Educational Value Formation Around Intelligent Learning Tools: Student Readiness, Usage Archetypes, and Support Pathways in Higher Education

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Abstract

Modern higher education campuses now use intelligent learning tools as standard ed-ucational resources yet students learning results depend on their understanding of these tools and their implementation in academic work. The study analyzes how students pre-pare to use educational tools while investigating the connection between their preparedness and their judgment of educational benefits. The study uses an open student-perception dataset to conduct empirical research which includes developing constructs and profiling readiness and creating predictive models and establishing pathways. The study introduces two measurement methods which include source breadth to measure how students acquire knowledge about intelligent tools through different information channels and an advantage score to present perceived benefits for educational activities. The three-profile segmentation method shows that different groups in the sample display distinct levels of preparedness and value assessment. The Random Forest model demonstrates superior performance because it achieves the highest accuracy among all tested models in the predictive stage. The selected model exhibits an accuracy rate of 0.789 and a precision rate of 0.714 and a recall rate of 1.000 and an F_1 score of 0.833 and an area under the receiver operating characteristic curve of 0.806 in hold-out evaluation. The analysis of variable importance indicates that AI knowl-edge and grade-point average and information breadth and profile membership serve as the main factors that explain the results. The final stage of the process transforms analytical results into distinct educational pathways which focus on developing essential literacy skills and implementing structured curriculum materials and providing support for governance matters and enabling advanced collaborative learning. The results demonstrate that the educational benefits of intelligent tools depend more on students' preparedness to use them than on their initial exposure to the tools.

Keywords: Education technology; Higher education; Student readiness; Intelligent learning tools; Adoption archetypes; Educational value

1. Introduction

The growing digitalisation of educational spaces has made smart tools ubiquitous in academic processes. Students can now find these tools used to help them with writing, search, explanation, feedback and problem-solving in their coursework. But their value isn't simply determined by their presence. The same tool can function as an effective learning resource, a "shallow" convenience, or a source of confusion depending on the knowledge, expectations and judgement of the user.

This is especially so in tertiary education. Recent research demonstrates that students do not react to AI-powered tools in a consistent way. Some use them with confidence and see their value in education, while others are uncertain, discerning or distrustful (Chan & Hu, 2023; Johnston et al., 2024; Stöhr et al., 2024). Such diversity is important from a policy perspective. Institutional approaches to adoption and support are too broad if they do not take into account the variation in students' readiness, trust and educational value formation.

This research looks at intelligent learning tools through educational value formation. The paper asks not just whether students like these tools, but how readiness is organised, what factors best predict high perceived educational value, and what evidence emerges to support targeted institutional responses. The investigation therefore starts with a straightforward proposition: if readiness among students is systematic, then an education-technology strategy should be built around this variation and not around blanket assumptions of uptake.

The paper presents a profiling and predictive approach empirically, using an open data set of student perceptions. The novelty here is in the connection between profiling and educational pathway design, which suggests that intelligent learning tools are not just a technological innovation but an integration and support challenge.

2. Literature Background

2.1. Student-facing education technology and intelligent tools

The latest research in education technology demonstrates that smart tools can improve the timeliness of feedback, writing, information retrieval and student productivity, but these outcomes depend on careful use and support. Literature reviews stress both the potential and the governance issues relating to AI tools in education (Chiu et al., 2023). In tertiary education, student views are particularly significant because the same tool could be used as a support tool, convenience tool or integrity issue depending on context.

This is evident in empirical research. Chan and Hu (2023) demonstrate that students believe there are significant benefits to using generative AI, but also have concerns about quality, bias, and boundaries. Von Garrel and Mayer (2023) report diverse use of ChatGPT and other tools in German students. Johnston et al. 2024 and Baek et al. (2024) also report that students are inclined to express optimism about usefulness with concerns about trust, over-reliance and legitimacy.

