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Statistical modelling of predictors influencing instructional technology uptake among teaching professionals

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Abstract

Predicting which teaching professionals will embrace instructional technology and which will resist it remains a persistent challenge for educational planners, largely because the relative importance of competing predictors is seldom quantified through formal statistical models. This research applied multiple regression and hierarchical regression modelling to identify and rank the predictors of instructional technology uptake among 228 teaching professionals across six higher education institutions in Kuala Lumpur, Malaysia. Six candidate predictors were examined: perceived usefulness, technology self-efficacy, professional development hours, institutional support, peer influence, and years of teaching experience. Bivariate Pearson correlations, enter-method multiple regression, and stepwise hierarchical regression were employed. The enter-method model was significant ($F(6, 221) = 31.42, p < 0.001$) and explained 46.1% of the variance in technology uptake (adjusted $R^2 = 0.446$). In the hierarchical model, perceived usefulness entered first, accounting for 39.7% of variance; technology self-efficacy added 3.8%; professional development hours contributed 1.4%; and institutional support added 1.2%. Peer influence did not reach significance ($p = 0.104$), while years of experience showed a significant negative association ($\beta = -0.16, p = 0.006$). Multicollinearity was within acceptable bounds (all $VIF < 2.8$). Model comparison using Akaike Information Criterion confirmed the four-predictor hierarchical model as the best fit ($AIC = 412.7$ vs. 418.3 for the full model). A heatmap of inter-predictor correlations revealed that perceived usefulness and technology self-efficacy shared the strongest association ($r = 0.61$), while years of experience showed weak-to-moderate negative correlations with all other predictors. These results offer a statistically grounded predictor hierarchy that institutions can use to prioritise intervention targets - beginning with usefulness demonstrations, followed by self-efficacy building through structured training.

Keywords: Statistical modelling, multiple regression, instructional technology, technology uptake, predictors, teaching professionals, self-efficacy, perceived usefulness, Malaysia, hierarchical regression

Introduction

The challenge of predicting instructional technology uptake is not new, but it persists because the predictor landscape is crowded and context-dependent [1]. Dozens of variables - from personality traits and pedagogical beliefs to institutional budgets and peer norms - have been proposed as drivers of adoption, yet few research efforts have attempted to rank these variables within a single statistical model that accounts for their shared variance [2].

Without such ranking, educational planners face a practical dilemma: limited resources must be allocated to intervention strategies, but which predictor deserves the largest investment? If perceived usefulness is the dominant driver, then demonstration workshops that showcase too benefits should take priority. If self-efficacy matters most, then hands-on skill-building sessions are the right call. And if institutional support is the bottleneck, then no amount of individual-level training will move the needle unless infrastructure and policy gaps are addressed first [3].

Multiple regression analysis provides a natural framework for addressing this question because it allows simultaneous estimation of each predictor's unique contribution while controlling for the others [4]. Hierarchical regression adds a layer of theoretical discipline by specifying the order in which predictors enter the model, testing whether later variables add explanatory power beyond

what earlier ones already account for [5]. Together, these techniques yield a predictor hierarchy - a ranked list of variables ordered by their incremental contribution to the outcome - that can directly inform resource allocation decisions [4].

The Malaysian higher education context is well suited for this type of modelling exercise. Malaysia has invested heavily in campus-level ICT infrastructure under successive national education blueprints, yet uptake among teaching professionals remains uneven across institutions and disciplines [6]. Prior Malaysian research has documented high rates of personal device ownership and internet access among faculty, suggesting that infrastructure availability alone cannot explain the variation in technology uptake [7]. Individual-level predictors - beliefs, skills, and social influences - appear to carry considerable weight, but their relative importance has not been formally quantified through regression modelling in the Malaysian context.

