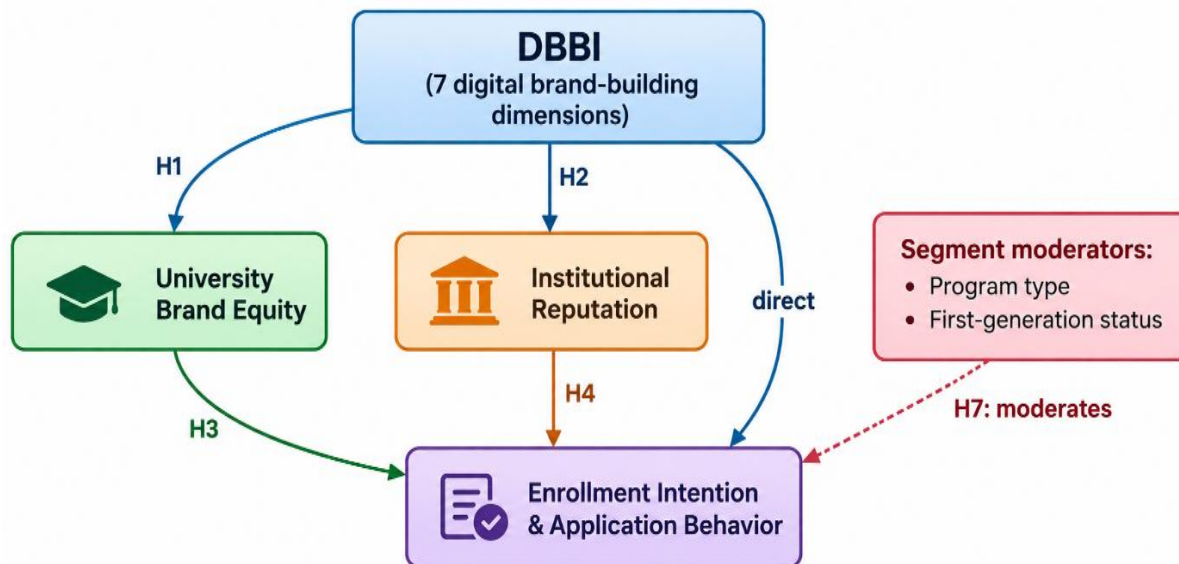


Figure 3. Conceptual model: DBBI as a distal driver of enrolment intention through university brand equity and institutional reputation, with direct and mediated paths (H1–H6) and segment moderation (H7).

METHODOLOGY

Research design

This is a sequential explanatory mixed-methods design with quantitative priority. Phase 1 is a predictive survey of applicants, analysed with PLS-SEM and PLSpredict. Phase 2 is a round of semi-structured interviews whose purpose is to explain the Phase 1 findings. The two strands are linked deliberately: Phase 1 results fix the Phase 2 sample and the interview guide, and a joint display is used to weigh the quantitative paths against the qualitative themes. For the DBBI program this is a genuine departure, since all prior evidence rested on single-method, cross-sectional scale development. Figure 4 maps the sequence.

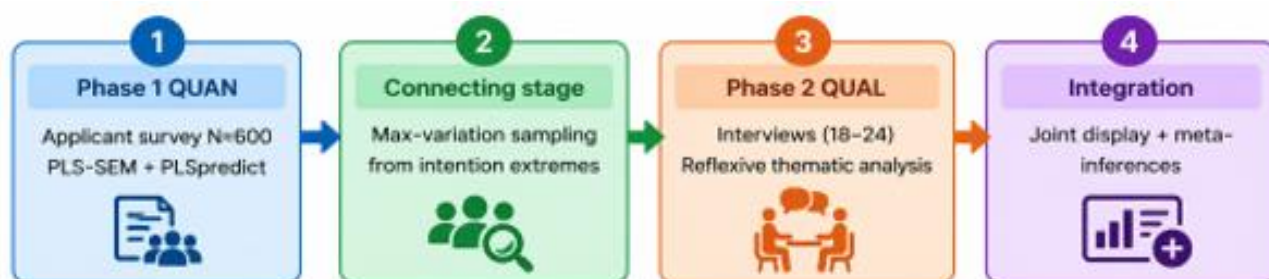


Figure 4. Design flow: Phase 1 quantitative strand, link stage, Phase 2 qualitative strand, and integration by joint-display meta-inference

Phase 1: quantitative predictive study

Population and sampling. We target applicants rather than enrolled students, and the reason is direct: the outcomes of interest are enrolment intention and application behaviour, and enrolled students are a selected group that has already settled both. The frame therefore covers students who applied to one or more private universities in Telangana in the most recent admission cycle, stratified first by institution and then by program level — the parent study's sampling logic re-aimed at the applicant pool. Following the parent samples ($n = 480$ and $n = 512$) and the PLS convention that sample size should track model complexity, we plan for about 600 completed responses.

