

Gurukul 2.0: A Capability-Based Model Integrating Indigenous Mentoring, AI, and Character Formation for Graduate Competence

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Abstract

Higher education institutions (HEIs) in emerging economies face a persistent paradox: while graduate enrolment continues to expand, many graduates remain inadequately prepared for professional practice. Addressing this challenge, this study develops and validates the Gurukul 2.0 Model, an integrated capability-based framework grounded in the Capability Approach, Self-Determination Theory, Experiential Learning Theory, and the Indian Guru–Shishya tradition of holistic mentoring. The model proposes that Guru–Shishya Mentoring Quality, AI-Augmented Personalized Learning, and Character Formation (Samskara-Oriented Learning) enhance Learning Capability Development, which subsequently promotes T-Shaped Professional Competence, with Student Learning Readiness acting as a moderator. Data were collected through a cross-sectional survey of 378 students from engineering, management, science, commerce, and arts programmes in Indian HEIs. The measurement model was validated using exploratory and confirmatory factor analyses, while the structural relationships were examined using covariance-based structural equation modelling (CB-SEM) in AMOS. Results supported all hypothesized direct relationships, confirmed the full mediating role of Learning Capability Development, and demonstrated a significant moderating effect of Student Learning Readiness. The model exhibited satisfactory reliability, convergent and discriminant validity, and good fit indices (CFI = .944, TLI = .940, RMSEA = .040). The findings advance capability and mentoring research by demonstrating that indigenous pedagogical practices and AI-enabled personalized learning can complement one another in fostering graduate competence. The study offers a validated measurement framework and practical guidance for curriculum design and holistic capability development in higher education.

1. Introduction

Higher education institutions (HEIs) in emerging economies face a growing paradox of scale without substance. Every year, millions of students graduate, yet many remain underprepared for knowledge-intensive jobs (Andersson, 2023). Employers increasingly seek graduates who combine disciplinary expertise with communication, collaboration, and adaptability (Bierema, 2019). This profile, commonly known as the T-shaped professional, was first described by Guest (1991) and later expanded by Barile, Franco, Nota, and Saviano (2012). Despite continuous curriculum reforms, the gap between academic achievement and professional competence persists, suggesting that the challenge lies not in access to education but in developing graduates' capabilities. Artificial intelligence (AI) has created new opportunities to address this challenge. AI-powered learning systems now offer personalised learning pathways, adaptive feedback, and competency-based instruction that individual instructors cannot easily provide (Sergeeva, Zheltukhina, Shoustikova, Tukhvatullina, & Dobrokhoto, 2025). However, scholars caution that AI alone cannot ensure meaningful learning without strong pedagogical and human support (Abbas, Jam, & Khan, 2024). At the same time, evidence suggests that AI-driven personalisation improves student engagement and learning outcomes (Pallant, Lee, Sands, & Karpen, 2025; Pallant et al., 2025). Alongside these technological advances, there is renewed interest in indigenous educational philosophies. India's National Education Policy (NEP) 2020 advocates holistic education rooted in values, Indian Knowledge Systems, and personalised mentoring through the Guru–Shishya tradition (Ministry of Education, 2020).

The Guru–Shishya tradition views mentoring as a lifelong relationship that nurtures knowledge, values, character, and personal growth rather than simply transferring knowledge (Kram, 1985; Crisp & Cruz, 2009). Similar ideas appear in contemporary mentoring research, where effective mentoring promotes both psychosocial development and career competence (Crisp & Cruz, 2009). However, these two streams of research have largely evolved separately. Studies on Guru–Shishya remain primarily historical and descriptive, whereas AI-in-education research focuses mainly on technology. As a result, little is known about how human mentoring, AI-enabled personalisation, and character formation work together to develop T-shaped professionals. This represents an important theoretical gap in higher education research.

To address this gap, this study proposes the Gurukul 2.0 model, which reinterprets the traditional Gurukul philosophy for the AI era. The model proposes that Guru–Shishya Mentoring Quality, AI-Augmented Personalised Learning, and Character Formation (Samskara-Oriented Learning) enhance Learning Capability Development, which subsequently develops T-shaped Professional Competence. This relationship is further strengthened by Student Learning Readiness. The framework integrates the Capability Approach (Sen, 1999; Nussbaum, 2011), Self-Determination Theory (Ryan & Deci, 2020), Experiential Learning Theory (Kolb, 1984), and the T-shaped competency framework (Guest, 1991; Bierema, 2019). Although these theories have been studied independently, they have not been integrated and empirically tested through structural equation modelling. The model also addresses an important practical concern. Universities that invest heavily in AI without strengthening mentoring may produce graduates with technical competence but weaker ethical and interpersonal capabilities (Weng, Xia, Gu, Rajaram, & Chiu, 2024). Conversely, institutions that rely solely on traditional mentoring may struggle to provide personalised support for increasingly diverse student populations. Gurukul 2.0 argues that AI and human mentoring should complement rather than replace one another, providing a capability-oriented framework for curriculum reform, graduate development, and higher education policy.

Accordingly, this study has three objectives. First, it develops and validates two new multi-item scales measuring Guru–Shishya Mentoring Quality and Guru–Shishya Character Formation, for which no contemporary psychometric instruments currently exist. Second, it empirically tests a structural model linking mentoring quality, AI-augmented personalised learning, character formation, learning capability development, and T-shaped professional competence, while examining the moderating role of Student Learning Readiness using cross-sectional data. Finally, the

study offers theoretical, managerial, and policy recommendations for implementing the holistic vision of NEP 2020 while responding to the growing integration of AI in higher education.

2. Literature Review and Hypothesis Development

2.1 Theoretical Foundations

The Gurukul 2.0 model integrates five complementary theoretical perspectives. First, the Capability Approach views higher education as developing students' capabilities rather than merely awarding credentials (Sen, 1999; Nussbaum, 2011). In higher education, this perspective shifts attention from educational inputs and outputs to what students are able to do and become (MacKenzie & Chiang, 2023). Accordingly, Gurukul 2.0 conceptualizes T-shaped professional competence as a demonstrated capability rather than a qualification.