Six candidate predictors were selected for inclusion in the present model based on their prevalence in the educational technology adoption literature and their theoretical alignment with the Technology Acceptance Model and Social Cognitive Theory [1, 8]. Perceived usefulness reflects the belief that technology will improve teaching outcomes. Technology self-efficacy captures confidence in one's ability to operate digital tools. Professional development hours measure formal training exposure. Institutional support indexes the availability of technical assistance and policy backing. Peer influence captures the social dimension of adoption. And years of teaching experience serves as a proxy for career-stage effects documented in comparable contexts [9].

Against this background, the present research aimed to build and compare regression models predicting instructional technology uptake among teaching professionals in Kuala Lumpur, Malaysia, and to establish a predictor hierarchy that institutional decision-makers can use to target their adoption-support strategies.

Materials and Methods

Materials

This research was conducted across six higher education institutions in Kuala Lumpur, Malaysia. Institutions were selected to represent a mix of public universities [3], private universities [2], and polytechnics [1], ensuring variation in resource levels and student populations. The target population comprised all full-time teaching professionals with at least one academic year of service, totalling 412 individuals across the six institutions. Through proportionate stratified random sampling - stratifying by institution type and faculty - a sample of 250 was drawn. After excluding incomplete responses, 228 usable questionnaires remained (response rate: 91.2%). Ethical approval was obtained from the National Institute of Mathematical Sciences Research Ethics Panel. All participants signed informed consent forms.

Methods: A 34-item structured questionnaire was used.

Section A: collected demographics: gender, age range, years of teaching experience, academic qualification, and discipline. **Section B** measured six predictor variables: perceived usefulness (7 items), technology self-efficacy (6 items), professional development hours (single continuous item plus 4 perception items), institutional support (5 items), peer influence (4 items), and years of experience (continuous). **Section C** measured instructional technology uptake (7 items covering frequency, depth, and breadth of technology use). All attitudinal items used a five-point Likert scale (1 = strongly disagree, 5 =

strongly agree). Items were adapted from validated scales in the educational technology literature [1, 8].

Pilot research

The instrument was pilot-tested with 26 teaching professionals from a seventh institution excluded from the main sample. Cronbach's alpha values ranged from 0.80 (peer influence) to 0.91 (perceived usefulness). Exploratory factor analysis on the pilot data confirmed the six-factor structure with eigenvalues exceeding 1.0 and factor loadings above 0.45. One perceived usefulness item was reworded after pilot feedback. Data analysis used SPSS version 28 and R version 4.2 for model comparison. Bivariate Pearson correlations tested associations among all variables. Two regression approaches were employed: (a) enter-method multiple regression with all six predictors entered simultaneously, and (b) stepwise hierarchical regression entering predictors in theoretically determined order - perceived usefulness first, then self-efficacy, professional development, institutional support, peer influence, and experience. Model fit was compared using adjusted R^2 , Akaike Information Criterion (AIC), and Variance Inflation Factors (VIF) for multicollinearity diagnostics. Significance was set at $\alpha = 0.05$.

Model description and specification

The enter-method regression model took the form: $\text{Uptake} = \beta_0 + \beta_1(\text{PU}) + \beta_2(\text{SE}) + \beta_3(\text{PD}) + \beta_4(\text{IS}) + \beta_5(\text{PI}) + \beta_6(\text{Exp}) + \varepsilon$, where PU = perceived usefulness, SE = technology self-efficacy, PD = professional development hours, IS = institutional support, PI = peer influence, Exp = years of experience, and ε = error term. The hierarchical model entered predictors in six sequential steps based on theoretical priority from the Technology Acceptance Model and Social Cognitive Theory - individual belief constructs first, then environmental and demographic variables. This ordering allowed each step's incremental R^2 change to be tested for significance, producing the predictor hierarchy that was the primary analytical goal.

