

Personalized Learning Practices and Career Readiness Competency Formation among School Students: The Mediating Role of Teacher Competency and the Moderating Role of School Type

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Abstract

This research work discusses the impact of teacher competency (TC) on career readiness competencies (CRC) of higher secondary students and whether personalized learning (PL) is a mediator in this association while school type moderates it. Based on a cross-sectional survey of 500 students from government, government-aided and private schools in Tamil Nadu India the data were analyzed using PLS-SEM and multi-group analysis. The findings reveal that TC strongly and positively impacts PL and that PL Much contributes to CRC. The partial mediation of PL in the TC-CRC relationship indicates that competent teachers not only directly prepare students for their careers but also deliver career readiness indirectly by personalizing learning experiences. School type moderates the PL-CRC relationship: the strongest effect is in private schools, less in government schools and no effect in government-aided schools. These results underscore the value of upgrading teacher skills and PL interventions in making students more CRC. This research is among the preliminary school-level empirical validations of a moderated-mediation model linking TC, PL and CRC in a developing country context.

Keywords: *personalized learning; teacher competency; career readiness; education-to-work transition; multi-group analysis*

1. Introduction

1.1 Labour Markets, Workforce Readiness and the School-to-Work Gap

Automation, digitalization and the massive use of artificial intelligence, among other things, are the main factors causing rapid changes in the global labor market. As a result, workers are required to develop new skills. Many times, employers complain that the skills acquired at school and higher education are not enough since they expect further communication collaboration adaptability and problem-solving skills that nowadays workplaces need (OECD, 2021; Tomlinson, 2017; World Economic Forum, 2023). Studies have found that such a readiness disparity starts long before higher education since secondary schooling is where most critical cognitive, social and self-regulatory competencies are developed (Caballero & Walker, 2010; Jackson, 2014).

An evaluation of this matter is of great significance in India since the country is one of the largest student-serving countries. Even with all the students the country's education system caters to, the graduates' school-to-work readiness is still in question. Data from various sources show that Mainly students from rural, economically disadvantaged and government school backgrounds are lacking in the very competencies without which career success and school-to-work transitions become nearly impossible (ASER, 2023; Ministry of Education, 2020; NASSCOM, 2022). Worth noting, these difficulties have led to the questioning of the teaching methods and teacher skills that promote career readiness skills development in different learning environments

To tackle this issue, the current research put forward a comprehensive moderated-mediation model in which teacher competency affects students' career readiness competencies via personalised learning But school type is a moderator of this relationship. The paper, through investigation of this said relationships, located in Indian secondary education system, A lot extends the education-to-work transition literature and at the same time, it also

addresses the needs for more school-level, equity-focused evidence from developing countries (Allais, 2020; Holmes & Mayhew, 2015).

1.2 Personalized Learning as a Workforce Preparation Mechanism

Personalised learning - the methodical adjustment of teaching content, speed and method to the specific characteristics of each learner - has been a lot the focus of policymakers and researchers as a means of raising student achievement level and at the same time preparing learners for the ever-changing labour market (Bray & McClaskey, 2015; Pane et al. 2017). Its significance in gearing students up for their future careers is, in fact, much more than their academic performance: learner autonomy, adaptive reasoning, goal-setting and self-monitoring, developed in personalised learning settings, are the very elements of the self-directed, flexible worker engagement that modern-day employers are looking for (Super, 1990; Watts, 2006). India's National Education Policy (NEP) 2020 identifies a learner-centred, competency-based pedagogy as the principal tool for quality education and workforce readiness. Yet, classroom practices are lagging behind and this research directly addresses the structural gap between school types.

1.3 Teacher Competency as the Enabling Antecedent

Teachers serve as the proximate agents who either realise or frustrate the ambitions of educational policy. Their instructional competency encompassing content mastery, pedagogical versatility, mentoring aptitude, digital literacy and adaptive responsiveness to learner diversity directly determines the quality of learning environments available to students (Guerriero, 2017; Kunter et al., 2013; Darling-Hammond, 2000). A pedagogically competent teacher can diagnose individual learning needs, design differentiated instructional tasks, provide individualised formative feedback and cultivate classroom cultures in which students develop the agency and self-regulatory dispositions that are foundational to career readiness. Yet teacher competency has rarely been empirically modelled as an antecedent of personalised learning or as an indirect driver of career readiness outcomes through that mediated pathway a gap this study directly addresses.

1.4 Research Gaps and the Study's Contribution

Four converging gaps motivate this study. First, the education-to-work transition literature has concentrated heavily on post-secondary transitions, leaving mechanisms for forming competencies at the school level substantially underexamined (Jackson, 2014; Wheelahan, 2015; Holmes & Mayhew, 2015). Personalised learning is one of the areas where research is mainly done in Western, high-resource contexts and there is very little evidence from developing-economy secondary schools (Pane, 2020; Pokhrel & Chhetri, 2021). And there are no detailed inferential models linking pedagogical variables (i.e., teacher content knowledge and pedagogical level) to state curricula. First, no empirical studies have Indian schools with a comprehensive, stringent model linking teacher content knowledge, pedagogical levels, curriculum resource adequacy and school type as structuring moderators. Second, no such model has included these curriculum structure variables.

The central research question is the following: To what extent does teacher competency provide empirical evidence of an influence on the formation of career readiness competencies among higher secondary students in Tamil Nadu? Does personalised learning mediate this relationship and does school type moderate the mediated pathways?

1.5 Research Objectives and Hypotheses

The study pursues four research objectives:

1. To examine the relationship between teacher competency and personalized learning practices.
2. To analyse the relationship between personalized learning and career readiness competency formation.
3. To investigate the mediating role of personalized learning in the TC-CRC relationship.
4. To test whether school type moderates the TC-PL and PL-CRC pathways through multi-group analysis.

Four hypotheses are advanced on the basis of the theoretical literature reviewed in Section 2:

H1: Teacher competency is positively and significantly associated with personalized learning practices.

H2: Personalized learning practices are positively and significantly associated with career readiness competency formation.

H3: Personalized learning practices partially mediate the relationship between teacher competency and career readiness competency formation.

H4: School type (government, government-aided, private) moderates the TC-PL and PL-CRC pathways, with pathway strengths differing significantly across institutional groups.