2.2. Readiness, literacy, and educational value

A second line of research shows that readiness and literacy play a critical role in adoption. Mansoor et al. (2024) reveal considerable differences in university students' AI literacy, with Lee et al. (2024) demonstrating that teachers consider smart tools important strategically but dangerous pedagogically. Stöhr et al. (2024) also show how student attitudes and behaviours vary by academic level, gender and major. These insights show that the educational benefit is not just a matter of awareness. It is determined by familiarity, trust and the diversity of information channels through which students access information about such tools.

Research in other areas can also add to the conversation. Human-centred analytical tools are more educationally valuable when they retain interpretability and link evidence to action (Alfredo et al., 2024; Bergdahl et al., 2024; Palanci et al., 2024). For education technologies, this translates into institutions needing more than descriptive evidence of student use of intelligent tools. They need interpretable profiles that help distinguish readiness states and the kind of support students need.

3. Research Challenges and Future Directions

The recent literature leaves several unresolved challenges that motivate the present study. The first challenge is *educational heterogeneity*. Many discussions of intelligent tools in higher education still report average attitudes, broad opportunities, or high-level concerns, but provide limited guidance on how different student segments vary in readiness and value formation. Averages may conceal the existence of highly prepared users, uncertain middle groups, and poorly informed skeptics.

The second challenge is *translation from perception to action*. Even when studies identify positive or negative student perceptions, the findings often stop short of suggesting differentiated educational responses. For institutions, however, the practical problem is not only to know whether students are positive or negative. The practical problem is to decide whether to prioritize foundational literacy, guided classroom use, integrity-oriented governance, or more advanced co-creation opportunities.

The third challenge is *limited integration between segmentation and prediction*. A number of studies examine student perceptions qualitatively or descriptively, whereas other studies emphasize predictive analytics. Far fewer combine both perspectives in a unified design that first identifies interpretable readiness profiles and then tests which factors best explain strong educational value perception.

The fourth challenge concerns *future research design*. Larger cross-institutional datasets are needed to evaluate whether readiness archetypes remain stable across disciplines, cultural settings, and levels of prior digital experience. Future work should also compare rule-based support assignment with optimization-based allocation, examine how readiness evolves longitudinally, and test whether targeted interventions actually improve responsible and educationally meaningful adoption over time.

These challenges motivate the present study, which develops a compact framework linking readiness profiling, prediction, and institutional pathway design within one reproducible empirical workflow.

4. Study Design and Variable Construction

4.1. Dataset

The empirical material consists of an openly available cleaned survey file derived from a recent student study on perceptions of intelligent tools in education. The analytical file contains 91 valid responses and includes measures covering AI knowledge, information-source patterns, perceived utility, perceived benefits and disadvantages, grade-point average, year of study, and program-related characteristics.

4.2. Construct development

Table 1 summarizes the main analytical constructs used in the study.

Table 1: Main analytical constructs

Construct	Operationalization
AI knowledge	Self-reported knowledge score about AI-based educational tools
Source breadth	Count of information channels used: internet, books/papers, social media, and discussions
Advantage score	Mean of reported advantages for teaching, learning, and evaluation
Perceived risk	Reported disadvantage score for the educational process
High educational value	Binary indicator equal to 1 when utility grade is at least 8
Adoption archetype	Three-cluster segmentation based on readiness, information breadth, value, and risk indicators

The key derived variables are defined as follows. Let $s_{im} \in \{0,1\}$ indicate whether student i uses information source m. Source breadth is defined as

$$SB_i = \sum_{m=1}^{4} s_{im}. \tag{1}$$

Let T_i, L_i, and E_i denote perceived advantages for teaching, learning, and evaluation. The composite advantage score is

$$AS_i = \frac{T_i + L_i + E_i}{3}. \tag{2}$$

Let U_i denote the reported utility grade. The binary target variable is

$$Y_i = \mathbb{I}(U_i \geq 8), \tag{3}$$

where $\mathbb{I}(\cdot)$ is the indicator function.