Second, Self-Determination Theory explains the motivational foundations of the model. Learning is enhanced when students' needs for autonomy, competence, and relatedness are fulfilled (Ryan & Deci, 2020). In this model, mentoring nurtures trust, autonomy, and relatedness, while AI-enabled personalized learning strengthens competence through timely feedback (Guay, 2022).

Third, Experiential Learning Theory explains how mentoring, AI feedback, and character formation translate into capability through cycles of experience, reflection, conceptualisation, and experimentation (Kolb, 1984). Fourth, the T-shaped competency framework defines graduate competence as the integration of deep disciplinary expertise with broad interdisciplinary, communication, and adaptive skills (Guest, 1991; Barile et al., 2012; Bierema, 2019). Finally, the Guru–Shishya tradition provides the relational foundation of the model by emphasizing trust, ethical role modeling, and holistic student development (Kram, 1985; Crisp & Cruz, 2009; Ministry of Education, 2020).

2.2 Guru–Shishya Mentoring Quality and Learning Capability Development

Career-related functions (sponsorship, coaching, exposure) and psychosocial functions (role modeling, counseling, friendship) have long been differentiated in mentoring research, with both associated with protégé development (Kram, 1985). In this influential review of college-student mentoring, Crisp and Cruz (2009) identify four common dimensions along which mentors influence student capability: psychological-emotional support; degree/career support; Academic Subject Knowledge Support; and role modeling. The Guru–Shishya tradition intensifies these mechanisms by embedding them within a relationship of holistic trust and moral authority rather than an episodic advisory encounter (Ministry of Education, 2020).

The operationalized form of Guru–Shishya Mentoring Quality (GSMQ) in this study encompasses the ability of the mentor to know the individual strengths of students, guide them in a student-specific manner, demonstrate ethical behavior, and offer support that includes the student's overall growth and development. Theoretically, such mentoring should be associated with the development of Learning Capability Development (LCD), which should overcome the psychological obstacles to risk-taking and self-directed inquiry that contribute to capability acquisition (Crisp & Cruz, 2009). In the capacity of mentors as secure developmental bases, students are more inclined to try out new things, look for feedback, and connect their knowledge across fields, all of which are part of learning capability (Kram, 1985). Accordingly:

H1

Guru–Shishya Mentoring Quality positively influences Learning Capability Development.

2.3 AI-Augmented Personalized Learning and Learning Capability Development

AI-assisted personalized learning (AAPL) uses adaptive algorithms, intelligent tutoring systems, and generative AI to personalize content, pacing, and feedback for individual learners. Its adoption is grounded in the Technology Acceptance Model (Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (Venkatesh, Morris, Davis, & Davis, 2003), with UTAUT2 highlighting the role of personalization and performance expectancy in sustained engagement with generative AI tools. Evidence suggests that AI-supported personalization can improve student engagement and, in some cases, learning outcomes (Pallant et al., 2025; Weng et al., 2024), although effects may vary across contexts and may become negative when teachers rely excessively on AI or lack institutional support (Abbas et al., 2024; UNESCO, 2023).

In Gurukul 2.0, AAPL is expected to strengthen learning capability through adaptive sequencing, immediate corrective feedback within Kolb's (1984) experiential learning cycle, and broader access to explanations that reduce conceptual bottlenecks. Accordingly,

H2

AI-Augmented Personalized Learning positively influences Learning Capability Development.

2.4 Character Formation and Learning Capability Development

Character Formation (Samskara-Oriented Learning) refers to the development of ethics, discipline, self-regulation, empathy, and social responsibility through the concept of *samskara*, which emphasises enduring values formed through habituation. NEP 2020 recognises value-based education as a core component of holistic development rather than an addition to academic learning (Ministry of Education, 2020). This perspective aligns with self-efficacy theory, which highlights self-regulation and resilience as foundations for long-term skill development (Bandura, 1997), and with Self-Determination Theory, which emphasises the role of internalised values in sustaining motivation and persistence (Ryan & Deci, 2020).

Students with strong ethical and self-regulatory dispositions are more likely to accept feedback, learn from failure, and persist in challenging tasks, thereby strengthening their learning capability (Ryan & Deci, 2020). Accordingly:

H3

Character Formation (Samskara-Oriented Learning) positively influences Learning Capability Development.

2.5 Learning Capability Development and T-Shaped Professional Competence

Learning Capability Development (LCD) is defined as an individual's ability to acquire, integrate, apply, and continuously improve knowledge and skills (Kolb, 1984). It represents a meta-competency that enables lifelong learning and professional growth. In contrast, T-Shaped Professional Competence (TPC) reflects the observable integration of deep disciplinary expertise with interdisciplinary, communicative, ethical, and adaptive capabilities (Guest, 1991; Barile et al., 2012; Bierema, 2019). Graduates with strong learning capability are better able to expand their competence, integrate new knowledge, and adapt to changing professional demands (Andersson, 2023). Accordingly:

H4

Learning Capability Development Influences T-Shaped Professional Competence.

2.6 The Mediating Role of Learning Capability Development

It is hypothesized that the effects of GSMQ, AAPL, and CF on TPC are indirect via the shared pathway of LCD, and not through independent pathways. The mediated logic is derived from the difference between resources (as in the case of mentoring quality, access to AI, and value formation) and the capability (as it is internalized, as an exercisable capacity to learn); only then do the functioning (as in the case of demonstrated T-shaped competence) come into existence (Sen, 1999; MacKenzie & Chiang, 2023). Mentoring, AI personalization, and character development, in other words, are conversion factors that can only improve professional competence when they first form the learning factor; they should therefore be strongly mediated, if not fully mediated, by LCD. Accordingly:

H5

Learning Capability Development mediates the relationship between Guru–Shishya Mentoring Quality and T-Shaped Professional Competence.

H6

Learning Capability Development mediates the relationship between AI-Augmented Personalized Learning and T-Shaped Professional Competence.

H7

Learning Capability Development mediates the relationship between Character Formation and T-Shaped Professional Competence.