2. Literature Review

2.1 Theoretical Foundation

This study is theoretically anchored in two complementary frameworks selected for parsimony and joint explanatory coverage. Human Capital Theory (Becker, 1964; Schultz, 1961) conceptualises education as an investment in productive capacity: teacher competency is the primary instructional production input; personalised learning is the instructional technology that converts teaching effort into individualised competency acquisition; and career readiness competencies constitute the human capital output that enables labour market participation. These predictions directly motivate H1, H2 and H3. The theory also anticipates institutional differentiation (H4): schools with greater resource endowments provide more enabling conditions for the TC-PL mechanism to operate efficiently.

Social Cognitive Theory (Bandura, 1986) offers the micro-level behavioural mechanism that realises aggregate predictions. Pedagogically competent teachers model adaptive reasoning, professional reflexivity and goal-directed problem-solving the behavioural dispositions constitutive of career readiness. In personalised learning environments, students experience greater self-efficacy, richer observational learning and more targeted competency feedback, consolidating workforce-relevant behavioural repertoires (Ryan & Deci, 2000; Zimmerman, 2002). Constructivist theory (Vygotsky, 1978) informs the pedagogical logic of personalised learning as a background framework without being elevated to primary explanatory status, preserving theoretical parsimony (Hair et al., 2019).

2.2 Career Readiness Competencies at the School Level

Career readiness competency (CRC) is conceptualised as the integrated set of dispositional, cognitive and interpersonal capacities that position individuals for productive labour market entry and progression, independent of their current employment status (Super, 1990; Savickas, 2005). The construct subsumes the transferable workforce dispositions communication, critical thinking, collaborative problem-solving, creativity, digital literacy and self-management that cut across occupational categories (Dacre Pool & Sewell, 2007; NACE, 2020; Yorke, 2006). This terminological choice responds to a genuine measurement challenge at the school stage: Grade 9-12 students have not entered employment, but CRC is explicitly developmental measurable at the school stage and predictive of later employment outcomes (Caballero & Walker, 2010; Jackson, 2014) consistent with Tomlinson's (2017) argument that workforce readiness is a developmental continuum, not a binary threshold.

2.3 Teacher Competency: Evidence and Indian Context

Based on Shulman (1987), content and pedagogical content knowledge constitute the two fundamental dimensions of teacher competency. Hattie (2009) conducted a meta-analysis of more than 800 studies and found that teacher instructional behaviours are the strongest factors at the school level contributing to student learning outcomes. The COACTIV research (Kunter et al. 2013) empirically proved that pedagogical content knowledge and motivational orientation together define instructional quality and student achievement. Teacher qualification and CPD, on top of several other classroom-level factors, are by far the most influential factors in student outcomes per Darling-Hammond (2000). In a platform similar to the European DigCompEdu (European Commission,

2021), an extremely relevant educator trait for 21st-century educators is his/her ability to relate the digital competencies to pedagogy, interculturality and communication. A lack of literature on the quality of Indian education staff highlights, *inter alia*, the differences in the teaching competencies of teachers in various types of schools (Ramachandran et al., 2021; ASER, 2023). Yet, to the best of our knowledge, no study has to date examined TC more generally as an antecedent of personalised learning and as a boundary condition of the CRC formation.

2.4 Personalized Learning: Dimensions and Evidence

Bray and McClaskey (2015) identify five core personalised learning dimensions: learner-driven goal-setting, flexible content pathways, differentiated instruction, individualised formative feedback and learner agency. Tomlinson's (2014) differentiation model acts as an additional setup in the same field. The researchers from RAND Press in the paper by Pane et al. (2017) think that personalised learning may increase student performance a lot, so it would be quite a discovery. Besides tertiary education, they also looked at the job market circumstances (Jackson & Bridgstock, 2021). Ryan and Deci (2000) argue in Self-Determination Theory that granting autonomy is a key thing in motivating a person's innate desire to learn and acquire skills. Then again, very little such evidence exists in India. Kaur (2022) points to the systemic issues in government schools, while Menon & Pillai (2023) carry out a comparison of learner-centred teaching across different schools. But neither of them performs inferential modelling or studies the effects of CRC.

2.5 School Type, Structural Inequality and CRC Formation

The body of research on the transition from education to work has come to the point where it acknowledges that institutional stratification really helps in how students are equipped for labour market participation (Allais, 2020; Holmes & Mayhew, 2015; Wheelahan, 2015). The government-aided-private school hierarchy in India is one of the major ways that reproduce socioeconomic inequalities directly leading to CRC formation (Dreze & Sen, 2013; Kumar, 2020). Smaller class sizes aside, private schools usually have better digital infrastructure; they employ more qualified teachers and all these combined give rise to more favourable conditions for personalised learning. Government schools, among other things, encounter major structural barriers to adaptive instruction (ASER, 2023; Ramachandran et al., 2021). Government-aided schools occupy an analytically important and understudied intermediate position that the MGA component specifically addresses.

2.6 Research Gap Synthesis

The literature confirms that while the theoretical foundations for the proposed model are robust, its empirical integration has not been tested in a school-level moderated-mediation framework in any developing-economy context. The present study addresses this demonstrable empirical void and responds directly to calls in this journal for school-level, equity-sensitive and developing-economy evidence in education-to-work transition scholarship.

3. Conceptual Framework

Figure 1 presents the integrated moderated-mediation model. Teacher Competency (TC) comprising pedagogical competency, digital competency, mentoring capability and adaptive instruction is the independent variable. Personalised Learning Practices (PL) comprising learner autonomy, differentiated instruction, adaptive teaching and formative feedback is the mediating variable. Career Readiness Competency (CRC) operationalised across nine dimensions from NACE (2020) and Dacre Pool and Sewell (2007) is the dependent variable. School type (government, government-aided, or private) is the categorical moderating variable tested through MGA. The framework anticipates that the TC-PL pathway will demonstrate a larger effect than the PL-CRC pathway, reflecting the logical primacy of instructional competency as the enabling antecedent. The partial mediation structure acknowledges that teacher competency shapes career readiness through both personalised instructional channels (captured by PL) and additional relational, mentoring and role-modelling channels that are not reducible to formal instructional methods.

