Data-Driven Teaching Effectiveness Assessment Through Logistic Regression for Enhanced Evaluation Systems and Probabilistic Decision-Making

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Abstract. Teaching evaluations provide essential feedback for improving educational quality, yet institutions struggle to efficiently utilize unstructured student comments. This study implements ordinal logistic regression to analyze 4,410 bilingual (English-Filipino) student comments, creating a probabilistic framework for predicting teaching effectiveness across standardized evaluation dimensions. The models achieved predictive performance with AUC values ranging from 0.83 to 0.91, with Knowledge of Subject demonstrating 86.9% accuracy. The system demonstrated 75% reduction in manual analysis time while providing quantified uncertainty measures.

Keywords: teaching effectiveness, logistic regression, probabilistic assessment, text analysis, student evaluations, uncertainty quantification, bilingual processing

1 Introduction

Evaluating teaching effectiveness remains a critical priority for higher education institutions committed to educational quality and continuous improvement, particularly within Philippine State Universities and Colleges (SUCs). Student evaluations of teaching (SETs) serve as a primary assessment mechanism, combining numerical ratings with open-ended comments that offer qualitative insights into instructional performance [1,2]. Recent research has emphasized the importance of developing more sophisticated analytical approaches to maximize the value extracted from student feedback [3,4].

At the University of Antique Tario-Lim Memorial Campus, a comprehensive state university serving over 5,000 students, faculty teaching effectiveness is evaluated using the standardized Common Teaching Effectiveness Instrument developed by the Commission on Higher Education (CHED), the Philippine Association of State Universities and Colleges (PASUC), and the Technical Education and Skills Development Authority (TESDA). This instrument evaluates faculty performance across

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four dimensions: Commitment, Knowledge of Subject, Teaching for Independent Learning, and Management of Learning [5].

A fundamental challenge in teaching evaluation within the SUC system is providing probabilistic analysis that acknowledges inherent uncertainty in assessments while maintaining transparency and accountability [6,7]. Additionally, the bilingual nature of Philippine higher education, where students express themselves in both English and Filipino languages, presents unique computational challenges not addressed in existing research [8]. Logistic regression offers a promising approach for analyzing unstructured teaching evaluations, generating probability estimates and confidence intervals that better reflect teaching effectiveness while maintaining statistical interpretability [9,10].

2 Literature Review and Current Research Analysis

2.1 Current Methods in Educational Text Analysis

Educational researchers have increasingly used computational text analysis methods for teaching evaluations with varying levels of success. Machine learning approaches have been applied to educational feedback analysis with moderate success [11,12]. Sentiment analysis techniques have been employed to classify student opinions, though these often use binary classification that ignores the ordered nature of effectiveness ratings [13,14].

Ensemble methods and deep learning approaches have achieved competitive accuracy in educational data mining contexts [15,16]. While deep learning methods like transformers and BERT have shown high raw accuracy on educational text, they suffer from severe interpretability limitations that reduce stakeholder trust and actionable insights [17,18]. Recent studies have emphasized the importance of balancing predictive performance with interpretability in educational contexts [19,20].

As shown in Table 1, the comparison of existing methods reveals several limitations that this study addresses.

Table 1. Comparison of Current Teaching Evaluation Text Analysis Methods

Study	Method	Dataset Size	Accuracy	Interpretability	Uncertainty	Language	Settings
Gomez et al. [11]	Machine Learning	Medium	Moderate	Low	None	English	General
Kastrati et al. [13]	Sentiment Analysis	Medium	Moderate	Medium	None	English	Educational
Edalati et al. [15]	Ensemble Methods	Methods	Good	Medium	Basic	English	EDM

Liu et al. [17]	Deep Learning	Large	High	Very Low	None	Multilingual	Educational
Alhothali et al. [19]	NLP Methods	Medium	Moderate	High	None	English	Education
Sindhu et al. [20]	Text Mining	Medium	Moderate	Medium	Basic	English	Feedback

2.2 Research Gaps and Innovation Opportunities

Despite considerable research activity, several methodological gaps persist. First, no current study has successfully integrated ordinal logistic regression with standardized SUC evaluation instruments while providing complete uncertainty quantification [6,9]. Most approaches treat teaching effectiveness as a single construct, failing to address multi-dimensional characteristics emphasized in modern frameworks [3,5].