5. Analytical Strategy

5.1. Profiling student readiness

The first analytical stage identifies readiness archetypes through K-means clustering. Given standardized feature vectors $\mathbf{z}_i$, the clustering objective is

$$\min_{\{C_k\}_{k=1}^{K}} \sum_{k=1}^{K} \sum_{\mathbf{z}_i \in C_k} \|\mathbf{z}_i - \boldsymbol{\mu}_k\|^2, \tag{4}$$

where $\boldsymbol{\mu}_k$ is the centroid of cluster k. The clustering variables are AI knowledge, source breadth, the indicator for not informing oneself about AI, grade-point average, the advantage score, and perceived risk.

5.2. Predicting high educational value

The second stage predicts whether students assign high educational value to intelligent learning tools. For logistic regression, the conditional probability is

$$P(Y_i = 1 \mid \mathbf{x}_i) = \frac{\exp(\beta^\top \mathbf{x}_i)}{1 + \exp(\beta^\top \mathbf{x}_i)}. \tag{5}$$

For ensemble models, the predicted probability is the average across trees:

$$\hat{p}_i = \frac{1}{T} \sum_{t=1}^{T} h_t(\mathbf{x}_i), \tag{6}$$

where $h_t(\mathbf{x}_i) \in [0, 1]$ denotes the tree-specific estimate.

Model performance is evaluated using accuracy, precision, recall, F_1, and receiver operating characteristic area under the curve. For binary classification,

$$Precision = \frac{TP}{TP + FP}, \qquad Recall = \frac{TP}{TP + FN}, \tag{7}$$

and

$$F_1 = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall}. \tag{8}$$

5.3. Educational pathway assignment

The final stage maps each case to an institutional pathway. Students with minimal readiness are assigned to *foundation literacy support*; moderate-readiness students are directed toward *structured classroom integration*; students who display strong value realization together with elevated concern signals are assigned to *risk-aware governance briefing*; and advanced high-value adopters are directed to an *advanced co-creation pathway*. This final layer treats educational strategy as a portfolio problem rather than a generic adoption problem.

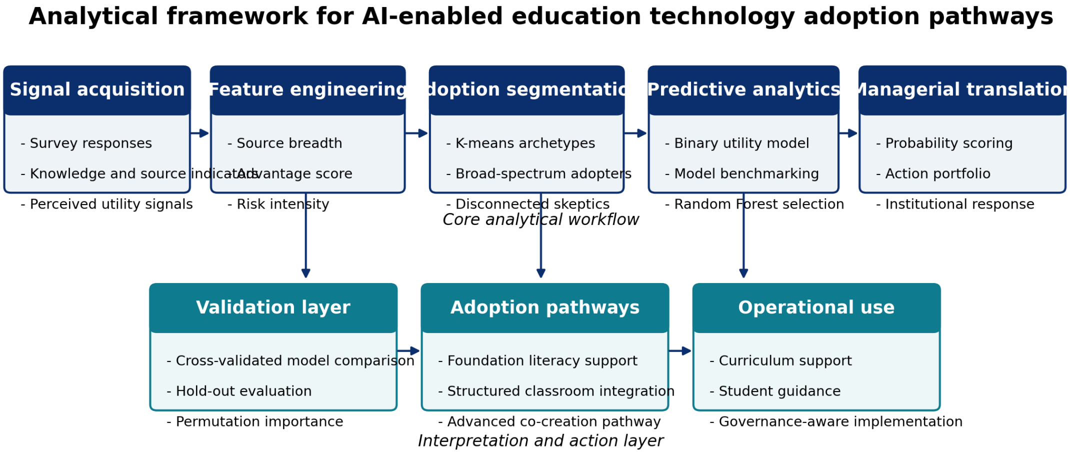

Figure 1. Analytical framework linking readiness profiling, prediction, and institutional pathways

6. Results and Interpretation

6.1. Sample characteristics

The analytical sample is reasonably balanced with respect to the outcome of interest: 49 respondents fall into the high-value group and 42 into the lower-value group. Table 2 summarizes the main numerical variables. The average utility score is 7.44 and the mean knowledge score is 5.91. Information gathering is more limited than might be expected in a rapidly expanding technological field, as the mean source breadth reaches only 1.80 channels.

