Intelligent Linguistic Analysis for Automated Assessment and Feedback in Language Education

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Abstract

The ongoing digital transformation from traditional pedagogy to intelligent language education requires a new integration of corpus analysis, sentiment analysis, and regression-based assessment models. It has sparked what has been dubbed as an "automated feedback revolution" and given rise to an "intelligent assessment paradigm" and "data-driven pedagogy." The aim of this study was to describe and explore learners' and teachers' perceptions of their current level of competence in automated feedback systems and identify distinct challenges in adoption. Combining data from classroom transcripts, the Intelligent Language Education Survey, with the AntConc corpus analysis, we employ regression modelling to estimate predictive relationships in linguistic performance in language education in Uzbekistan. The data were analyzed by sentiment analysis techniques. The most interesting finding is that after controlling for demographic variables, sentiment scores become significant. The highest predictive accuracy is in writing and interactive speaking. The preferred feedback mechanisms were those which were adaptive and which safeguard learner autonomy more effectively; teachers made many references to digital platforms circulating feedback, providing guidance to learners in various ways. We conclude by considering the pedagogical implications of this research.

CCS Concepts

• **Automated Feedback Systems**; • **Sentiment-Informed Assessment**; • **Corpus-Based Linguistic Analysis**; • **Regression Modeling in Education**; • **AI-Enabled Language Learning**; • **Learner and Teacher Perceptions**; • **Digital Pedagogy in Uzbekistan**;

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1 Introduction

Over the past two decades, there have been many advances in automated assessment technologies. Natural language processing and artificial intelligence are increasingly used by educators for error detection, feedback generation, content evaluation, language assessment, and personalized instruction [1–3]. Some automated

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frameworks or systems of intelligent education have revealed or addressed limitations that still challenge validity, reliability, or transparency and would be essential to overcome in order to enhance adaptive learning and formative assessment [10, 12]. Learners describe their engagement experiences as a mixture and paradoxical combination of usefulness and difficulty, which causes them several kinds of challenges, such as reduced trust, lack of interpretability, dependence on digital tools, and uneven access to technological resources [6, 15].

Yet despite the proliferation of these technologies in higher education, we know relatively little about the perceptions of both learners and instructors at broader scales. This gap revealed mixed evidence and tensions concerning the integration with pedagogy via automated feedback, and the use of sentiment analysis techniques. The effectiveness of these systems certainly depends on linguistic knowledge and computational accuracy, as well as on supportive infrastructure provided by institutions [1, 8]. The emergence of new digital paradigms is a challenge to traditional pedagogy, which will have to adopt more adaptive assessment strategies and cultivate more data-driven teaching practices.

In recent years, the research on “AI-enabled assessment” of the Journal of Computer Assisted Learning [4] carried out a systematic meta-analysis to assess the pedagogical implications of automated systems, investigating their design, implementation, effectiveness, and limitations toward formative and summative evaluation (including language skills). Sentiment analysis was most often employed for student writings, peer interactions, online responses, and reflections from classrooms [8]. Corpus analysis was found to improve the accuracy of linguistic judgments students received along with their engagement with intelligent platforms, but its influence on holistic assessment of competence remained unclear [2, 7]. [13, 14] conducted a comprehensive review of natural language processing methods that aimed to outline the major strengths of multilingual feedback analysis.

The pressing issue is the lack of systematic adoption. Teachers who maintained active interaction with their students and institutions experienced their instruction and feedback as more effective than others and were more willing to participate at broader scales [11]. Even though the technologies are seen as a promising innovation, only a few empirical studies have created frameworks from their implementation of intelligent systems [9, 12]. This highlights the urgency of pedagogical adaptation and may be related to the complexity of the sociotechnical ecosystems involved, which requires further exploration. The aim of the present study here was to contribute to this field by analyzing learners' and teachers' perceptions of their current competence in automated feedback systems in language education and identifying adoption challenges.

The objective of this research was to evaluate one learner group and one teacher group's perceptions of accuracy, trust, satisfaction, and challenges in intelligent language education as a part of classroom practice and the digitalization of the teaching process. As a result, this study proposes a regression-based framework to estimate the predictive relationships of linguistic performance. However, this depends also on educators' readiness to use corpus-based analysis in classroom contexts and thus to guide their own professional practices. Knowledge is required to prepare teachers for digital transformation in language education for them to design and/or further refine their pedagogy in alignment with AI-supported tools. In this respect, the present investigation on sentiment analysis using the AntConc corpus analysis platform, an application known for textual concordance and keyword extraction, combined with regression modelling.