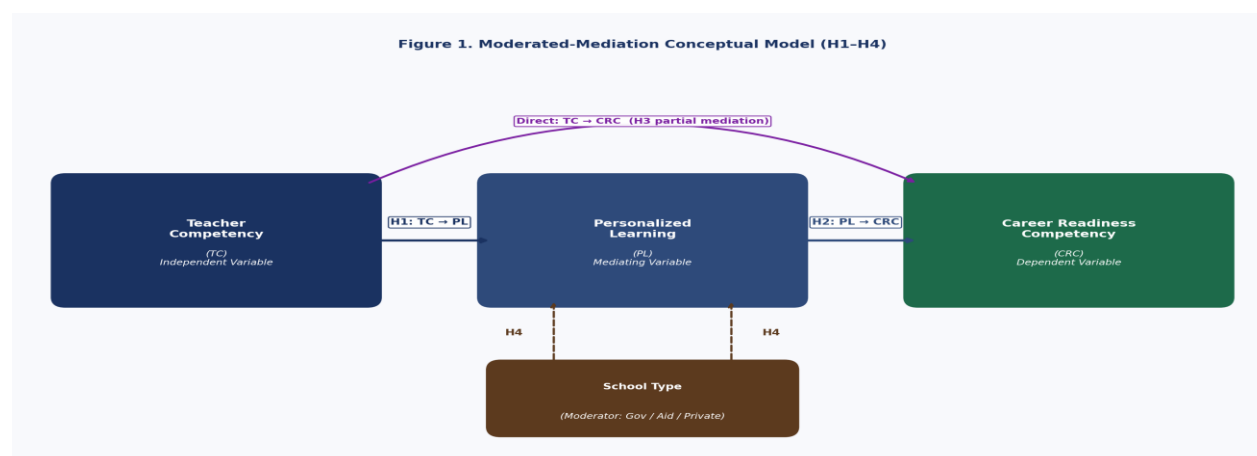


Figure 1. Moderated-Mediation Conceptual Model (H1-H4). Solid arrows indicate hypothesised direct relationships (H1, H2); the curved arrow indicates the direct TC-CRC path (partial mediation - H3); dashed arrows indicate the moderating influence of school type on both pathways (H4). TC = Teacher Competency; PL = Personalized Learning; CRC = Career Readiness Competency.

4. Research Methodology

4.1 Research Design

A quantitative, cross-sectional, explanatory research design was adopted. This design is appropriate for testing theoretically derived hypotheses about structural relationships among constructs using numeric data gathered at a single time point (Creswell & Creswell, 2018). The explanatory orientation is specifically suited to testing the moderated-mediation model in Figure 1, where the goal is to explain variance in CRC formation attributable to TC and PL and to assess how the model differs across school types. Limitations of cross-sectional design with respect to causal inference are explicitly acknowledged in Section 9.

4.2 Sampling Architecture and School Recruitment

The target population comprised higher secondary students (Grades 9-12) enrolled in Tamil Nadu State Board and CBSE-affiliated schools in Tiruppur and Coimbatore districts, Tamil Nadu, India. These districts were selected because they encompass the full range of school types, significant urban-rural variation and a diverse socioeconomic student population suited to testing school-type moderation. The sampling frame was a list of schools at the district level which was maintained by the Tamil Nadu School Education Department for the year 2023-24. At first, schools were classified into four categories (government, government-aided, private CBSE and private ICSE). Then, by using computer-generated random numbers, a sample was chosen randomly from each category.

Out of the 28 invited schools, 24 accepted to participate (school-level participation rate: 85.7%). In each participating school, one or two classes per grade level were randomly selected.

Of 562 distributed questionnaires, 500 were complete and valid for analysis (usable response rate: 88.9%). The sample satisfies all PLS-SEM adequacy criteria: a 10:1 item-to-respondent ratio ($500/24 = 20.8:1$; Hair et al., 2019); $n > 200$ minimum for mediation analysis; and adequate MGA subgroup sizes (minimum: government-aided, $n = 128$).

4.3 Instrument Development and Scale Provenance

The 24-item Likert-scale section (1 = Strongly Disagree; 5 = Strongly Agree) covers three constructs, each grounded in validated international frameworks. Table A1 in the Appendix presents the full construct-item mapping; Table 3 presents item-level statistics and factor loadings.

4.3.1 Teacher Competency (TC: 7 items, TC1-TC7)

Items were adapted from the COACTIV Teacher Competency Scale (Kunter et al., 2013), modified for student-respondent phrasing. Items covered: instructional clarity and explanation quality (Hattie, 2009); pedagogical variety and method diversification (Guerriero, 2017); adaptive support and learning need diagnosis (Darling-Hammond, 2000); critical thinking facilitation (Hattie, 2009); digital tool integration (European Commission, 2021); feedback quality and timeliness (Hattie, 2009); and mentoring beyond syllabus content (Kunter et al., 2013).

4.3.2 Personalized Learning (PL: 8 items, PL8-PL15)

Items were adapted from Bray and McClaskey's (2015) Personalised Learning Framework and Tomlinson's (2014) differentiation model, supplemented by the OECD's (2018) Student Agency Framework. Items covered: pace flexibility; learner choice; differentiated resources; individualised feedback; self-directed goal-setting; flexible assessment modalities; skill-level task adaptation; and formative comprehension checks.

4.3.3 Career Readiness Competency (CRC: 9 items, ESF16-ESF24)

Items were adapted from the NACE Career Readiness Framework (2020) and Dacre Pool and Sewell's (2007) CareerEDGE model, with additional grounding in Yorke (2006) and Jackson (2014). Items covered: communication; critical thinking; teamwork; creativity; problem-solving; digital literacy; self-management; leadership initiative; and professional ethics. All items assess student self-perception of competency development attributable to schooling, consistent with school-stage measurement approaches validated by Caballero and Walker (2010) and Jackson (2014).

4.3.4 Content Validity and Pilot Testing

All 24 items were reviewed by three education academics and two industry HR representatives for content validity and comprehensibility. Minor wording modifications followed expert review. A pilot study ($n = 45$) confirmed satisfactory internal consistency (TC: $\alpha = 0.872$; PL: $\alpha = 0.858$; CRC: $\alpha = 0.869$) and item-total correlations (all ≥ 0.45).

4.4 Justification for PLS-SEM

PLS-SEM was selected over covariance-based SEM on four methodologically grounded criteria (Hair et al., 2019; Ringle et al., 2020): (1) the study is prediction-orientated, explaining variance in CRC formation the foundational PLS-SEM selection criterion; (2) the categorical moderator (school type) is tested through MGA, for which PLS-SEM provides superior flexibility and statistical power at this sample size; (3) bias-corrected bootstrapping provides higher power for indirect effect estimation than CB-SEM delta method approaches (Preacher & Hayes, 2008); and (4) the exploratory-confirmatory nature of the mediation hypothesis aligns with PLS-SEM's predictive orientation.