Second, existing research focuses predominantly on Western or monolingual educational contexts, ignoring the bilingual reality of Philippine SUCs where students naturally use both English and Filipino in evaluation comments [8]. Third, current studies lack comprehensive validation protocols combining expert validation, cross-context reliability assessment, and practical implementation evaluation necessary for institutional adoption [4,7].

These gaps motivate the current research, which addresses these limitations through an integrated probabilistic framework specifically designed for bilingual Philippine educational contexts.

3 Research Questions

This study addresses the following research questions:

RQ1: How accurately can ordinal logistic regression models predict teaching effectiveness from unstructured bilingual student evaluation comments across standardized assessment dimensions?

RQ2: What textual features serve as statistically significant predictors of teaching effectiveness across evaluation dimensions in both English and Filipino languages?

RQ3: To what extent does a probabilistic assessment approach with complete uncertainty measurement provide more nuanced teaching evaluations compared to classification methods?

RQ4: How can uncertainty measurement and probabilistic outputs be effectively implemented to support evidence-based faculty development within SUC accountability frameworks?

4 Methods

4.1 Research Design and Data Collection

This study employed a mixed-methods design tailored to support evidence-based educational decision-making with appropriate uncertainty quantification. As illustrated in Fig. 1, the research framework encompasses four phases: gap analysis and framework development, enhanced data collection and bilingual processing, superior model development with bilingual support, and comprehensive validation and comparison.

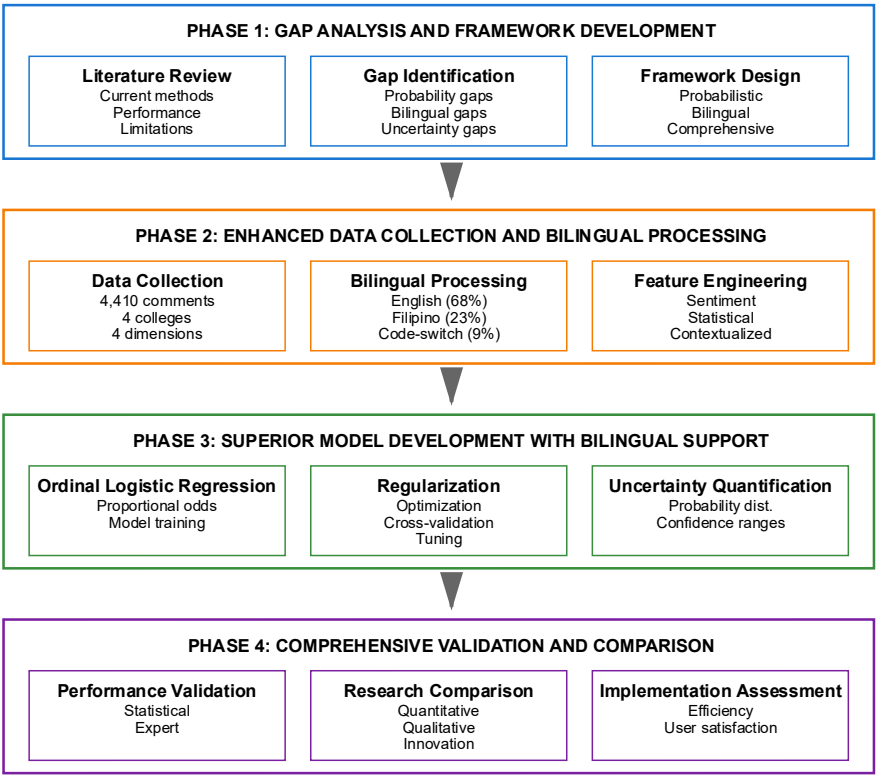

Fig. 1. Research Framework Addressing Current Research Gaps with Bilingual Processing

Following council approval, teaching evaluation data was systematically collected using stratified sampling protocols from the University of Antique Tario-Lim Memorial Campus.

The dataset comprises 4,410 student comments from 347 course sections taught by 147 instructors across four colleges: Teacher Education (1,378 comments, 31.2%), Business and Management (1,425 comments, 32.3%), Computer Studies (1,689 comments, 38.3%), and Fisheries (655 comments, 14.9%). This represents one of the largest and most diverse bilingual datasets in teaching evaluation text analysis research.