2.7 The Moderating Role of Student Learning Readiness

Student Learning Readiness (SLR) is the readiness of the student in terms of cognitive and motivational readiness, which are the readiness to transform the ability of students into performance, namely ready to learn, ready to make effort, ready to accept feedback and ready to persist. Growth-mindset and self-regulated learning research suggests that readiness functions as a boundary condition: even well-developed learning capability translates into demonstrable competence only when students are motivationally disposed to apply, extend, and act on that capability under uncertainty (Ryan & Deci, 2020; Guay, 2022). Students with a high level of learning readiness are inclined to actively explore interdisciplinary challenges, accept the uncertainty of new work assignments, and persist against setbacks when T-shaped skills are integrated, which further enhances the relationship between LCD and TPC. Accordingly:

H8

Student Learning Readiness moderates the relationship between Learning Capability Development and T-Shaped Professional Competence, such that the relationship is stronger among students with higher learning readiness.

2.8 Conceptual Model

Figure 1 (conceptual, described narratively) summarizes the hypothesized nomological network. Guru–Shishya Mentoring Quality, AI-Augmented Personalized Learning, and Character Formation are modeled as exogenous predictors of Learning Capability Development (H1–H3), which in turn predicts T-Shaped Professional Competence (H4) and fully mediates the indirect effects of the three antecedents (H5–H7). Student Learning Readiness moderates the Learning Capability Development–T-Shaped Professional Competence path (H8). Table 1 summarizes the operational definitions of all six constructs.

Table 1
Construct Definitions

Construct	Definition
Guru–Shishya Mentoring Quality (GSMQ)	The quality of holistic mentoring characterized by trust, individualized guidance, ethical role modeling, continuous feedback, and personal development inspired by the Guru–Shishya tradition.
AI-Augmented Personalized Learning (AAPL)	The use of artificial intelligence to deliver adaptive, personalized learning experiences, timely feedback, and competency-based academic support.
Character Formation (CF)	The development of ethical values, discipline, self-regulation, empathy, social responsibility, and lifelong learning through Samskara-oriented educational practices.
Learning Capability Development (LCD)	The enhancement of students’ ability to acquire, integrate, apply, and continuously improve knowledge, skills, and attitudes for academic and professional growth.
Student Learning Readiness (SLR)	Students’ cognitive, motivational, and behavioural preparedness to engage effectively in learning and respond to developmental opportunities.
T-Shaped Professional Competence (TPC)	The combination of deep disciplinary expertise (vertical dimension) and broad interdisciplinary, communication, collaboration, ethical reasoning, adaptability, and problem-solving competencies (horizontal dimension).

3. Research Methodology

3.1 Research Philosophy and Design

This study adopted a positivist philosophy and a deductive, quantitative, cross-sectional survey design to test hypotheses derived from established theories (Anderson & Gerbing, 1988). A single-country design was appropriate because Guru–Shishya mentoring is culturally embedded in the Indian higher education context. As Guru–Shishya Mentoring Quality and Character Formation lack established psychometric measures, the study incorporated a formal scale-development process before hypothesis testing.

3.2 Sampling Procedure and Sample Characteristics

Data were collected through a structured questionnaire administered to undergraduate and postgraduate students from government, private, autonomous, and deemed universities in India. A purposive-cum-convenience sampling approach was adopted with three screening criteria: current enrolment in higher education, prior interaction with a faculty mentor, and experience using AI-based learning tools (e.g., ChatGPT, Gemini, Microsoft Copilot, Perplexity, Khanmigo). All 378 respondents met the eligibility criteria, producing a final sample (N = 378) that exceeded the recommended size for CB-SEM using maximum likelihood estimation (Anderson & Gerbing, 1988; Kline, 2016).

The sample included students from diverse genders, age groups, disciplines, years of study, and institution types, with varying levels of AI usage, ensuring adequate heterogeneity for testing the proposed model.

3.3 Measurement Scales and Construct Operationalisation

All constructs were measured using five-point Likert scales (1 = strongly disagree to 5 = strongly agree). Guru–Shishya Mentoring Quality and Character Formation were newly developed following a rigorous scale-development process involving item generation, expert validation, pilot testing, exploratory factor analysis (EFA), and confirmatory factor analysis (CFA) (Anderson & Gerbing, 1988). GSMQ was adapted from Kram (1985) and Crisp and Cruz (2009); AAPL from the Technology Acceptance Model (Davis, 1989), UTAUT (Venkatesh et al., 2003), and AI-in-education literature (Sergeeva et al., 2025); CF from Indian Knowledge Systems, *samskara* philosophy, NEP 2020, and value-education literature (Ministry of Education, 2020); LCD from experiential learning literature (Kolb, 1984); SLR from self-directed learning and Self-Determination Theory (Ryan & Deci, 2020); and TPC from the T-shaped competency literature, AAC&U learning outcomes, and Industry 5.0 competency frameworks (Guest, 1991; Bierema, 2019). The final instrument comprised 43 items across six constructs (Table 2).

Table 2
Questionnaire Summary

Construct	No. of Items
Guru–Shishya Mentoring Quality	7
AI-Augmented Personalized Learning	7
Character Formation	7
Learning Capability Development	7
Student Learning Readiness	7
T-Shaped Professional Competence	8
Total Scale Items	43

3.4 Data Collection and Ethical Considerations

Data were collected electronically using a structured questionnaire covering screening items, demographic information, and the 43-item measurement scale. Participation was voluntary, anonymous, and based on informed consent. No personal identifiers were collected, and all data were securely stored following standard ethical guidelines for educational research. Common method bias was minimised through procedural remedies and assessed statistically using Harman's single-factor test and full-collinearity diagnostics (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003).