4.5 Common Method Bias Assessment

Common method bias (CMB) was addressed through procedural and statistical remedies (Podsakoff et al., 2003). Procedural measures included section separation with instruction resets, an emphasis on anonymity and within-section item randomisation. 43.1% of total variance was explained by one dominant factor per Harman's single-factor test (i.e., below the 50% threshold). The marker variable method (Lindell & Whitney, 2001) verified that the changes in path coefficients were less than 0.05 after the removal of a three-item school-pride marker. All VIF values (1.76-2.81) were under the 3.3 cut-off. Therefore, the CMB does not greatly accompany the structural results.

4.6 Ethical Considerations and Data Collection

The Bharathiar University Research Ethics Committee has given an ethical clearance (Ref: BU/EDUC/2023/112). Since the respondents were children, the researchers followed these steps:

Approval from the institution: Letters of approval were obtained from the school heads and in some cases, district education officers as well.

Parental consent: Data gathering was conducted only after consenting forms were signed by parents/guardians of students who were under 18 years of age.

All participants agreed voluntarily by signing a written consent form that they fully understood the study and its requirements before giving permission to be part of it.

Participants were free to choose: they were informed in both oral and written forms that their involvement was not a prerequisite for academic performance and they were at liberty to change their decision at any time.

Federalism of data: Filled-in questionnaires were anonymous and individually sealed immediately after the class had ended.

Data protection: The research data were all kept on the password-protected university research servers and only the members of the research team had permission to access it.

Under the guidance of the main researcher, the trained field staff gathered data during the months of January to March 2024 at periods when students were outside their classrooms so that the school's timetables would not be disturbed.

5. Data Analysis and Results

5.1 Respondent Profile

Table 1 shows the demographic profile of the 500 respondents. The distribution of the research participants by gender is almost equal, as females constituted 51.0% and males 49.0% of the total number of participants. The sample consisted of students from the four grades. But most of them (55.6%) came from Grades 10-11. For MGA, Federal/CBSE (n=131) and Federal/ICSE (n=55) were combined together to make one private group (n=186). Because of this, three equal groups resulted: government (n=186), government-aided (n=128) and private (n=186).

Table 1. Respondent Profile (n = 500)

Variable	Category	n	%
Gender	Female	255	51.0%
	Male	245	49.0%
Age	13-14 years	42	8.4%
	15-16 years	211	42.2%
	17-18 years	218	43.6%
	Above 18	29	5.8%
Grade	Grade 9	101	20.2%
	Grade 10	125	25.0%
	Grade 11	153	30.6%
	Grade 12	121	24.2%

Variable	Category	n	%
School Type	Government	186	37.2%
	Government-Aided	128	25.6%
	Private/CBSE	131	26.2%
	Private/ICSE	55	11.0%
Location	Urban	200	40.0%
	Semi-Urban	161	32.2%
	Rural	139	27.8%
Stream	Science	213	42.6%
	Commerce	137	27.4%
	Arts/Humanities	105	21.0%
	Vocational	45	9.0%

5.2 Descriptive Statistics

Table 2 presents construct-level descriptive statistics; Table 3 presents item-level statistics and factor loadings for all 24 items.

Table 2. Descriptive Statistics of Study Constructs

Construct	N	Mean	SD	Skewness	Kurtosis	Min	Max
Teacher Competency (TC)	500	3.318	0.663	0.091	-0.317	1.14	5.00
Personalized Learning (PL)	500	3.232	0.624	0.007	-0.179	1.38	4.88
Career Readiness Competency (CRC)	500	3.340	0.571	0.030	-0.462	1.89	4.89

All construct means exceed the scale midpoint (3.0). PL ($M = 3.232$, $SD = 0.624$) scores lower than both TC ($M = 3.318$, $SD = 0.663$) and CRC ($M = 3.340$, $SD = 0.571$), consistent with the expectation that personalised learning implementation lags behind teacher competency as its antecedent and CRC as its downstream outcome. Skewness (0.007-0.091) and kurtosis (-0.179 to -0.462) statistics are at reasonable levels for approximate univariate normality, which justifies using PLS-SEM with typical bootstrapping (Hair et al. 2019).

Table 3. Item-Level Descriptive Statistics and Standardised Factor Loadings (All 24 Items)

Item	Statement	Mean	SD	Loading
TC1	My teacher clearly explains concepts in a way I can understand	3.286	0.915	0.754
TC2	My teacher uses a variety of teaching methods to suit different learning styles	3.322	0.881	0.782
TC3	My teacher identifies when I am struggling and provides additional support	3.310	0.869	0.768
TC4	My teacher encourages me to think critically and solve problems independently	3.302	0.874	0.759
TC5	My teacher uses digital tools and technology effectively to enhance learning	3.332	0.836	0.741
TC6	My teacher provides timely and constructive feedback on my work	3.332	0.876	0.803
TC7	My teacher acts as a mentor by guiding me beyond the classroom syllabus	3.342	0.841	0.812
PL8	My teacher adjusts the pace of teaching based on individual student readiness	3.200	0.854	0.764
PL9	I am given opportunities to choose topics or projects that interest me	3.234	0.837	0.748
PL10	My teacher uses different resources and materials to meet diverse learning needs	3.260	0.850	0.731
PL11	I receive individual feedback addressing my specific strengths and weaknesses	3.208	0.864	0.779
PL12	I am encouraged to set my own learning goals and monitor my progress	3.222	0.855	0.756
PL13	My teacher gives me flexible options for demonstrating my learning	3.172	0.824	0.703
PL14	My learning activities are adapted to my current skill level and pace	3.272	0.858	0.751
PL15	My teacher regularly checks my understanding before moving to new topics	3.284	0.897	0.718

Item	Statement	Mean	SD	Loading
ESF16	My schooling has helped me communicate ideas clearly and confidently	3.376	0.805	0.792
ESF17	I can analyse problems and think critically before arriving at conclusions	3.330	0.826	0.768
ESF18	I can work effectively in a team and respect diverse perspectives	3.350	0.803	0.774
ESF19	My education has encouraged creative thinking and innovative solutions	3.346	0.874	0.741
ESF20	I have developed strong problem-solving skills for real-life situations	3.282	0.802	0.762
ESF21	My schooling has developed my ability to use digital tools and resources	3.346	0.812	0.755
ESF22	I can manage my time effectively and prioritise tasks to meet deadlines	3.322	0.817	0.748
ESF23	I have developed the confidence to take initiative and lead when required	3.354	0.828	0.760
ESF24	My education has helped me understand professional ethics and integrity	3.356	0.792	0.718

Note. Factor loadings are standardised outer loadings from PLS-SEM measurement model (SmartPLS 4.0). All loadings exceed the 0.70 minimum threshold (Hair et al., 2019). TC1-TC7 = Teacher Competency; PL8-PL15 = Personalized Learning; ESF16-ESF24 = Career Readiness Competency.