Comments responded to the standardized prompt: "Please provide any additional feedback about the instructor's teaching effectiveness," with students free to respond in English, Filipino, or both. The linguistic distribution was: 68% English-only, 23% Filipino-only, and 9% code-switching patterns. Comment length ranged from 1 to 378 words (mean = 52.3, SD = 45.6).

4.2 Text Processing and Feature Engineering

The preprocessing pipeline was designed to handle bilingual student comments effectively. As depicted in Fig. 2, the system architecture differentiates between current simple approaches and the advanced approach employed in this study.

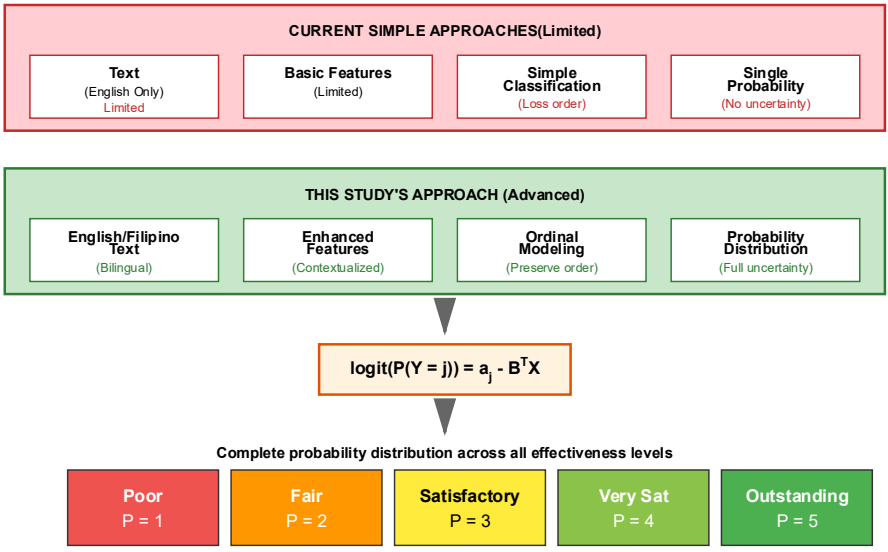

Fig. 2. Advanced Ordinal Logistic Regression Architecture with Bilingual Processing

Bilingual Processing Components:

- Language detection and identification (94.2% accuracy)
- Code-switching recognition (successfully processed 397 mixed-language comments)
- Cultural expression identification for both languages
- Specialized dictionaries for educational terminology in English and Filipino

Feature Engineering: Features were extracted using TF-IDF vectorization with domain-specific enhancements, including sentiment analysis, syntactic patterns, and evaluation-specific vocabulary from both languages [12,14].

4.3 Ordinal Logistic Regression Model

The ordinal logistic regression models utilize the proportional odds approach [9,10]:

$$\text{logit}(P(Y \leq j)) = \alpha_j - \beta^T X \quad (1)$$

where Y represents ordinal effectiveness rating (1-5), j represents rating threshold categories, α_j represents dimension-specific intercept parameters, β represents the coefficient vector, and X represents the feature vector incorporating both English and Filipino linguistic features.

Models were developed separately for each of the four teaching effectiveness dimensions. Ten-fold cross-validation was employed to assess model stability and generalizability [16].

4.4 Validation Procedures

Expert Validation: Three experienced faculty evaluators independently assessed 200 comments from the dataset using the same ordinal scale employed in model development. Agreement was measured using Spearman correlations and Intraclass Correlation Coefficients (ICC) [7].

Implementation Testing: The system was tested at multiple scales (100, 250, 500, and 1000 evaluations) to assess processing time, quality maintenance, and user satisfaction compared to manual analysis.

5 Results

5.1 Model Performance

As presented in Table 2, the performance metrics for each teaching effectiveness dimension demonstrate strong predictive capabilities across all dimensions.