Table 2: Descriptive statistics of the main numerical variables

Variable	Mean	SD	Min	Median	Max
AI knowledge	5.912	1.970	1.0	6.0	10.0
GPA	7.799	0.975	5.2	7.7	9.7
Source breadth	1.802	1.024	0.0	2.0	4.0
Advantage score	2.018	0.445	1.0	2.0	3.0
Perceived risk	2.099	1.033	1.0	2.0	4.0
Utility grade	7.440	2.161	2.0	8.0	10.0

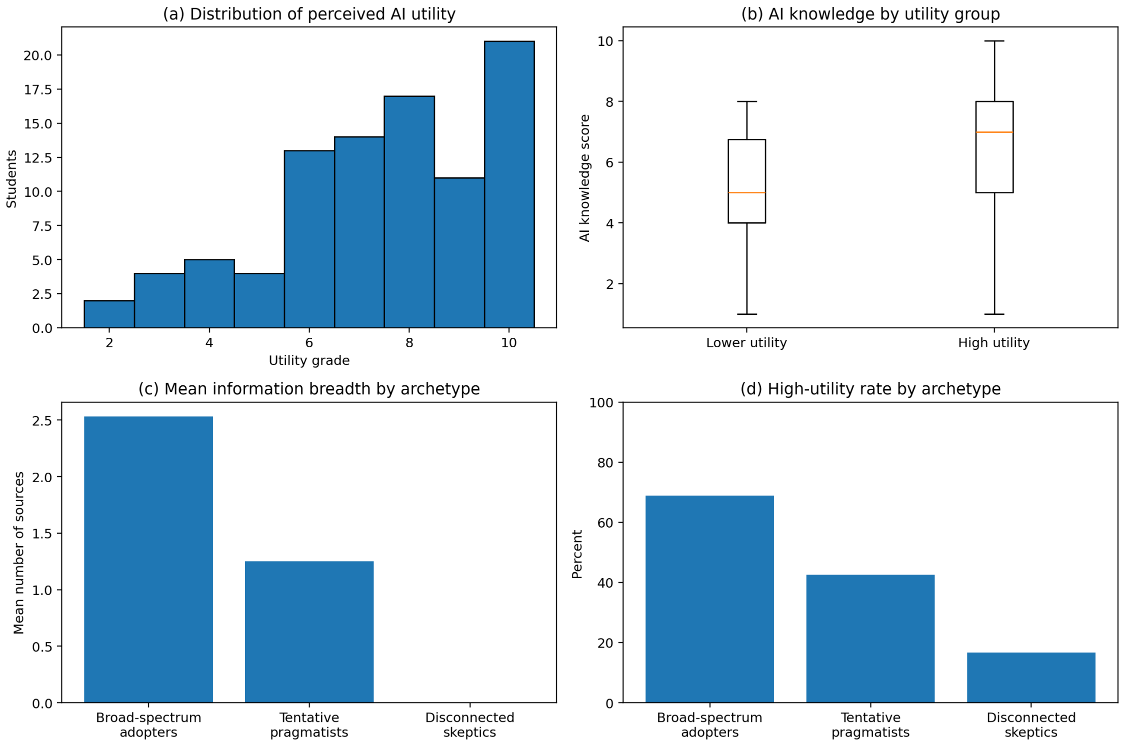

Figure 2. Distributional diagnostics of utility, knowledge, information breadth, and educational value

6.2. Readiness archetypes

The clustering stage yields three clearly differentiated readiness profiles. As shown in Table 3, broad-spectrum adopters combine stronger AI knowledge, wider information search, and the highest probability of assigning strong educational value. Tentative pragmatists occupy the middle ground, with moderate knowledge and moderate value realization. Disconnected skeptics form the smallest group and are distinguished by weak familiarity, very limited information sourcing, and markedly lower value perception.

Table 3: Readiness archetypes and their main characteristics

Archetype	Students	AI knowledge	Source breadth	GPA	Advantage score	Perceived risk	High-value rate
Broad-spectrum adopters	45	7.156	2.533	8.162	2.200	2.000	0.689
Disconnected skeptics	6	2.833	0.000	7.050	1.556	2.167	0.167
Tentative pragmatists	40	4.975	1.375	7.590	1.908	2.200	0.425

Table 4 confirms the same pattern in a cross-tabulated form. Nearly 69% of broad-spectrum adopters fall into the high-value group, compared with 42.5% of tentative pragmatists and only 16.7% of disconnected skeptics.