Instruments. The questionnaire carries the validated 24-item DBBI, the university brand equity and institutional reputation measures used in the parent nomological test, a new multi-item enrolment intention

scale, a self-reported behavioural block (application submitted, application accepted, offer accepted), and demographic items covering program type and first-generation status.

Analytic strategy. Paths are estimated with 5,000 bootstrap resamples, and assessment runs in the two-stage order of Figure 5: the measurement model first, then the structural model. The measurement stage checks internal consistency (α and composite reliability $\geq .80$), convergent validity (AVE $\geq .50$), and discriminant validity through HTMT against the .85 ceiling used in the parent validation. The structural stage reports R^2 , f^2 effect sizes, Q^2 from blindfolding, and PLSpredict out-of-sample diagnostics; H5 and H6 are tested with bootstrap indirect effects and H7 with multigroup analysis, carrying the parent study's invariance logic beyond gender and program level to first-generation status.

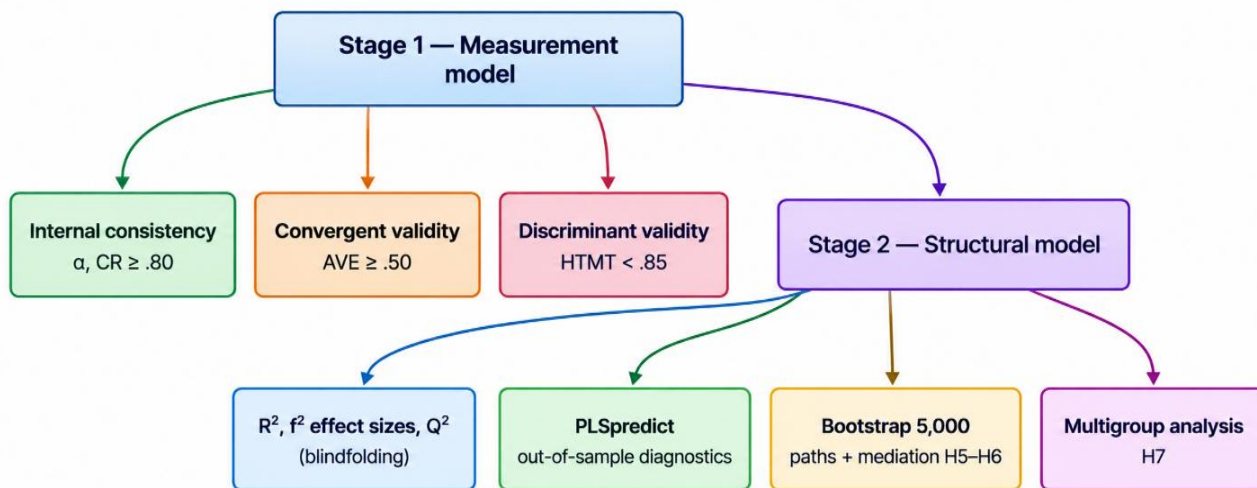


Figure 5. Two-stage PLS-SEM assessment protocol used in Phase 1.

Phase 2: qualitative explanatory study

From the Phase 1 respondents we will draw a maximum-variation purposive sample of 18–24 students, deliberately oversampling the extremes of the enrolment-intention distribution, as the connecting logic of explanatory designs prescribes. Interviews centre on how each digital touchpoint entered the decision, which ones prevailed over others, and why. The transcripts are analyzed using reflexive thematic analysis. Member checking is used to assess the interpretation against participants. This strand provides the interpretive depth lacking in the parent study's quantitative-only design.

Integration

Integration is built in, not tacked on. The results from Phase 1 detail the sampling for Phase 2 and the interview guide at the junction. At the meta-inference point, statistical paths and themes are placed side-by-side in a joint display, and convergent and discordant evidence is explicitly examined rather than smoothed over. The planned structure is shown in Figure 6.

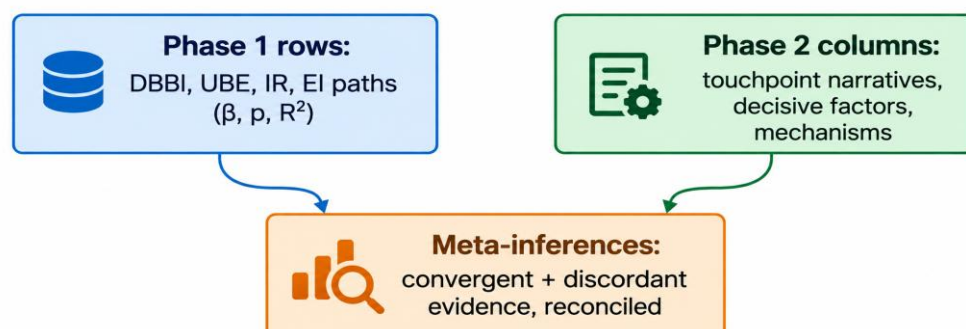


Figure 6 Planned joint display: rows are Phase 1 constructs and paths; columns contrast the statistical result with the Phase 2 themes that account for it. To be populated post data collection.