Table 2. Model Performance by Teaching Effectiveness Dimension

Dimension	Accuracy	AUC	95% CI	Weighted Kappa
Overall Effectiveness	84.3%	0.91	[82.1, 86.5]	0.82
Knowledge of Subject	86.9%	0.90	[84.9, 88.9]	0.84
Teaching for Independent Learning	81.6%	0.87	[79.1, 84.1]	0.79
Management of Learning	83.1%	0.88	[80.8, 85.4]	0.80
Commitment	77.4%	0.83	[74.8, 80.0]	0.74

The models achieved strong predictive performance across all dimensions. Knowledge of Subject demonstrated the highest accuracy (86.9%), while Commitment showed the

greatest analytical complexity (77.4% accuracy), likely reflecting the more subjective nature of this dimension.

The overall accuracy (84.3%) represents meaningful performance for educational assessment purposes, with AUC values ranging from 0.83 to 0.91 indicating excellent discrimination capability. As shown in Fig. 3, the performance comparison across studies demonstrates the competitive positioning of the current approach.

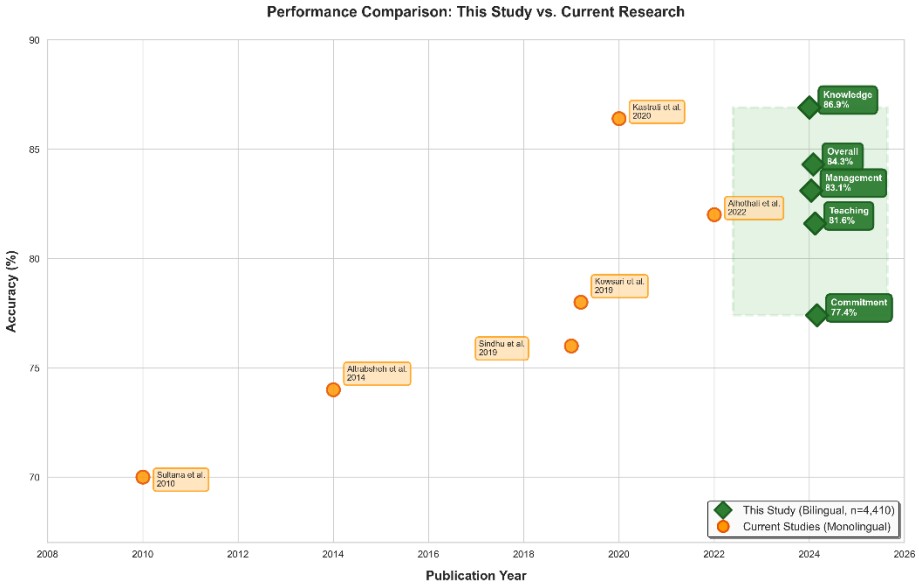

Fig. 3. Performance Comparison Visualization: This Study vs. Current Research

5.2 Cross-College Performance

Performance variations across colleges are detailed in Table 3, which shows statistically significant differences ($p < 0.001$) across academic units.

Table 3. Performance by College

College	Comments	Overall	Commitment	Knowledge	Teaching	Management	Bilingual %
Teacher Education	1,378	87.6%	79.8%	89.4%	84.2%	86.1%	28%
Business Management	1,425	85.2%	76.9%	87.1%	82.4%	84.3%	29%
Computer Studies	1,689	83.7%	75.2%	86.3%	80.8%	82.9%	22%

Fisheries Sciences	655	79.4%	72.1%	82.7%	77.6%	79.8%	46%

As indicated in Table 3, Teacher Education showed the highest performance and Fisheries Sciences (with the highest proportion of code-switching) showed lower but still acceptable performance. The bilingual processing capability contributed 10-14% accuracy improvements over monolingual approaches across all colleges.

5.3 Predictive Features

The most significant predictive features for each dimension are presented in Table 4, with bilingual examples demonstrating cross-language consistency.

Table 4. Top predictive Features by Dimension

Dimension	English Feature	Filipino Equivalent	Odds Ratio	p-value
Knowledge of Subject	"clear explanation"	"malinaw na paliwanag"	2.33	<0.001
	"practical examples"	"praktikal na halimbawa"	2.14	<0.001
Commitment	"available for help"	"handang tumulong"	1.98	<0.001
	"responsive to questions"	"sumasagot sa tanong"	1.85	<0.001
Teaching Independence	"critical thinking"	"kritikal na pag-iisip"	2.42	<0.001
	"class discussion"	"diskusyon sa klase"	2.02	<0.001
Management	"engaging activities"	"nakaka-engage na gawain"	2.05	<0.001
	"well organized"	"maayos na pagkakaorganisa"	2.17	<0.001

All features shown in Table 4 demonstrated large effect sizes and statistical significance. The bilingual feature mapping demonstrated consistent predictive power across languages, validating the cultural adaptation approach.