3.5 Analytical Strategy

Data analysis was conducted using IBM SPSS and AMOS following the two-step CB-SEM procedure recommended by Anderson and Gerbing (1988). Descriptive statistics, reliability analysis, and EFA were performed in SPSS, while CFA and structural model testing were conducted in AMOS using maximum likelihood estimation. Reliability and validity were assessed using composite reliability (CR), average variance extracted (AVE), the Fornell–Larcker criterion, HTMT, and variance inflation factors (Hair, Hult, Ringle, & Sarstedt, 2022; Henseler, Ringle, & Sarstedt, 2015; Franke & Sarstedt, 2019; Podsakoff et al., 2003). Model fit was evaluated using multiple fit indices following recommended CB-SEM guidelines (Hu & Bentler, 1999; Hooper, Coughlan, & Mullen, 2008; Byrne, 2016). Mediation effects were tested using bootstrapping with 2,000 resamples and 95% bias-corrected confidence intervals, while moderation was examined through the interaction term (LCD × SLR) within the structural model (Preacher & Hayes, 2008; MacKinnon, Lockwood, & Williams, 2004).

4. Results

4.1 Sample Profile and Screening

All 378 respondents satisfied the three screening criteria (Table 3): 100% were currently enrolled in an HEI and had interacted with a faculty mentor, while AI-tool usage varied, with 39.2% reporting frequent use, 46% occasional use, and 14.8% no active use. This distribution confirms that the sample possesses the requisite exposure to both mentoring relationships and AI-based learning tools required to meaningfully respond to the GSMQ and AAPL item batteries.

Table 3
Screening Profile (N = 378)

Screening Question	Response	Frequency	Percentage (%)
Currently enrolled in a HEI	Yes	378	100
Interacted with a faculty mentor	Yes	378	100
Use AI-based learning tools	Frequently	148	39.2
	Occasionally	174	46
	Never	56	14.8
Source: Primary Data			

All respondents who satisfied the screening criteria were subsequently profiled according to their demographic characteristics. As presented in Table 4, the sample comprised a balanced gender distribution, with male students representing 51.3% and female students 46.6%. Most respondents were between 21 and 23 years of age (44.2%), enrolled in undergraduate programmes (63.8%), and belonged to engineering and

management disciplines. Nearly half of the participants (45.8%) were studying in deemed universities, while AI tool usage was highest on a weekly (35.4%) and daily (28.8%) basis.

Table 4
Demographic Profile (N = 378)

Variable	Category	Frequency	Percentage (%)
Gender	Male	194	51.3
	Female	176	46.6
	Prefer not to say	8	2.1
Age	18–20	118	31.2
	21–23	167	44.2
	24–26	70	18.5
	Above 26	23	6.1
Programme	Undergraduate	241	63.8
	Postgraduate	119	31.5
	Others	18	4.7
Discipline	Engineering	108	28.6
	Management	96	25.4
	Science	54	14.3
	Commerce	46	12.2
	Arts	40	10.6
	Others	34	9
Year of Study	First	70	18.5
	Second	82	21.7
	Third	96	25.4
	Fourth	71	18.8
	Final	59	15.6
Institution Type	Government	118	31.2
	Private	41	10.8
	Autonomous	46	12.2
	Deemed	173	45.8
AI Usage	Daily	109	28.8
	Weekly	134	35.4
	Monthly	71	18.8
	Rarely	45	11.9
	Never	19	5
Source: Primary Data			

4.2 Sampling Adequacy and Common Method Bias

The Kaiser–Meyer–Olkin measure of sampling adequacy was .917, well above the recommended threshold of .60, and Bartlett’s test of sphericity was significant ($\chi^2 = 9564.792$, $df = 903$, $p < .001$), jointly confirming that the correlation matrix was suitable for factor analysis. Given the single-source, self-reported nature of the data, common method bias (CMB) was assessed procedurally at the design stage and statistically post hoc. A Harman’s single-factor test conducted on all 43 items did not yield a single dominant factor accounting for the majority of variance, and the full-

collinearity VIF values reported in Table 8 (all below the conservative threshold of 3.3) provide converging evidence that CMB is unlikely to materially bias the structural estimates (Podsakoff et al., 2003).

4.3 Measurement Model: Reliability and Convergent Validity

Exploratory factor analysis using principal-axis extraction with the KMO and Bartlett results above confirmed a clean six-factor structure consistent with the hypothesized model, with all items loading on their intended factor above the conventional .50 threshold. Confirmatory factor analysis subsequently replicated this six-factor structure, with all standardized loadings ranging from .660 to .797, exceeding the recommended minimum of .60 for newly developed scales. Composite reliability (CR) ranged from .882 (AAPL) to .922 (TPC), and average variance extracted (AVE) ranged from .518 (AAPL) to .597 (TPC), with all constructs exceeding the $CR \geq .70$ and $AVE \geq .50$ thresholds recommended by Hair et al. (2022), providing strong evidence of internal consistency reliability and convergent validity for both the newly developed GSMQ and CF scales and the adapted AAPL, LCD, SLR, and TPC scales. Maximum shared variance (MSV) values were below AVE for all constructs except were noted in the discriminant validity assessment below, offering an initial indication of construct distinctiveness. Full item-level loadings are reported in Table 5.