Ethics

Both phases are performed under informed consent, anonymization, and secure storage, according to institutional requirements for student data. Participants are free to withdraw at any time.

RESULTS

Measurement foundation from the parent validation

The extension is based on a proven measurement basis. In the parent study, EFA on 480 responses ($KMO = .897$; Bartlett's $\chi^2(378) = 8,109.49$, $p < .001$) yielded a seven-factor solution that accounted for 70.0% of the total variance, with loadings ranging from .75 to .85 and communalities ranging from .61 to .80. CFA on the independent sample of 512 confirmed the structure with good fit ($\chi^2/df = 2.41$; $CFI = .956$; $TLI = .949$; $RMSEA = .053$; $SRMR = .046$). The reliability and convergent validity of all dimensions were confirmed (Table 1) (S & POGUL, 2025).

Table 1. Reliability and convergent validity from the parent DBBI validation (CFA, N = 512)

Construct	Items	Cronbach's α	CR	AVE
Content Quality	4	.83	.86	.60
Social Engagement	4	.85	.87	.62
Electronic Word of Mouth	4	.86	.87	.62
Search Visibility	4	.86	.88	.63
Website Experience	4	.84	.86	.61
Paid Media Breadth	4	.83	.85	.59
Online Reputation	4	.89	.91	.70

Discriminant validity was satisfied as well: $\sqrt{AVE}$ exceeded inter-construct correlations for every pair, and HTMT ratios ranged from .272 to .412, under the .85 ceiling

The baseline we build upon

The parent study also reports the antecedent relationships operationalized by this model: DBBI to university brand equity ($\beta = .64$, $R^2 = .42$) and DBBI to institutional reputation ($\beta = .49$, $R^2 = .24$), invariant across gender and program level ($\Delta CFI \leq .010$; $\Delta RMSEA \leq .015$) (S & POGUL, 2025). For calibration, similar predictive work on university digital engagement achieved $R^2 \approx 45.4\%$ in recruitment outcomes (Rutter et al., 2016), showing that downstream prediction is achievable given a sufficiently appropriate structural specification.

Estimates in the extension period

The statistics for the extension phase – H1–H4 path coefficients, bootstrap indirect effects for H5–H6, multigroup contrasts for H7, and PLSpredict error statistics – will be generated from the Phase 1 applicant dataset described in Section 3.2. The collection is not yet complete and no coefficients are reported here. The protocol for their production is fixed in Section 3.2. The thresholds above (fit, HTMT, AVE and R^2 baselines) define the standards of judgment. The qualitative strand will be reported on once the analysis of Phase 1 has identified the interview sample.

DISCUSSIONS

This contribution is methodological rather than substantive. The parent study showed that digital touchpoints influence student perceptions. This design investigates whether they influence student behavior, using variance-based SEM and out-of-sample validation of the instrument's predictive reach in place of EFA/CFA on cross-sectional perception data. H5 and H6 explicitly state the mechanism: digital brand building accumulates equity and reputation, and these drive intention. H7 relates to evidence that digital strategies operate at different funnel stages for different audiences (Eum, 2025) and that influence is transmitted through interest (Kurniawan et al., 2024).

The qualitative phase responds to a limitation that no perception survey can escape: association without narrative. The literature's funnel-stage findings get a local, applicant-level grounding when applicants tell us which touchpoints were decisive, and why — just the student-voice direction that the DBBI authors recommended.

In practice, the design alters what marketers get from the index. The output resembles a forecast rather than percentile bands for benchmarking: what segments of applicants have a lower enrollment intention than the digital brand-building profile of their university would lead us to expect, and what touchpoints have the greatest predicted leverage.

CONCLUSION AND LIMITATIONS

DBBI provided a validated measure of digital brand building for the Telangana private universities. This study provides the methodology for the next question: does that measure predict enrollment. The sequential explanatory design combines the predictive ability of PLS-SEM with the explanatory ability of qualitative inquiry, so the research program can answer both whether digital brand building works and why. Three limitations need to be openly recognized. Phase 1 is still cross-sectional with self-reported behavioral measures, so longitudinal causality is pending cohort tracking. The extent of single state limits generalization to public institutions and other area. Applicant self-selection could overstate the apparent impact of digital sources. Future work can respond by combining DBBI scores with administrative admissions data across cycles, extending the design to other states, and adding platform-level engagement traces in addition to self-reports.

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