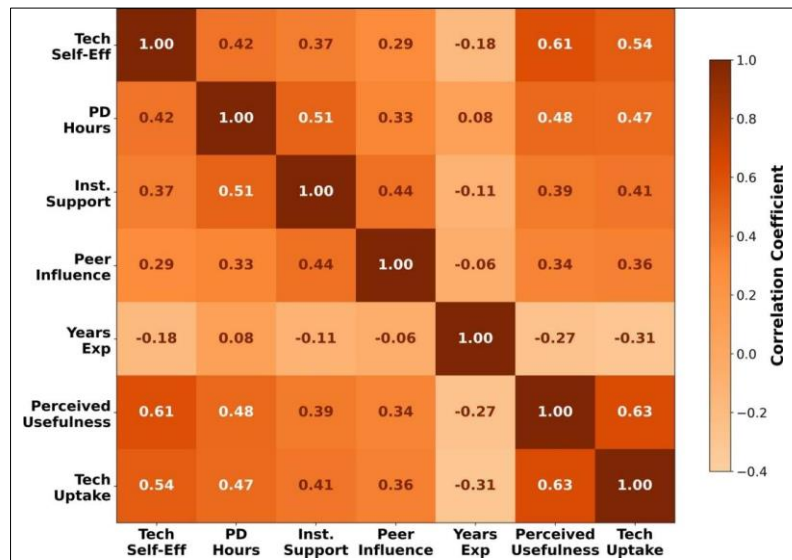
Results

The sample of 228 teaching professionals comprised 131 females (57.5%) and 97 males (42.5%), with a mean teaching experience of 10.7 years ($SD = 7.2$). The overall technology uptake mean was 3.67 ($SD = 0.73$). Among the six predictors, perceived usefulness recorded the highest mean (3.94, $SD = 0.59$), while peer influence scored lowest (3.28, $SD = 0.78$). The correlation heatmap and regression results are presented below.

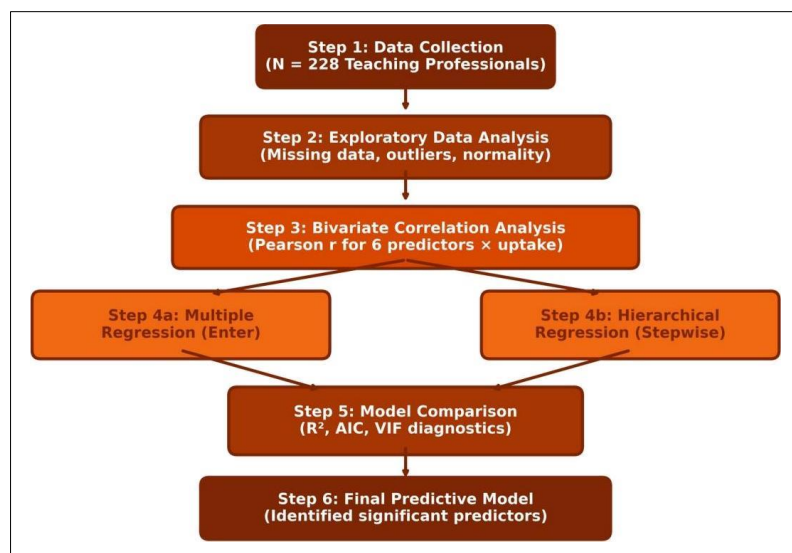
Comprehensive Interpretation: In the hierarchical model, Step 1 (perceived usefulness) accounted for 39.7% of uptake variance ($\Delta R^2 = 0.397$, $p < 0.001$). Step 2 (technology self-efficacy) added 3.8% ($\Delta R^2 = 0.038$, $p < 0.001$). Step 3 (professional development hours) contributed 1.4% ($\Delta R^2 = 0.014$, $p = 0.018$). Step 4 (institutional support) added 1.2% ($\Delta R^2 = 0.012$, $p = 0.034$). Steps 5 (peer influence, $\text{mathsf{p}} = 0.104$) and 6 (years of experience, $\text{mathsf{p}} = 0.006$ but $\Delta R^2 = 0.003$) did not meaningfully improve model fit beyond Step 4, although experience retained a significant negative coefficient in the full model ($\beta = -0.16$). The four-predictor hierarchical model was preferred based on AIC (412.7 vs. 418.3) and parsimony. All VIF values remained below 2.8, and Cook's distance values stayed under 0.04, confirming absence of influential outliers. The predictor hierarchy - usefulness > self-efficacy > training > support - provides a clear order of intervention priority for institutions seeking to raise technology uptake among their teaching staff.