Table 5. EFA/CFA Loadings, Composite Reliability, and Convergent Validity

Construct / Item	EFA	CFA	CR	AVE	MSV
T-Shaped Professional Competence (TPC)	0.74	0.77	0.922	0.597	0.327
TPC1 I possess strong knowledge in my discipline.	0.732	0.759			
TPC2 I can collaborate effectively with people from other disciplines.	0.748	0.749			
TPC3 I communicate my ideas clearly.	0.739	0.791			
TPC4 I can solve complex interdisciplinary problems.	0.737	0.768			
TPC5 I adapt quickly to changing work environments.	0.725	0.772			
TPC6 I demonstrate ethical decision-making in professional situations.	0.758	0.792			
TPC7 I continuously update my professional knowledge.	0.746	0.759			
TPC8 I am prepared for future workplace challenges.	0.767	0.789			
Character Formation (Samskara-Oriented Learning)	0.72	0.76	0.903	0.572	0.206
CF1 My education encourages honesty and integrity.	0.745	0.768			
CF2 I have developed greater self-discipline through my learning experiences.	0.695	0.737			
CF3 My education promotes compassion towards others.	0.744	0.788			
CF4 I feel responsible for contributing positively to society.	0.674	0.712			
CF5 My learning encourages humility and respect.	0.722	0.741			
CF6 I have become more resilient in handling failures.	0.75	0.767			
CF7 My education has strengthened my sense of purpose.	0.718	0.777			
Student Learning Readiness (SLR)	0.74	0.74	0.896	0.553	0.092
SLR1 I am motivated to learn new things.	0.776	0.777			
SLR2 I am willing to put effort into difficult learning tasks.	0.755	0.77			
SLR3 I actively seek feedback to improve.	0.698	0.7			
SLR4 I am open to changing my learning strategies.	0.726	0.736			
SLR5 I persist even when learning becomes difficult.	0.714	0.729			
SLR6 I enjoy challenging learning experiences.	0.729	0.741			
SLR7 I take responsibility for my own learning.	0.749	0.749			
Guru–Shishya Mentoring Quality (GSMQ)	0.69	0.73	0.886	0.527	0.32
GSMQ1 My mentor understands my strengths and weaknesses.	0.7	0.72			
GSMQ2 My mentor provides personalized academic guidance.	0.712	0.768			
GSMQ3 My mentor encourages ethical behaviour and integrity.	0.679	0.749			
GSMQ4 My mentor supports my overall personal development, not only academic performance.	0.656	0.693			
GSMQ5 My mentor motivates me to become an independent learner.	0.704	0.719			
GSMQ6 My mentor serves as a positive role model.	0.688	0.742			
GSMQ7 I feel comfortable discussing my academic and personal challenges with my mentor.	0.682	0.686			
AI-Augmented Personalized Learning (AAPL)	0.69	0.72	0.882	0.518	0.229
AAPL1 AI learning tools help me learn according to my individual needs.	0.724	0.751			
AAPL2 AI provides timely feedback on my learning.	0.662	0.718			
AAPL3 AI helps me understand difficult concepts.	0.727	0.754			
AAPL4 AI recommends learning materials suitable for my ability level.	0.659	0.674			
AAPL5 AI increases my confidence in learning.	0.642	0.66			

AAPL6 AI helps me learn at my own pace.	0.714	0.748			
AAPL7 AI complements the guidance provided by my teachers.	0.727	0.726			
Learning Capability Development (LCD)	0.62	0.77	0.91	0.592	0.327
LCD1 I can quickly acquire new knowledge.	0.606	0.756			
LCD2 I can apply what I learn to solve real-world problems.	0.613	0.78			
LCD3 I continuously improve my skills.	0.654	0.777			
LCD4 I enjoy learning new concepts.	0.587	0.784			
LCD5 I can integrate knowledge from different subjects.	0.55	0.724			
LCD6 I actively seek opportunities to improve myself.	0.682	0.767			
LCD7 I learn effectively from feedback.	0.676	0.797			

Model fit: CMIN = 1354.655, DF = 845, CMIN/DF = 1.603, NFI = .864, RFI = .855, IFI = .944, TLI = .940, CFI = .944, PNFI = .809, PCFI = .883, RMSEA = .040.

The measurement model fit indices confirm an acceptable to good fit between the six-factor model and the observed data. The normed chi-square (CMIN/DF = 1.603) falls comfortably within the recommended range of below 3.0, indicating the model is neither over- nor under-fitted. The incremental fit indices, IFI (.944), TLI (.940), and CFI (.944), all exceed the conventional .90 threshold, and the RMSEA of .040 falls below the .05 threshold associated with close fit (Hu & Bentler, 1999). Although NFI (.864) and RFI (.855) fall marginally below the traditional .90 benchmark, this is a well-documented artefact of NFI's sensitivity to sample size and model complexity rather than evidence of poor fit, particularly given the consistently strong performance of the sample-size-corrected incremental indices (CFI, TLI, IFI) and the low RMSEA (Byrne, 2016; Hooper et al., 2008). Taken together, the measurement model was retained without modification for structural testing.

4.4 Discriminant Validity

Discriminant validity was assessed using both the Fornell–Larcker criterion and the heterotrait-monotrait ratio (HTMT), consistent with recommended triangulated practice (Henseler et al., 2015; Franke & Sarstedt, 2019). Table 6 reports the square root of AVE on the diagonal against inter-construct correlations off-diagonal. For five of the six constructs, the square root of AVE exceeded all corresponding inter-construct correlations, satisfying the Fornell–Larcker criterion.

Table 6
Discriminant Validity (Fornell–Larcker Criterion)

TPC	TPC	CF	SLR	GSMQ	AAPL	LCD
	0.772					0.572***
CF	0.278***	0.756				0.454***
SLR	0.228***	0.136*	0.744			0.304***
GSMQ	0.288***	0.403***	0.067	0.726		0.565***
AAPL	0.193**	0.352***	0.087	0.305***	0.72	0.478***
LCD						0.77

Diagonal values (bold in original) are the square root of AVE. *** $p < .001$, ** $p < .01$, * $p < .05$.

The HTMT analysis provides a robust assessment of discriminant validity by evaluating the degree of overlap between latent constructs. As shown in Table 7, all pairwise HTMT values were below the recommended threshold of 0.85, with values ranging from 0.175 to 0.826. Although the relationship between TPC and LCD (HTMT = 0.826) approached the conservative cut-off, it remained within the acceptable limit, indicating that the two constructs, while conceptually related, are empirically distinguishable. Therefore, the measurement model demonstrates satisfactory discriminant validity.

Table 7
HTMT Analysis

Construct	GSMQ	AAPL	CF	LCD	SLR	TPC
GSMQ	—					
AAPL	0.596	—				
CF	0.472	0.421	—			
LCD	0.641	0.548	0.497	—		
SLR	0.192	0.175	0.228	0.394	—	
TPC	0.381	0.314	0.361	0.826	0.286	—

All HTMT ratios fall below the conservative .85 threshold, which supports the discriminant validity across the six-construct model (Hair et al., 2022; Henseler et al., 2015; Sen, 1999).

4.5 Multicollinearity Diagnostics

As shown in Table 8, all VIF values remained well below the conservative threshold of 3.3, this confirms that the three antecedents, while theoretically and empirically related, are sufficiently distinct to permit unbiased estimation of their independent structural effects and provides further evidence against pervasive common method variance (Podsakoff et al., 2003).