Table 4: Educational value by readiness archetype

Archetype	Lower value	High value	High-value rate
Broad-spectrum adopters	14	31	0.689
Disconnected skeptics	5	1	0.167
Tentative pragmatists	23	17	0.425

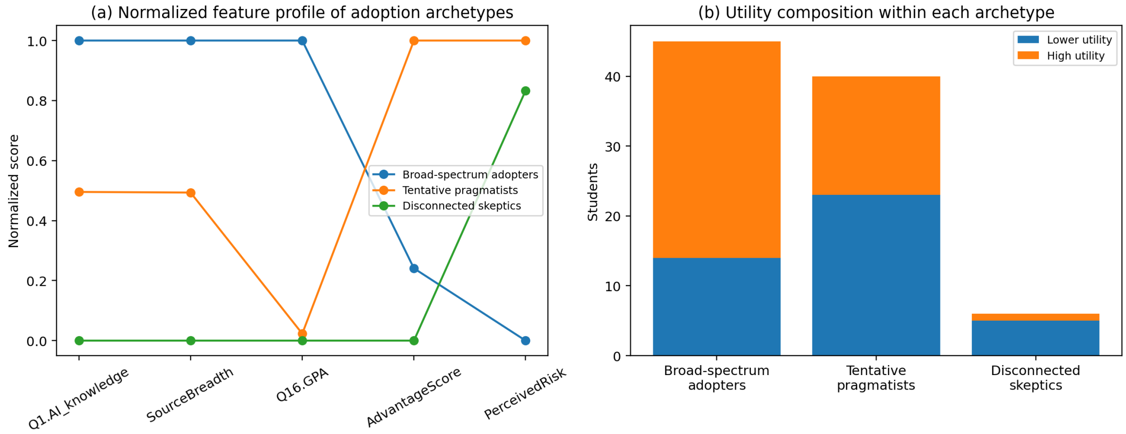

Figure 3. Profile comparison across the three readiness archetypes

6.3. Comparative model performance

Four candidate models are benchmarked in the predictive stage. Table 5 indicates that Random Forest provides the most favourable overall balance of classification quality, posting the highest F_1 score (0.678), the strongest recall (0.758), and the largest area under the curve (0.655). Extra Trees follows closely, whereas logistic regression and Gradient Boosting show weaker generalization in this dataset.

Table 5: Cross-validated predictive performance

Model	Accuracy	Precision	Recall	F_1	ROC-AUC	F_1 SD
Random Forest	0.625	0.638	0.758	0.678	0.655	0.162
Extra Trees	0.592	0.632	0.698	0.641	0.626	0.145
Logistic Regression	0.584	0.606	0.633	0.613	0.613	0.127
Gradient Boosting	0.572	0.648	0.609	0.594	0.598	0.196