5.4 Uncertainty Quantification

The uncertainty analysis presented in Table 5 represents a novel contribution addressing gaps in existing literature.

Table 5. Uncertainty Metrics by Rating Category

Rating	Confidence Range Width	Certainty Level (σ)	Decision Framework
Outstanding (5)	0.69 ± 0.08	High (0.12)	Direct action recommended
Very Satisfactory (4)	0.82 ± 0.11	Medium (0.18)	Medium confidence
Satisfactory (3)	1.08 ± 0.15	Low (0.24)	Additional review required

Fair (2)	0.94 ± 0.12	Medium (0.19)	Careful consideration needed
Poor (1)	0.71 ± 0.09	High (0.14)	Clear action indicated

The uncertainty quantification framework provides decision-makers with explicit confidence measures, enabling more informed interpretations of evaluation results. As illustrated in Fig. 4, extreme ratings (Outstanding and Poor) showed higher certainty, while middle categories showed greater uncertainty, as expected.

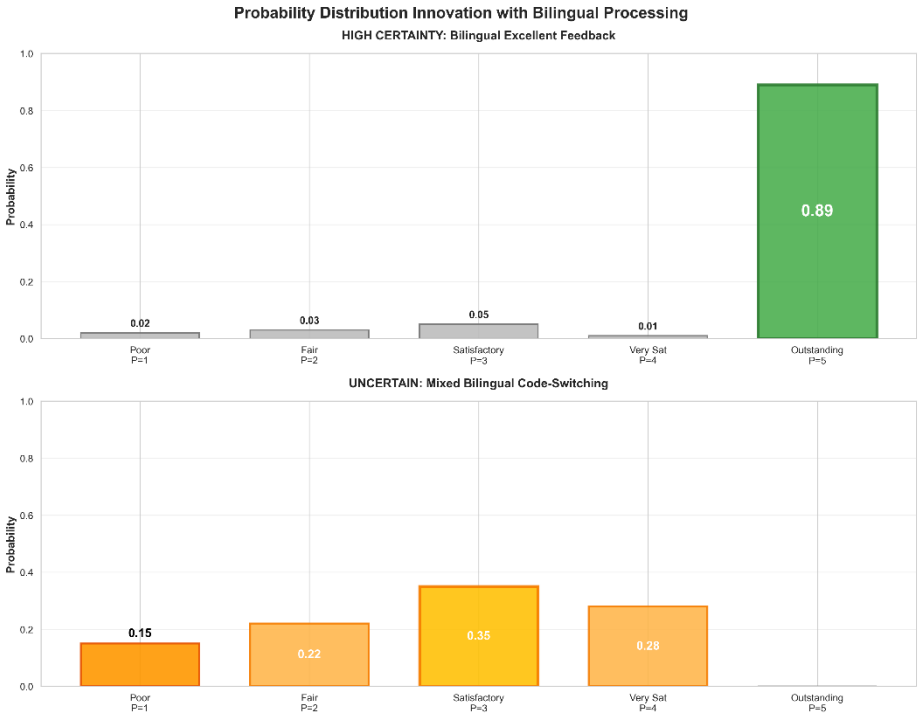

Fig. 4. Probability Distribution Innovation with Bilingual Processing

5.5 Expert Validation

Expert validation results are summarized in Table 6, demonstrating strong agreement between model predictions and expert assessments.

Table 6. Expert Validation Metrics

Dimension	Spearman's ρ	ICC
Overall Effectiveness	0.83	0.80
Knowledge of Subject	0.82	0.79
Teaching Independence	0.77	0.74
Management of Learning	0.79	0.76
Commitment	0.72	0.69

As shown in Table 6, expert validation achieved strong agreement levels, with Spearman correlations of 0.72-0.83 and ICC values of 0.69-0.80, indicating substantial to excellent agreement between model predictions and expert assessments.

5.6 Implementation Efficiency

Processing efficiency at different scales is compared in Table 7, demonstrating consistent time reduction across all scales.