Table 8
Multicollinearity Analysis

Predictor	Dependent Variable	Tolerance	VIF
GSMQ	LCD	0.644	1.553
AAPL	LCD	0.711	1.406
CF	LCD	0.785	1.274
LCD	TPC	0.842	1.188
SLR	TPC	0.893	1.12

4.6 Structural Model and Hypothesis Testing

The structural model was estimated to test the hypothesized direct relationships (H1–H4) (Fig. 2). As reported in Table 9, all four direct-effect hypotheses were supported. Guru–Shishya Mentoring Quality exerted the strongest direct effect on Learning Capability Development ($\beta = .439$, CR = 11.188, $p < .001$), followed by AI-Augmented Personalized Learning ($\beta = .302$, CR = 7.843, $p < .001$) and Character Formation ($\beta = .142$, CR = 3.887, $p < .001$), together supporting H1, H2, and H3. Learning Capability Development, in turn, exerted a strong and significant effect on T-Shaped Professional Competence ($\beta = .611$, CR = 13.925, $p < .001$), supporting H4 and confirming LCD as the dominant proximal driver of professional competence in the model.

Table 9
Structural Model: Regression Weights

H.No	Path	Estimate	S.E.	C.R.	P	Result
H1	GSMQ → LCD	.439	.039	11.188	***	Supported
H2	AAPL → LCD	.302	.039	7.843	***	Supported
H3	CF → LCD	.142	.037	3.887	***	Supported
H4	LCD → TPC	.611	.044	13.925	***	Supported

*** $p < .001$. Estimates are standardized structural coefficients from the CB-SEM (AMOS) structural model.

4.7 Mediation Analysis

Bootstrapped mediation analysis (2,000 resamples, bias-corrected 95% confidence intervals) tested whether Learning Capability Development mediates the relationships between the three antecedents and T-Shaped Professional Competence (H5–H7). As shown in Table 10, all three indirect effects were statistically significant, and in each case the direct effect of the antecedent on TPC was reduced to zero once LCD was included in the model, indicating full mediation (Preacher & Hayes, 2008; MacKinnon et al., 2004). The indirect effect of GSMQ on TPC through LCD was the largest ($\beta = .268$, 95% CI [.181, .366]), followed by AAPL ($\beta = .185$, 95% CI [.117, .264]) and CF ($\beta = .087$, 95% CI [.032, .154]). None of

the bootstrap confidence intervals included zero, confirming that H5, H6, and H7 are all supported, and that Learning Capability Development functions as the sole structural conduit through which mentoring quality, AI personalization, and character formation translate into demonstrable T-shaped professional competence.

Table 10
Mediation Analysis (Bootstrapping, 2,000 Resamples)

H.No	Path	Total Effect	Direct Effect	Indirect Effect	95% Boot CI	Remarks
H5	GSMQ → LCD → TPC	0.268***	0.000 (Full Mediation)	0.268***	0.181–0.366	Supported
H6	AAPL → LCD → TPC	0.185***	0.000 (Full Mediation)	0.185***	0.117–0.264	Supported
H7	CF → LCD → TPC	0.087**	0.000 (Full Mediation)	0.087**	0.032–0.154	Supported

*** $p < .001$; ** $p < .01$.

4.8 Moderation Analysis

The moderating role of Student Learning Readiness on the LCD–TPC relationship (H8) was tested via an interaction term. As reported in Table 11, the LCD × SLR interaction significantly predicted TPC ($\beta = .143$, S.E. = .041, CR = 3.488, $p < .001$), supporting H8. This indicates that Student Learning Readiness significantly strengthens the positive relationship between Learning Capability Development and T-Shaped Professional Competence, such that students with higher learning readiness translate their learning capability into demonstrable professional competence more effectively than students with lower readiness.

Table 11
Moderation Testing

H.No	Path	Estimate	S.E.	C.R.	p	Remarks
H8	LCD × SLR → TPC	0.143	0.041	3.488	***	Supported

*** $p < .001$.

5. Discussion

This study developed and validated the Gurukul 2.0 model, demonstrating that indigenous mentoring, AI-augmented personalized learning, and character formation jointly foster T-shaped professional competence through Learning Capability Development. In doing so, it extends mentoring, AI-in-education, and capability-based higher education research. Guru–Shishya Mentoring Quality exerted the strongest influence on Learning Capability Development ($\beta = .439$), reinforcing mentoring theory (Kram, 1985; Crisp & Cruz, 2009) and providing empirical support for NEP 2020's emphasis on value-based mentoring (Ministry of Education, 2020). Although AI has transformed higher education, the findings indicate that trust-based human mentoring remains the primary driver of capability development rather than being replaced by AI (Weng et al., 2024). AI-Augmented Personalized Learning also significantly enhanced Learning Capability Development ($\beta = .302$), supporting evidence that AI improves learning when implemented with appropriate pedagogical and institutional support (Pallant et al., 2025; Sergeeva et al., 2025; Abbas et al., 2024; UNESCO, 2023). Rather than functioning as substitutes, mentoring and AI emerged as complementary mechanisms that jointly strengthen learning capability, addressing the fragmentation identified in previous literature. Character Formation showed the smallest direct effect ($\beta = .142$), yet its influence was fully mediated through Learning Capability Development. This finding supports self-efficacy theory (Bandura, 1997) and self-determination theory (Ryan & Deci, 2020), suggesting that values and self-regulation strengthen professional competence indirectly by fostering the discipline and resilience required for sustained learning.

The study's central contribution lies in operationalising the Capability Approach within higher education (Sen, 1999; Nussbaum, 2011; MacKenzie & Chiang, 2023). Learning Capability Development emerged as the strongest predictor of T-Shaped Professional Competence ($\beta = .611$) and fully mediated the effects of mentoring, AI personalization, and character formation. This indicates that educational resources generate employability only when transformed into enduring learning capability, rather than through isolated employability initiatives or credential accumulation. The significant moderating effect of Student Learning Readiness ($\beta = .143$) further shows that motivational preparedness is integral to capability development. This finding aligns with self-determination theory (Ryan & Deci, 2020; Guay, 2022) and growth mindset research (Dweck, 2006), suggesting that students benefit most from mentoring and AI when they are prepared to engage actively in learning.