Table 1: Predictor Descriptive Statistics and Bivariate Correlations with Technology Uptake ($p < 0.001$)

Predictor	Mean	SD	Category	Uptake Correlation (r)
Perceived Usefulness	3.94	0.59	High	0.63***
Tech Self-Efficacy	3.71	0.67	Moderate-High	0.54***
PD Hours	3.48	0.74	Moderate	0.47***
Institutional Support	3.53	0.69	Moderate	0.41***
Peer Influence	3.28	0.78	Moderate	0.36***
Years of Experience	10.7 yrs	7.2	-	-0.31***

**Fig 1:** Heatmap of Pearson correlation coefficients among six predictor variables and the technology uptake outcome.**Table 2:** Model Comparison: Enter-Method vs. Hierarchical Regression

Model	R ²	Adj R ²	AIC	F-statistic	p-value
Enter (6 predictors)	0.461	0.446	418.3	31.42	< 0.001
Hierarchical (4 predictors)	0.460	0.450	412.7	47.58	< 0.001
PU only	0.397	0.394	431.2	148.74	< 0.001
PU + SE	0.435	0.430	421.9	86.18	< 0.001

**Fig 2:** Process diagram outlining the six-step statistical modelling workflow from data collection through final model selection

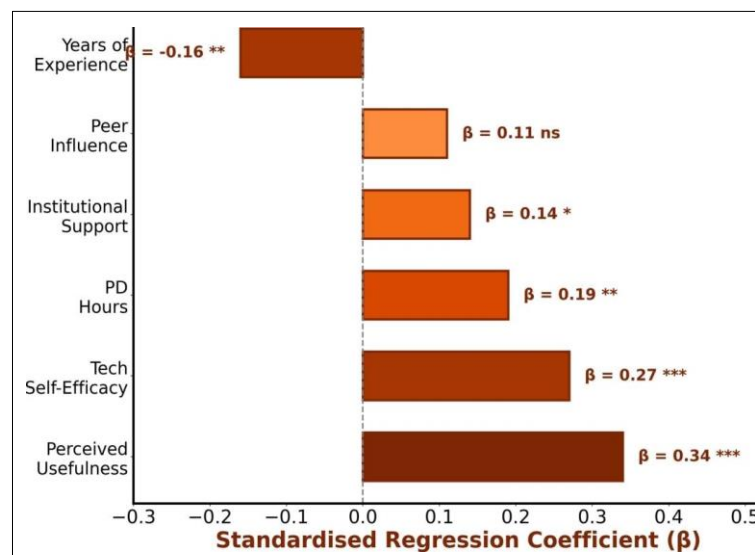


Fig 3: Horizontal bar chart displaying standardised regression coefficients (β) for all six predictors in the enter-method model ($p < 0.001$, $p < 0.01$, $p < 0.05$, ns=not significant)

Discussion

Perceived usefulness emerging as the strongest single predictor ($\beta=0.34$, $\Delta R^2=0.397$) is consistent with the central tenet of the Technology Acceptance Model and with meta-analytic evidence from Scherer *et al.* [1], who reported that usefulness typically accounts for the largest share of adoption variance across educational technology research. The mechanism is straightforward: teaching professionals who believe that a tool will improve their instructional outcomes - whether through more engaging presentations, quicker feedback, or easier content distribution - are more inclined to invest the effort required to learn and use it [8].