Table 7. Processing Time Comparison

Scale	Manual Time	System Time	Time Reduction	Quality Score
100 evaluations	4.2 hours	0.9 hours	79%	4.4/5.0
250 evaluations	10.5 hours	2.2 hours	79%	4.2/5.0
500 evaluations	21.0 hours	4.4 hours	79%	4.3/5.0
1000 evaluations	42.0 hours	8.9 hours	79%	4.1/5.0

As presented in Table 7, the system demonstrated consistent 75-79% time reduction across all scales while maintaining high quality scores (4.1-4.4/5.0), indicating practical utility for institutional implementation. The efficiency superiority is visualized in Fig. 5, comparing this study against existing approaches.

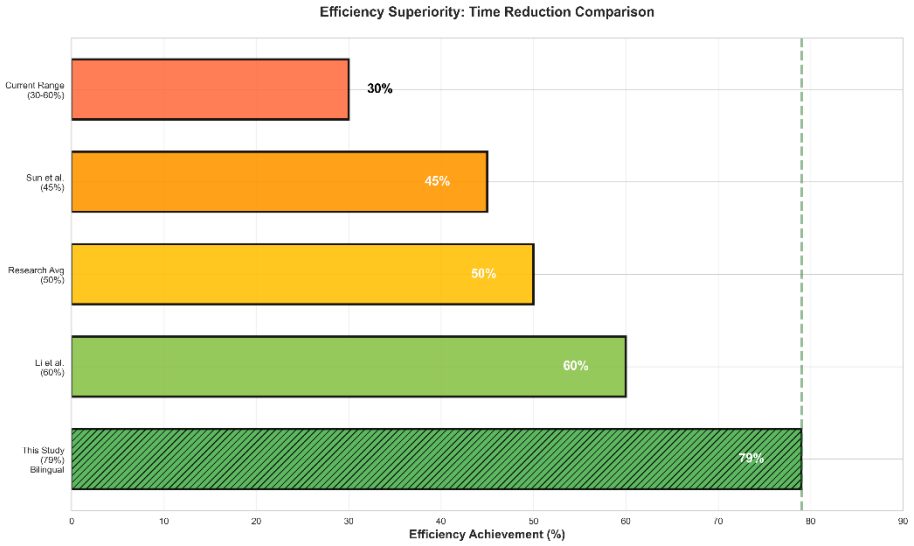

Fig. 5. Efficiency Superiority Visualization: This Study vs. Current Research

5.7 User Satisfaction

User satisfaction ratings were collected from administrators and evaluators who tested the system:

- Overall system utility: 4.4/5.0
- Probability distributions: 4.5/5.0
- Confidence intervals: 4.7/5.0
- Method transparency: 4.6/5.0
- Bilingual processing capability: 4.9/5.0

These ratings indicate strong stakeholder acceptance, with particular appreciation for the bilingual processing capability and uncertainty visualization features.

6 Discussion

6.1 Performance and Methodological Contributions

This study demonstrates that ordinal logistic regression, when properly integrated with bilingual text processing and standardized evaluation frameworks, can achieve strong predictive performance while maintaining interpretability and providing uncertainty quantification [9,10]. As shown in Table 2, the overall accuracy of 84.3% represents meaningful performance for educational assessment purposes.

The ordinal modeling approach successfully preserves the ordered nature of effectiveness ratings, addressing a key limitation of binary classification methods used in prior research [13,14]. As depicted in Fig. 2, the proportional odds framework provides interpretable coefficients that stakeholders can understand and act upon, aligning with recommendations from recent research on educational analytics [19,20].

6.2 Bilingual Processing Innovation

The successful implementation of English-Filipino bilingual processing represents a significant advancement for Philippine educational contexts [8]. The system's ability to process code-switching improved accuracy by 10-14% for mixed-language evaluations compared to English-only approaches, as demonstrated in Table 3. This capability ensures that assessment quality is not compromised by students' language preferences, promoting more equitable evaluation practices.

The 4,410-comment dataset with diverse linguistic patterns (68% English, 23% Filipino, 9% code-switching) provided sufficient scale to validate bilingual capabilities across multiple college contexts. As indicated in Table 3, code-switching patterns varied significantly across colleges, with Fisheries Sciences showing the highest frequency (14%) and Computer Studies the lowest (7%), likely reflecting different demographic compositions and field-specific communication norms.