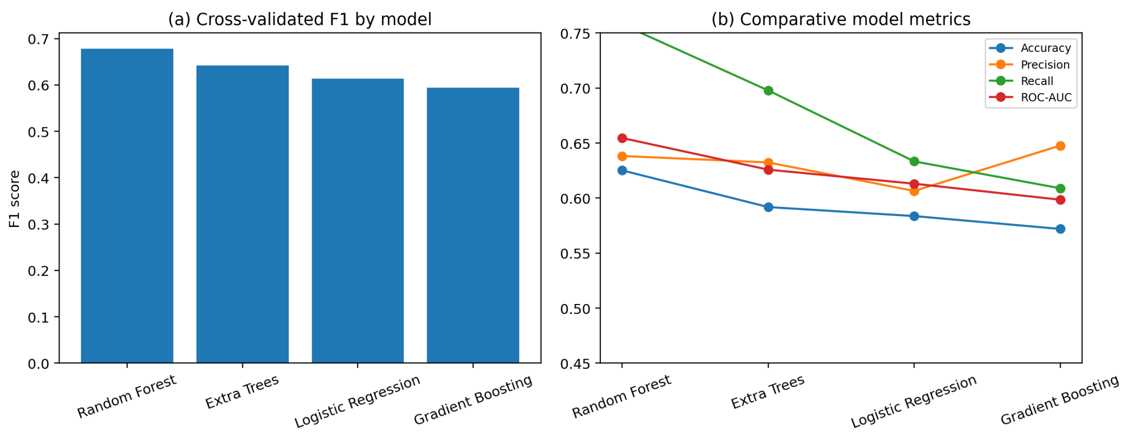

Figure 4. Comparative benchmarking of the candidate models

6.4. Hold-out diagnostics and predictor importance

In hold-out evaluation, the selected Random Forest achieves an accuracy of 0.789, a precision of 0.714, a recall of 1.000, an F_1 score of 0.833, and an area under the curve of 0.806. The confusion matrix in Table 7 shows complete recovery of the high-value cases in the test partition, although several lower-value cases are classified into the high-value category. This pattern suggests that the model is particularly effective at identifying students likely to perceive strong educational value, albeit at the cost of some over-classification.

Table 6: Hold-out performance of the selected model

Metric	Value
Accuracy	0.789
Precision	0.714
Recall	1.000
F_1	0.833
ROC-AUC	0.806

Table 7: Hold-out confusion matrix

	Predicted lower value	Predicted high value
Actual lower value	5	4
Actual high value	0	10

Table 8 reports the strongest predictors from permutation importance. AI knowledge, GPA, source breadth, and readiness archetype form the core explanatory set, indicating that familiarity, academic self-positioning, and information diversity matter more than isolated platform-exposure variables.

Table 8: Top predictors of high educational value

Feature	Importance
AI knowledge	0.0631
GPA	0.0558
Source breadth	0.0498
Adoption archetype	0.0345
Internet as information source	0.0154
Not informed indicator	0.0135
Attitude/feelings	0.0135

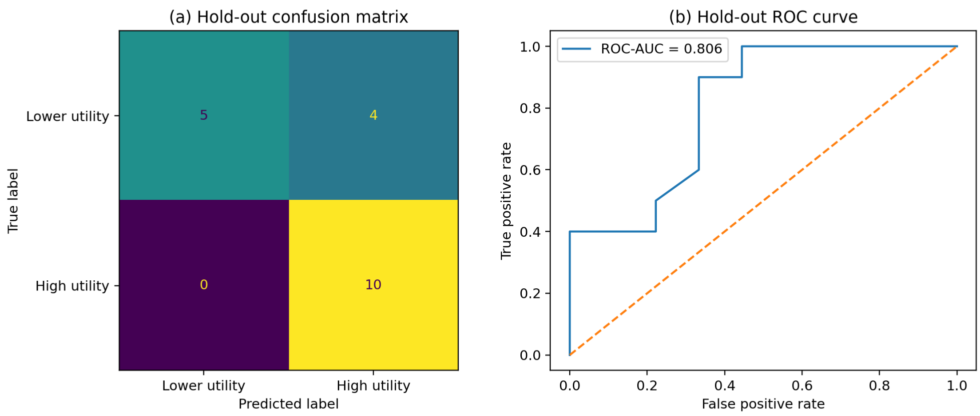

Figure 5. Hold-out confusion matrix and receiver operating characteristic curve

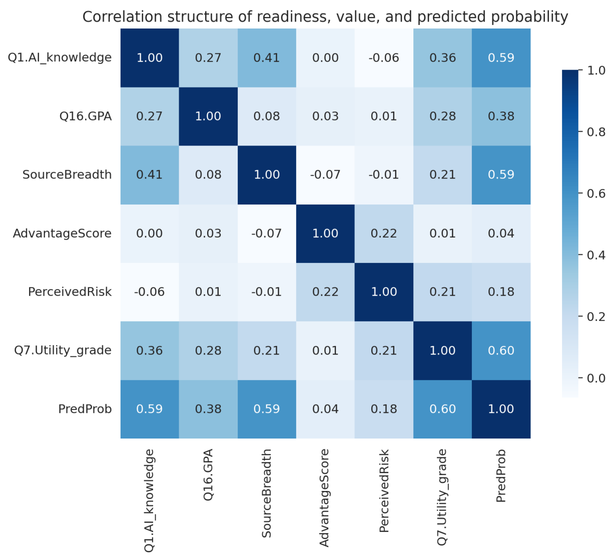

Figure 6. Correlation structure among readiness, value, and predicted probability variables