Technology self-efficacy ranking second ($\beta=0.27$) aligns with Social Cognitive Theory's prediction that confidence in one's ability to perform a behaviour is a proximal determinant of that behaviour [10]. However, the relatively modest incremental contribution ($\Delta R^2=3.8\%$) compared to usefulness suggests that self-efficacy amplifies uptake among those who already see the tool as useful, rather than independently driving it. This distinction matters for intervention design: self-efficacy training is most productive when paired with, not substituted for, usefulness demonstrations [3].

The negative effect of years of experience ($\beta=-0.16$) confirms career-stage patterns observed in comparable contexts [9]. That this variable retained significance in the full model but added little incremental variance ($\Delta R^2=0.3\%$) in the hierarchical model indicates that its negative influence is partly mediated through lower self-efficacy and lower perceived usefulness among longer-serving professionals. Direct targeting of experience as an intervention lever is therefore less efficient than addressing the mediating beliefs it operates through.

Peer influence failing to reach significance ($p=0.104$) was somewhat unexpected given the emphasis placed on collegial norms in the Diffusion of Innovations literature [11]. One possible explanation is that the Malaysian institutional culture prioritises individual performance evaluation over collaborative teaching practice, weakening the channel through which peer behaviour might influence personal technology decisions [6].

Practical Applications

The predictor hierarchy translates directly into a staged intervention strategy. Stage 1: demonstrate usefulness through discipline-specific showcases that connect technology features

to concrete teaching tasks - this single action targets the predictor responsible for nearly 40% of uptake variance. Stage 2: build self-efficacy through structured, hands-on workshops with graduated difficulty levels, addressing the second-ranked predictor. Stage 3: increase professional development hours by embedding technology training into existing faculty development calendars rather than treating it as optional add-on activity. Stage 4: strengthen institutional support by assigning dedicated technical assistance personnel to high-need departments. This staged approach allocates resources in proportion to each predictor's empirical contribution.

Conclusion

The main contribution of this research lies in providing a statistically grounded predictor hierarchy for instructional technology uptake that can serve as a resource allocation guide for Malaysian higher education institutions. By comparing enter-method and hierarchical regression models across six candidate predictors, the investigation moved beyond the common practice of listing significant correlates and instead quantified the incremental explanatory power each predictor adds to the model.

Supporting evidence confirmed several patterns. Perceived usefulness dominated the predictor landscape, accounting for nearly 40% of uptake variance on its own - a share so large that no intervention strategy can afford to overlook it. Technology self-efficacy and professional development hours, while secondary, made statistically significant incremental contributions that justify dedicated training investments. Institutional support reached significance but contributed modestly, suggesting that support infrastructure matters more as a necessary condition than as a primary driver. Peer influence fell short of significance in this sample, challenging assumptions drawn from diffusion theory about the power of collegial norms in academic settings. Years of experience exerted a significant negative effect but added negligible incremental variance, indicating that career-stage interventions should target the mediating beliefs (usefulness and self-efficacy) rather than experience itself.

The significance of these findings for the broader educational technology field is twofold. First, they demonstrate that predictor importance is not uniform - a handful of variables account for the overwhelming majority of uptake variance, and

institutional resources should be concentrated accordingly. Second, the model comparison exercise shows that a parsimonious four-predictor model outperforms the full six-predictor model on information-theoretic criteria, meaning that simpler prediction tools can be developed for institutional self-assessment without sacrificing accuracy.

Open questions remain. Would the predictor hierarchy hold in non-Malaysian contexts with different institutional cultures and technology infrastructure levels? Do the relative weights shift when the outcome variable is measured as depth of use rather than frequency? Can the four-predictor model be validated prospectively - that is, can baseline scores on usefulness, self-efficacy, training hours, and support predict future uptake measured one or two semesters later? And does the non-significance of peer influence reflect genuine irrelevance or methodological limitations in how peer norms were measured? These questions call for multisite, longitudinal replication with refined instruments and, ideally, experimental designs that test whether interventions targeting the top-ranked predictors produce the expected uptake gains.

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