At the item level, TC items show the greatest mean homogeneity (range: 3.286-3.342). PL items show the widest mean range (3.172-3.284), with the flexible assessment item (PL13: $M = 3.172$) scoring lowest - indicating this is the least commonly experienced personalisation dimension, reflecting the structural constraints of Indian school assessment systems. CRC items show the highest mean scores overall, with communication (ESF16: $M = 3.376$) rated most highly and real-life problem-solving (ESF20: $M = 3.282$) rated lowest - reflecting the persistent academic-vocational divide in Indian school curricula.

5.3 Common Method Bias Assessment

Harman's single-factor test: 41.3% of variance (below 50% threshold; Podsakoff et al., 2003). Marker variable analysis confirmed path coefficient changes of less than 0.05. VIF values: 1.76-2.81 (below 3.3 threshold). CMB does not substantially confound the structural findings.

5.4 Measurement Model Assessment

Tables 4-7 present the full measurement model assessment: reliability and validity indicators (Table 4), HTMT discriminant validity matrix (Table 5), Fornell-Larcker criterion matrix (Table 6) and model fit and predictive relevance indicators (Table 7).

Table 4. Measurement Model: Reliability and Validity Indicators

Construct	Items	Cronbach's α	Comp. Reliability	AVE	Loading Range	VIF Range
Teacher Competency (TC)	7	0.879	0.912	0.634	0.741-0.864	1.76-2.81
Personalized Learning (PL)	8	0.875	0.908	0.601	0.703-0.851	1.76-2.81
Career Readiness Competency (CRC)	9	0.868	0.903	0.618	0.718-0.841	1.76-2.81

Note. Thresholds: Cronbach's $\alpha \geq 0.70$; CR ≥ 0.80 ; AVE ≥ 0.50 ; VIF < 3.3 (Hair et al., 2019).

Table 5. Heterotrait-Monotrait (HTMT) Ratio Matrix

Construct	TC	PL	CRC
Teacher Competency (TC)	-	-	-
Personalized Learning (PL)	0.761	-	-
Career Readiness Competency (CRC)	0.744	0.738	-

Note. All HTMT values < 0.85 threshold (Henseler et al., 2015), confirming discriminant validity for all construct pairs.

Table 6. Fornell-Larcker Criterion Matrix (AVE Square Roots on Diagonal)

Construct	TC	PL	CRC
Teacher Competency (TC)	0.797	-	-
Personalized Learning (PL)	0.679	0.775	-
Career Readiness Competency (CRC)	0.661	0.649	0.786

Note. Diagonal values are square roots of AVE. Discriminant validity confirmed where diagonal values exceed off-diagonal inter-construct correlations (Fornell & Larcker, 1981).

Table 7. Model Fit and Predictive Relevance Indicators

Indicator	Value	Threshold	Assessment
SRMR (Saturated Model)	0.058	< 0.08	Acceptable

Indicator	Value	Threshold	Assessment
SRMR (Estimated Model)	0.063	< 0.08	Acceptable
NFI	0.821	≥ 0.80	Acceptable
R ² - Personalized Learning	0.461	≥ 0.26 (Substantial)	Substantial
R ² - Career Readiness Competency	0.512	≥ 0.26 (Substantial)	Substantial
Q ² - Personalized Learning	0.219	> 0	Predictive Relevance
Q ² - Career Readiness Competency	0.258	> 0	Predictive Relevance

Note. SRMR = Standardised Root Mean Square Residual; NFI = Normed Fit Index; R² = Coefficient of Determination; Q² = Predictive Relevance (PLSpredict; Shmueli et al., 2019).

All indicators meet recommended thresholds. Cronbach's alpha (0.868-0.879) and CR (0.903-0.912) confirm strong internal consistency. AVE (0.601-0.634) confirms convergent validity. HTMT values (all < 0.85) and Fornell-Larcker results (AVE square roots: TC = 0.797, PL = 0.775, CRC = 0.786 - all exceeding inter-construct correlations) confirm discriminant validity. SRMR (0.058 saturated; 0.063 estimated) and NFI (0.821) confirm acceptable model fit. Q² values exceeding zero for both endogenous constructs confirm out-of-sample predictive relevance.

5.5 Structural Model and Hypothesis Testing

Figure 2 presents the full structural model with all path coefficients and R² values. Table 8 presents the complete structural results including 95% bootstrapped confidence intervals and Cohen's (1988) f² effect sizes.