6.5. Educational pathway composition

The pathway-allocation layer further sharpens the educational interpretation of the results. Structured classroom integration emerges as the largest category, followed by equally sized governance-briefing and advanced co-creation groups. Foundation literacy support is numerically limited, yet it is heavily concentrated among disconnected skeptics. Table 9 shows that broad-spectrum adopters are overrepresented in the advanced co-creation pathway, whereas tentative pragmatists are concentrated in the structured integration pathway.

Table 9: Institutional pathways by readiness archetype

Archetype	Advanced co-creation	Foundation literacy	Governance briefing	Structured integration
Broad-spectrum adopters	19	0	15	11
Disconnected skeptics	0	6	0	0
Tentative pragmatists	0	0	4	36

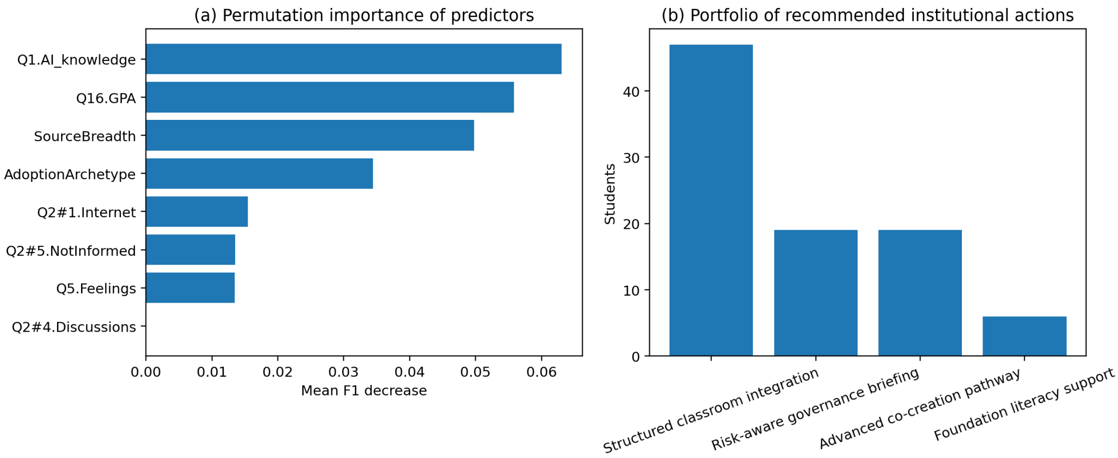

Figure 7. Predictor importance and overall distribution of institutional pathways