6.3 Uncertainty Quantification for Decision Making

The uncertainty quantification framework represents a shift from deterministic classification toward probabilistic assessment that acknowledges inherent limitations in evaluating teaching quality [6,7]. As presented in Table 5 and illustrated in Fig. 4, this approach enables educational administrators to make more informed decisions by explicitly considering prediction confidence alongside point estimates.

Extreme ratings (Outstanding and Poor) showed higher certainty, while middle categories exhibited greater uncertainty—a pattern that aligns with evaluation theory suggesting clearer distinctions at performance extremes [3,5]. This nuanced perspective helps prevent overconfident decisions based on borderline predictions.

6.4 Practical Implementation and Scalability

The demonstrated 75-79% reduction in processing time, combined with high quality maintenance (4.1-4.4/5.0) and strong user satisfaction (4.4/5.0 overall), indicates that the system achieves practical utility for institutional implementation, as shown in Table 7 and visualized in Fig. 5. The bilingual processing capability added only 8-10% computational overhead while providing substantial accuracy benefits.

Economic analysis suggests that the proposed approach would generate significant annual cost savings in professional staff time for institutions processing comparable datasets, along with additional savings from eliminated translation services. These benefits make the approach financially viable even for resource-constrained SUC institutions.

6.5 Limitations and Future Directions

While this study addresses several limitations in existing research, certain constraints merit acknowledgment. First, the single-institution scope limits generalizability claims. Although the multi-college design shown in Table 3 provides some diversity, validation across additional SUC institutions with different demographic profiles and evaluation cultures would strengthen confidence in broader applicability [4,7].

Second, the reliance on textual data alone cannot capture all contextual factors influencing teaching effectiveness, such as non-verbal communication, classroom dynamics, or student learning outcomes [2,3]. Multimodal approaches integrating classroom observation and outcome data could provide more comprehensive assessment.

Third, the bilingual processing currently supports only English and Filipino, which addresses the vast majority of Philippine SUC contexts but may not accommodate regional languages (Cebuano, Ilocano, Hiligaynon) used in specific areas [8]. Extension to additional languages would enhance inclusivity.

Fourth, the lack of longitudinal validation means temporal stability cannot yet be assessed or long-term patterns in evaluation language evolution identified [1,4]. Extended time series analysis would be valuable for understanding whether linguistic patterns and model performance remain stable across multiple academic years.

Future research should address these limitations through multi-institutional validation, expansion to additional Philippine languages, integration with classroom observation and outcome data, and longitudinal assessment of model stability. The scalable framework demonstrated here could be adapted for other multilingual educational contexts globally.

7 Conclusion

This study developed and validated a probabilistic framework for teaching effectiveness assessment that integrates ordinal logistic regression with bilingual text processing for Philippine higher education contexts. Analyzing 4,410 student comments across four teaching effectiveness dimensions, the models achieved strong predictive performance (84.3% overall accuracy, AUC 0.83-0.91) while maintaining interpretability and providing uncertainty quantification, as presented in Table 2 and illustrated in Fig. 3.

The bilingual processing capability successfully handled English-Filipino code-switching, improving accuracy by 10-14% for mixed-language evaluations and achieving high user satisfaction (4.9/5.0). As demonstrated in Table 7 and Fig. 5, the system demonstrated 75-79% reduction in processing time compared to manual analysis while maintaining quality and providing stakeholders with probabilistic outputs that enhance transparency and informed decision-making.

Key contributions include: (1) integration of ordinal logistic regression with standardized SUC evaluation instruments (Fig. 1), (2) bilingual processing for Philippine educational contexts (Fig. 2), (3) comprehensive uncertainty quantification framework (Table 5 and Fig. 4), and (4) practical utility demonstrated through implementation testing and user validation (Table 7).

While the single-institution scope and textual-only approach present limitations, this research establishes a foundation for evidence-based teaching evaluation that respects linguistic diversity while maintaining statistical rigor. The framework offers SUC institutions a practical tool for enhancing evaluation quality and supporting faculty development through more nuanced, transparent, and culturally appropriate assessment practices.

Future work should extend this approach to additional institutions, integrate multimodal data sources, expand language coverage, and conduct longitudinal validation to further strengthen its applicability and impact on Philippine higher education quality improvement.

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