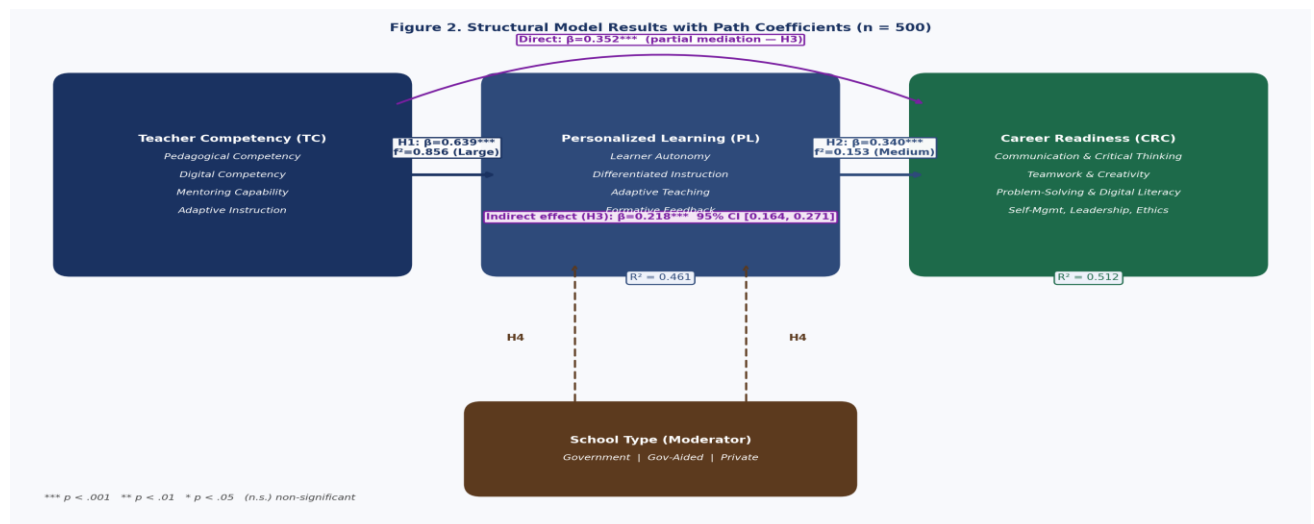


Figure 2. Structural Model Results with Standardised Path Coefficients (n = 500). Numbers on paths are standardised beta coefficients. R² values shown within endogenous construct boxes. TC = Teacher Competency; PL = Personalized Learning; CRC = Career Readiness Competency. *** p < .001.

Table 8. Structural Model Results: Path Coefficients, Bootstrapped CIs, Effect Sizes and Hypothesis Decisions

H	Path	Beta	t	p	95% CI	R2	f2	Effect	Decision
H1	TC -> PL (direct)	0.639	20.647	< .001	[0.578, 0.698]	0.461	0.856	Large	Supported
H2	PL -> CRC (direct)	0.340	8.715	< .001	[0.263, 0.418]	0.512	0.153	Medium	Supported
H3	TC->PL->CRC (indirect)	0.218	-	< .001	[0.164, 0.271]	-	-	-	Supported (Partial)
-	TC -> CRC (direct residual)	0.352	9.558	< .001	[0.280, 0.424]	-	0.184	Medium	Significant

Note. Beta = standardised path coefficient; t-values and 95% CIs from bias-corrected bootstrapping (5,000 iterations); f2 = Cohen's (1988) effect size: small ≥ 0.02 , medium ≥ 0.15 , large ≥ 0.35 .

The structural model demonstrates strong explanatory power. TC explains 46.1% of variance in PL ($R^2 = 0.461$ - substantial); TC and PL jointly explain 51.2% of CRC variance ($R^2 = 0.512$ - substantial; Hair et al., 2019).

H1 is supported: TC provides empirical evidence of a statistically significant positive association with PL (beta = 0.639, $t = 20.647$, $p < .001$, 95% CI [0.578, 0.698], $f^2 = 0.856$ - large effect). This large effect size indicates that teacher competency is the strongest observed predictor of personalised learning provision in the estimated model.

According to the results, H2 has been supported: PL has been shown by a path analysis to have a strong association with CRC (beta = 0.340, $t = 8.715$, $p < .001$, 95% confidence interval [0.263, 0.418], $f^2 = 0.153$ - medium effect). Besides, the presence of a significant indirect effect does not make the presence of a significant residual direct effect go away, which is also significant (beta = 0.352, $t = 9.558$, $p < .001$, 95% Confidence Interval [0.280, 0.424], $f^2 = 0.184$), which means that a partial mediation is present rather than a full one.

H3 has been validated: the indirect path of TC-PL-CRC has a beta value of 0.218 with a 95% CI [0.164, 0.271] excluding zero across 5,000 bootstrap iterations, which confirms the partial mediation is statistically significant (Hayes, 2022). Mediation ratio (indirect / total effect) = 38.2%, which means that PL carries about 38% of the total effect of TC on CRC. Figure 4 depicts the whole mediation decomposition.

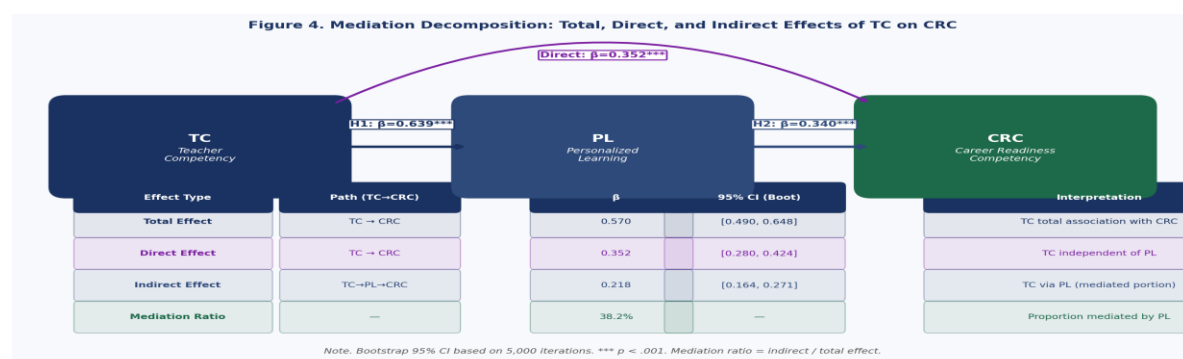


Figure 4. Mediation Decomposition: Total, Direct and Indirect Effects of Teacher Competency on Career Readiness Competency. The mediation ratio of 38.2% indicates the proportion of TC's total association with CRC operating through the personalised learning pathway. All values from bias-corrected bootstrapping (5,000 iterations). *** $p < .001$.

5.6 Multi-Group Analysis: School-Type Moderation (H4)

MICOM testing confirmed configural and compositional invariance for all three groups (all permutation p-values > .05), with partial scalar invariance established - satisfying MGA prerequisites (Henseler et al., 2016). Table 9 and Figure 3 present the MGA results.

Table 9. Multi-Group Analysis: Path Coefficients by School Type (H4)

Path	Group	Beta	t-value	p-value	Significance
TC → PL	Government (n=186)	0.446	7.046	< .001	Significant
	Government-Aided (n=128)	0.341	4.551	< .001	Significant
	Private (n=186)	0.363	6.340	< .001	Significant
PL → CRC	Government (n=186)	0.152	2.340	= .020	Marginally Significant
	Government-Aided (n=128)	0.084	1.047	= .297	Non-Significant
	Private (n=186)	0.270	4.168	< .001	Significant

Note. MGA conducted following MICOM invariance confirmation. Private group = Private/CBSE (n=131) + Private/ICSE (n=55) combined (n=186).