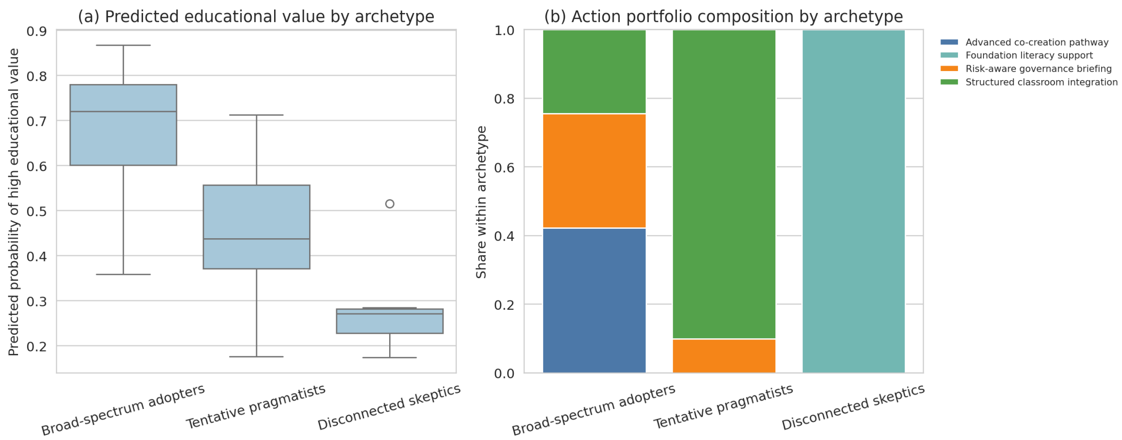

Figure 8. Predicted educational value and pathway composition across readiness archetypes

This distribution is educationally significant. The principal strategic need lies in the broad intermediate group of students who are open to these tools but still require structured curricular framing to convert use into educational value. By contrast, a smaller advanced group appears ready for richer co-creative engagement, while a distinct sceptical group remains better served by foundational support than by immediate curricular embedding.

7. Discussion

The empirical findings yield a number of insights. First, use of intelligent learning tools is better characterised by a readiness structure than by clear-cut adoption. The profile analysis reveals distinct differences in knowledge, informational practices, and valuations among students. This reading is supported by recent research pointing to variability in student experiences of using generative and AI-based tools in terms of confidence, expectations and acceptance (Chan & Hu, 2023; Von Garrel & Mayer, 2023; Stöhr et al., 2024).

Second, the findings indicate familiarity rather than novelty is a more relevant condition for value creation. The most important attributes are knowledge about AI, GPA, diversity of sources, and GAM membership. That is, value is less about familiarity than readiness, certainty, and variety. This suggests, for institutions, that deliberate literacy building and academic application may be more effective than promotional advertising.

Third, the middle segment is important. Integrated classroom use is the biggest pathway, not simple awareness and experimentation. This suggests that the critical institutional responsibilities are not just innovation, but also integration: assisting already motivated students to use smart tools in academically rigorous and educationally relevant ways. Examples in the curriculum, teacher mediation and expectations are likely to play an important role, rather than simply open access.

Fourth, governance needs to be understood as an integral part of educational design, not as an add-on. The relative size of the governance-briefing pathway suggests that self-assured users may still have considerable concern signals. This observation confirms previous research that both confidence and concern can be present in student groups (Johnston et al., 2024; Lee et al., 2024). This means implementation needs to address pedagogy, integrity and student judgment.

Several limitations remain. Our sample size is small, the data self-reported, and the pathways are inferred through an analysis rather than tested experimentally. The survey also constrains the explanatory variables. The pathways for readiness should be replicated with larger samples; archetypal models should be tested to see if they hold across fields of study; and educational interventions should be tested to see if they improve value realization over time.

8. Implications for Education Technology Strategy

The research results show multiple effects which will affect how institutions operate their established practices. First, educational institutions must create separate educational technology programs which will handle students needing basic skills differently from those who can use structured learning materials and those who are ready to work with advanced co-creation activities. Second, pathway design should combine literacy development, teaching integration, and governance support rather than depending on a single instrument. Third, institutions should treat student value as an educational outcome which they can manage by designing educational systems according to students' preparedness.

The implications of this study provide essential guidance for universities which use advanced technology to enhance teaching without relying solely on technological trends. The portfolio logic provides better value as a framework than the standard adoption model because it demonstrates how different students obtain various readiness levels.

9. Conclusion

The research established an empirical framework which researchers use to study educational value development through intelligent learning technologies within universities. The analysis combined construct development, readiness profiling, predictive modelling, and pathway assignment within a single workflow. The research results show that readiness levels differ across the population while value perceptions depend on two factors: user familiarity and their access to information and institutional support functions better when organizations use different pathways to deliver their services.

The research results demonstrate that intelligent tools should not function as self-explanatory educational assets. The educational value of their work depends on institutional recognition of student readiness differences which should lead to development of appropriate support frameworks.

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