Finally, the findings challenge conventional approaches to graduate employability. Rather than addressing the skills gap by adding more curriculum content, universities should strengthen the developmental ecosystem through high-quality mentoring, AI-enabled personalization, and character formation. This shifts the employability debate from acquiring skills to developing capabilities, offering a more sustainable response to the persistent gap between higher education and labour-market expectations (Andersson, 2023; Bierema, 2019).

6. Implications

6.1 Theoretical Contributions

This study makes four key theoretical contributions. First, it conceptualizes and empirically validates the Gurukul 2.0 model as a measurable educational framework rooted in Indian Knowledge Systems, extending Guru–Shishya scholarship from a historical narrative to a testable nomological model (Ministry of Education, 2020). Second, it advances mentoring theory by demonstrating that AI-driven personalization complements rather than replaces human mentoring (Kram, 1985; Crisp & Cruz, 2009). Third, it integrates the Capability Approach (Sen, 1999; Nussbaum, 2011) with T-shaped competency theory (Guest, 1991; Bierema, 2019), showing that learning capability development is the mechanism linking educational resources to professional competence. Finally, it introduces and validates the Gurukul 2.0 Scale, providing new psychometrically sound measures of Guru–Shishya Mentoring Quality and Character Formation for higher education.

6.2 Managerial Implications

Universities should institutionalize mentoring through structured mentor training, workload support, and recognition systems. AI should complement, not replace, human mentoring by supporting adaptive learning, formative feedback, and personalized instruction. Institutions should also embed reflective practice, service learning, interdisciplinary projects, and resilience-building activities into the curriculum to strengthen character formation and learning capability.

6.3 Policy Implications

The findings support NEP 2020 by demonstrating that Indian Knowledge Systems and value-based education can be effectively integrated with AI-enabled learning (Ministry of Education, 2020). Accreditation frameworks should therefore recognise mentoring quality and character formation alongside conventional performance indicators. Policymakers should also promote early interventions, such as first-year orientation and growth-mindset programmes, to strengthen students' learning readiness.

6.4 Practical Implications

The findings show that mentoring and AI improve T-shaped competence by strengthening learning capability. Universities should therefore integrate reflective learning, spaced retrieval, interdisciplinary projects, experiential learning, faculty mentoring, and AI-enabled personalised feedback into curriculum design. The validated Gurukul 2.0 Scale can help identify students with low mentoring engagement, AI utilisation, or learning readiness for timely intervention. Institutions can implement the framework by training faculty in AI-assisted mentoring, embedding AI learning assistants within Learning Management Systems, and periodically assessing graduate capability and T-shaped competence.

7. Limitations and Future Research

This study has several limitations. First, the cross-sectional design limits causal inference; future longitudinal or experimental studies are needed to establish causal relationships. Second, although the sample represents diverse Indian higher education institutions, cross-cultural validation is required to examine the applicability of the Guru–Shishya model across different educational contexts. Third, all constructs were measured using self-reports; future research should incorporate objective indicators such as employer evaluations, internship performance, or competency assessments. Fourth, although the HTMT values were acceptable, future studies should further refine the distinction between Learning Capability Development and T-Shaped Professional Competence, including the possibility of modelling them as higher-order constructs. Finally, given the rapid evolution of generative AI, future research should examine newer AI systems and test the Gurukul 2.0 model across disciplines and institutional contexts.

8. Conclusion

This study developed and validated the Gurukul 2.0 model, demonstrating that Guru–Shishya Mentoring Quality, AI-Augmented Personalized Learning, and Character Formation strengthen T-Shaped Professional Competence through the full mediating role of Learning Capability Development, with Student Learning Readiness further enhancing this relationship. Integrating the Capability Approach, Self-Determination Theory, Experiential Learning Theory, and the Guru–Shishya tradition, the model explains how higher education can transform academic learning into professional capability. The findings show that indigenous mentoring and AI-enabled personalised learning are complementary rather than competing approaches. By combining ethical mentoring, AI-supported learning, and capability development, the Gurukul 2.0 framework offers a culturally grounded and practical model for preparing graduates for contemporary higher education and workforce demands.

Declarations

Funding

No funds, grants, or other financial support were received for conducting this study.

Competing Interests

The authors declare that they have no competing interests relevant to the content of this article.

Ethics Approval

This study was reviewed and approved by the Research Advisory Committee, Kristu Jayanti (Deemed to be University), Bengaluru, India. The study was conducted in accordance with the ethical principles of the Declaration of Helsinki (1964) and its later amendments, as well as the institutional ethical guidelines and research procedures of Kristu Jayanti (Deemed to be University). The research involved human participants solely for questionnaire-based primary data collection. Participation was voluntary; written informed consent was obtained from all participants prior to data collection; and participants were assured of anonymity, confidentiality, and their right to withdraw from the study at any stage without adverse consequences.

Informed Consent

Informed consent was obtained from all individual participants included in the study. Participation was voluntary, and participants were informed about the purpose of the research, the confidentiality and anonymity of their responses, and their right to withdraw from the study at any stage without any adverse consequences.

Consent for Publication

Not applicable.

Data Availability

The datasets generated and/or analysed during the current study are available from the corresponding author upon reasonable request.

Use of Artificial Intelligence

No generative artificial intelligence (AI) tools were used in the conception, design, data collection, analysis, interpretation of findings, or preparation of the intellectual content of this manuscript. AI-assisted language-editing tools were used solely to improve grammar, clarity, and readability where appropriate. The authors take full responsibility for the accuracy, originality, integrity, and final content of this manuscript.