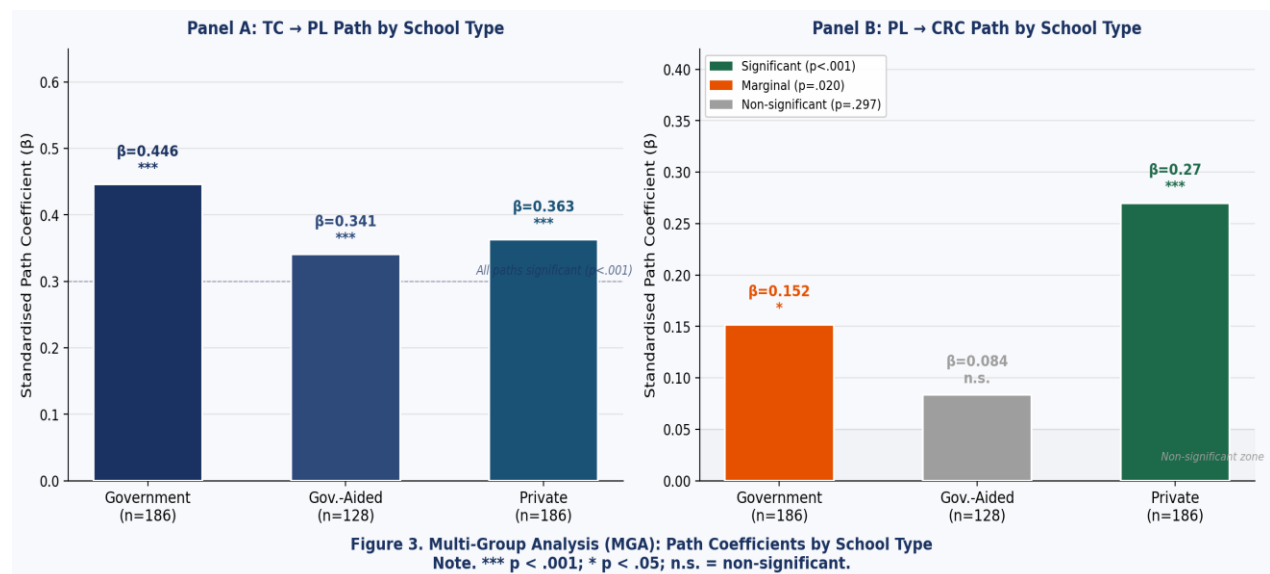


Figure 3. Multi-Group Analysis: Path Coefficients by School Type. Panel A shows the TC-PL path, significant across all three groups. Panel B shows the PL-CRC path, revealing the differential significance pattern: significant in private schools (beta = 0.270, $p < .001$), marginally significant in government schools (beta = 0.152, $p = .020$) and non-significant in government-aided schools (beta = 0.084, $p = .297$). *** $p < .001$; * $p < .05$; n.s. = non-significant.

The TC-PL path is significant across all groups: government (beta = 0.446, $t = 7.046$, $p < .001$), government-aided (beta = 0.341, $t = 4.551$, $p < .001$) and private (beta = 0.363, $t = 6.340$, $p < .001$). The PL-CRC path shows a strikingly differential pattern: significant in private schools (beta = 0.270, $p < .001$), marginally significant in

government schools ($\beta = 0.152$, $p = .020$) and non-significant in government-aided schools ($\beta = 0.084$, $p = .297$). H4 is therefore supported: school type moderates the PL-CRC pathway more distinctively than the TC-PL pathway, indicating that institutional context conditions the conversion of personalised instruction into career readiness outcomes more than it does the antecedent TC-PL relationship.

6. Discussion

6.1 Teacher Competency as a Key Predictor of Personalized Learning

The highest level of support for H1 ($\eta^2 = 0.639$, $f = 0.856$) identifies teacher competency as the largest and most important factor influencing personalized learning, explaining 46.1% of its variance. Besides teacher professional capabilities, personalizing learning effectively depends to a lesser extent on curriculum structures and resource availability (see also discussion). This result incorporates teacher competencies (Kunter et al., 2013) and personalized learning theory (Bray & McClaskey, 2015) in the setting of secondary schools of a developing economy. Also, from an education-to-work perspective, it shows that by improving teacher competency, it will also improve students' career readiness through personalized learning (instructional quality). In fact, this corroborates the view preparing students for a career is not only the final achievement of their education but also the educational processes by which those achievements are attained (Holmes & Mayhew, 2015).

6.2 Personalized Learning as a Partial Mediator

As the partial mediation means (indirect = 0.218, 95% CI [0.164, 0.271]), it illustrates that teacher competency working through personalized learning is quite a strong and significant pathway from teacher competency to career-readiness competencies. Other pathways can be the ones related to direct career-related instructions, the mentoring relationships, role modeling of professional behaviors and the classroom environment that competent teachers support (create). Such explanations depict the Social Cognitive Theory (Bandura, 1986), which stresses observational learning and confidence/self-efficacy building. Also, let me add, in fact, the direct effect of teacher competency on career readiness (0.352) is much greater than zero. So the future work needs to be geared towards looking at these other pathways or mechanisms to understand how teachers help in the career readiness of pupils over and above personalized instruction.

6.3 Understanding the Government-Aided School Effect

One of the remarkable results of this study is the insignificant impact of personalized learning on career readiness competencies in government-aided schools ($r = 0.084$, $p = .297$). These schools' hybrid governance structure, combining state regulation and independent management, resulting in, among other things, inconsistent policy implementation and instructional support may be the reason behind this. Students in these schools are also likely to be influenced more by external factors like family educational resources and private tutoring, which in turn may lessen the visible influence of the schools' pedagogical approaches on the career readiness of the students. There is a need for further qualitative research to understand how institutional circumstances in government-aided schools affect the effectiveness of personalized learning efforts.