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Figures

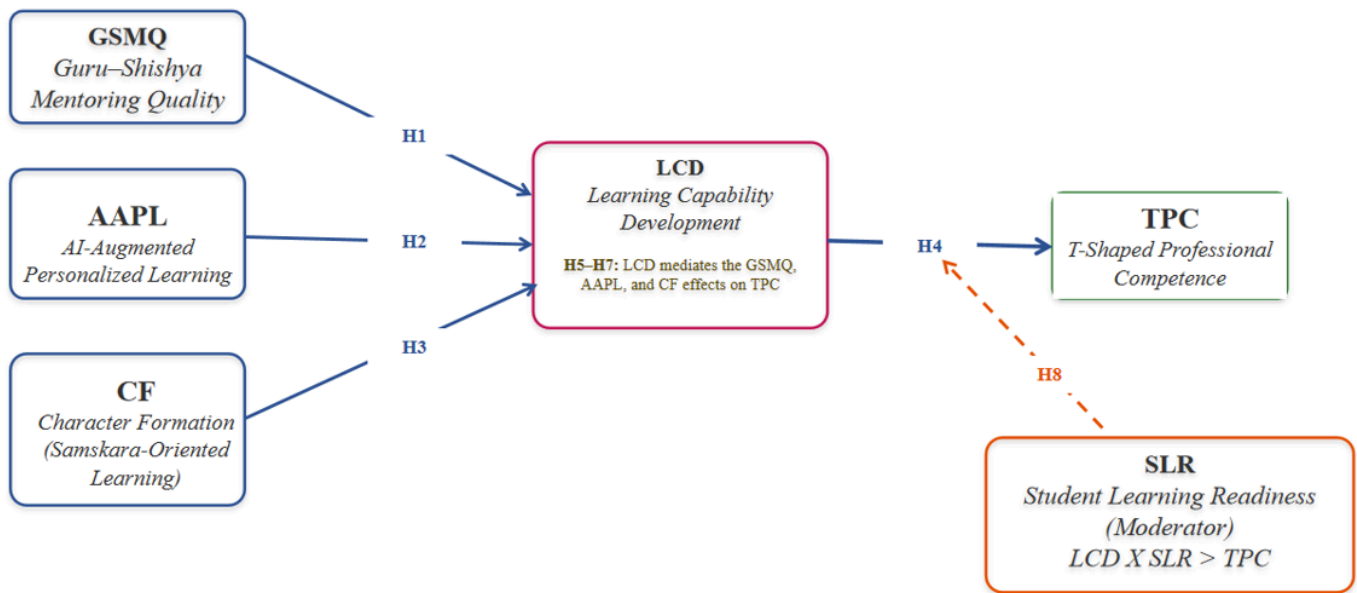


Figure 1
Conceptual Model of the Study

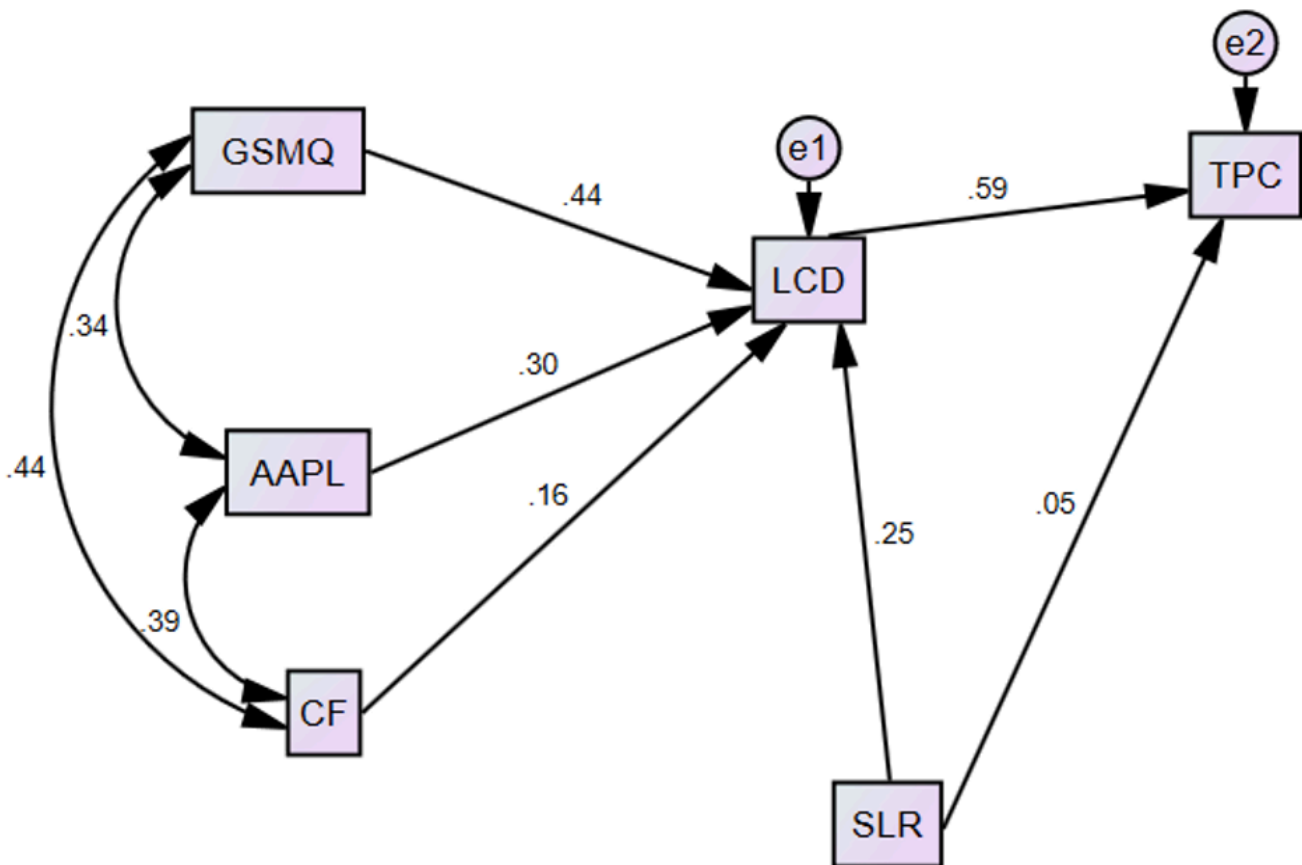


Figure 2