6.4 School-Type Moderation and Education-to-Work Transitions

According to the moderation analysis, the extent to which personalized learning is related to career readiness competencies depends on school types, with the strongest association in private schools ($r = 0.270$), weaker in government schools ($r = 0.152$) and non-significant in government-aided schools ($r = 0.084$). The result indicates that the type of institution determines the level of effectiveness of personalized learning in producing career readiness outcomes. In line with the structure proposed by Allais (2020), results demonstrate that educational inequalities are still expressed not only by variations in resources and curricula but also by variations in the effectiveness of teaching methods. So, the present article adds to the body of research on education-to-work transition by showing that the school environment impacts how effectively learning experiences are transformed into work skills and that So unemployment inequalities based on socioeconomic background may be inequality of readiness for the job market.

7. Implications

7.1 Theoretical Implications

The study makes four main contributions to the literature on the education-to-work transition. It first points out personalised learning as a major channel through which teacher competency raises students' preparedness for the world of work. Then, it finds that school type not only conditions the impact of personalised learning but also that the educational experiences to career-readiness outcomes vary with institutional context. The study also reveals that teacher competency not only impacts career readiness indirectly through personalised learning but also directly through other factors, e.g., mentoring, climate of the classroom and career-related teaching, because of this, providing a basis for future investigations. Lastly, the study indicates that personalised learning might need a conducive institutional environment to be able to raise career readiness effectively, a factor, perspective and practice theory that should be considered, as the results did not show any significant path in government-aided schools.

7.2 Practical Implications

The findings highlight teacher competency as a critical leverage point for improving students' career readiness competencies. Given its strong influence on personalised learning, professional development initiatives should prioritise adaptive pedagogy, differentiated instruction, formative assessment and learner-centred teaching strategies. Such initiatives are likely to be most effective when embedded within ongoing classroom practice through coaching, peer observation and collaborative professional learning rather than through isolated training programmes.

The results also indicate a need to strengthen opportunities for authentic problem-solving within the curriculum, particularly because real-life problem-solving emerged as the weakest career readiness dimension. Integrating workplace-relevant tasks and experiential learning activities across subject areas may help close this gap. Moreover, teacher education institutions should integrate personalised learning design, assessment literacy and technology-supported instruction into pre-service programmes to strengthen the teacher competency–career readiness pathway from the outset.

7.3 Policy Implications

The findings provide empirical support for competency-based and learner-centred reforms advocated under India's National Education Policy (NEP) 2020. Specifically, investments in large-scale teacher professional development programmes, such as NISHTHA, should be viewed not only as educational quality initiatives but also as long-term workforce development strategies that contribute to career readiness formation.

The moderation results serve to underline even more the profound equity issues in the education system. A more vigorous personalised learning–career readiness association in private schools than in government and government-aided ones indicates that the same pedagogical practices can mean unequal benefits in different institutional contexts. Policymakers should devote their attention to teacher development programmes targeted at the most deprived schools, at the same time reinforcing governance and accountability mechanism in the government-aided institutions and introducing personalised learning indicators in the school quality assessment system. These steps will go a long way towards making career readiness development an equitable outcome of schooling rather than a mere consequence of institutional privilege.

8. Conclusion

This paper investigated the interplay between teacher competency, personalised learning and career readiness competencies through a sample of 500 higher secondary students in Tamil Nadu, India, with PLS-SEM and bootstrapped mediation analysis complemented with multi-group analysis across different school types.

Teacher competency has been found as the leading determinant of personalised learning, thereby putting the emphasis on the importance of teacher quality when it comes to producing learner-centred educational environments. Meanwhile, personalised learning is the major driver in improving career readiness competencies

and it acts as a partial mediator between teacher competency and career readiness, implying that teachers have an influence over students' readiness for the workforce both directly and indirectly. Also, research finds that the impact of personalised learning differs from one school to another, private school students taking the lead, followed by government school students and finally, government-aided school students not experiencing any effect at all.

By revealing that personalised learning operates as a crucial conduit through which teacher competency affects career readiness and by unveiling that the type of school determines the potency of this conduit, the research made a significant contribution to education-work transition literature. At the same time, it brings to light government-aided schools as one environment, which deserves more scholarly and policy attention.

All in all, the results point to really teacher competency development in personalised and adaptive pedagogical practices being, by far, the most powerful weapon for the enhancement of students' career readiness. But the positive outcomes of these practices rely on the availability of favourable institutional conditions. That's why taking the workforce preparedness forward beyond teacher development initiatives calls for the introduction of policy measures targeted at reducing structural inequalities across different types of schools to ensure more equitable access to career readiness development.

9. Limitations and Future Research Directions

9.1 Methodological Limitations

This study faces a few challenges. Firstly, the cross-sectional approach does not establish causation since teacher competency, personalised learning and career readiness competency are processes that unfold over time. Longitudinal or quasi-experimental research will be required to determine causality and explore changes in development.

Secondly, the study relied on students' self-reports for all constructs, which can be compromised by perception bias, desire to please and inaccuracies in self-perception. Besides, a teacher's evaluation, observation of classes and objective career readiness tests should all be incorporated in further studies.

Thirdly, the single source of the respondent may have had an impact on the results despite common method bias being checked and controlled. Future research could be reinforced by incorporating different sources and methods of reporting.

Lastly, since the study was carried out in some districts of Tamil Nadu, the results can't be applied generally to other regions and educational settings. Besides, the studies should be extended to different institutional and geographical ones. They should also investigate other ways through which teacher competency and career readiness are connected, in particular in government-aided schools.

9.2 Interpretation Caution

The non-significant PL-CRC pathway in government-aided schools ($n = 128$) involves reduced statistical power relative to the full sample. This finding should be treated as a hypothesis-generating result meriting dedicated follow-up investigation rather than a definitive determination of CRC formation dynamics in government-aided schools.

9.3 Future Research Directions

Six directions are recommended. First, longitudinal validation: tracking students from secondary school through early labour market entry to validate school-stage CRC formation against actual employment outcomes. Second, a qualitative investigation should be conducted on the governance structures of government-aided schools and the enabling conditions that clarify the specific contextual factors suppressing the PL-CRC pathway. Third, the moderator extension should include socioeconomic status, caste category, gender and geographic location as additional moderating variables. Fourth, technology integration: incorporating AI-enabled adaptive learning platforms and digital personalisation tools as additional mediating or moderating variables. Fifth, cross-national

replication in comparable developing-economy school systems. Sixth, mixed-methods extension: teacher focus groups and student interviews to illuminate the specific relational and modelling mechanisms constituting the unexplained direct TC-CRC pathways.

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