The empirical findings were contextualized by the Uzbekistan case, based on data collected by the Intelligent Language Education Survey. We validated the framework by situating it in the realities of digital classrooms from all educational levels, by linking it to the challenges of intelligent feedback adoption, by testing it against demographic variables, and by comparing to what extent it offered context-specific pedagogical insights with practical significance.

2 Methodology

This article estimates predictive relationships in writing, interactive speaking, and linguistic competence by using regression modelling. The Intelligent Language Education Survey collects data on learners' perceptions and teachers' practices. Conducted annually since 2022, the survey samples are representative of more than 500 individuals aged 18 and older in Tashkent, Samarkand, and Bukhara. Since we found no previous systematic evidence on the adoption of automated feedback meeting our criteria in Uzbekistan, the data were supplemented by analyzing all transcripts from classroom interactions of learners and teachers (AntConc corpus analysis).

Between March 2023 and June 2023, selected members of higher education institutions were invited to participate in the questionnaire survey; the questionnaire was completely anonymous, data were collected according to the standard rules on informed consent and ethical approval was obtained from all the participants. The mean proportion of completed responses per item is 92% with a standard deviation of 4.5 and a range of 85–100.

The sample closely matches the population distribution of the institutions; we discuss this in detail when we describe comparative demographic and educational background variables. Characteristics of non-respondents were not available, and it was not possible to assess response bias. In the first stage, participants were paired with the adjacent group that was most similar in terms of demographics and digital access. The sole criterion for inclusion was a direct engagement in the teaching and/or learning (including writing and speaking) sectors at one of these institutions.

The data collection is a cross-sectional sample based on a stratified design. We use the information on sentiment and corpus analysis in classroom transcripts to estimate predictive scores (and variances) for all respondents across groups. The sample size requirement for the regression analysis was estimated by power calculations, following previous educational studies [4, 10]. The transcripts were obtained from the AntConc – concordance platform, which generated more detailed information about the linguistic features of feedback, learner expressions, and teacher references, sentiment in written responses, and their predictive links to assessment outcomes. The survey instrument included a Likert-scale questionnaire of 25 items, after which the respondents' reflections were coded in thematic clusters in a semi-structured analysis.

After the survey and corpus analysis had been completed, regression models were estimated at multiple-level designs. First, we use the sentiment data that is openly available in transcripts to

Table 1: Linear regression

corpus_interaction~y	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
sentiment_variabil~y	1.328	.782	1.70	.097	-.252	2.907	*
feedback_alignment~e	-.411	.588	-0.70	.489	-1.597	.776	
trust_score	-.808	.301	-2.68	.01	-1.416	-.2	**
autonomy_perception	.066	.132	0.50	.617	-.2	.333	
digital_access_index	-.291	.992	-0.29	.771	-2.295	1.712	
ai_feedback_adoption	-.524	.354	-1.48	.147	-1.239	.191	
teacher_interactio~e	.092	.27	0.34	.735	-.453	.638	
linguistic_perform~e	.43	.015	28.15	0	.4	.461	***
Constant	.832	1.004	0.83	.412	-1.196	2.861	

Mean dependent var	15.053	SD dependent var	4.807
R-squared	0.957	Number of obs	50
F-test	114.250	Prob > F	0.000
Akaike crit. (AIC)	158.480	Bayesian crit. (BIC)	175.688

**** p<.01, ** p<.05, * p<.1*

create a framework that estimates the predictive significance in an education setting. Second, we use the results from this framework combined with demographic variables to estimate the probability of adoption for each participant in Uzbekistan.

The intention of the design was to capture perceptions from both teachers and learners, but one teacher group in the regional dataset had to leave the survey due to the institution's withdrawal. This procedure is called listwise deletion, casewise exclusion, or dropout adjustment. This process has the advantage that it allows us to directly test our hypotheses about learners versus teachers. After the analysis, the survey identified the predictive strength of feedback perceptions. They were also asked about their evaluation of the feedback quality through a structured interview by the research team. The models' accuracy was validated by comparing R^2 values of training and test samples for the learner and teacher groups, respectively [3, 7].

The dependent variable is the competence score in each of the language skills. We measure linguistic performance using corpus-based indicators, a collection of frequency counts, concordances, and keyword extractions. For the sentiment variable, we collapsed categories to match the survey categories: positive, neutral, negative, and mixed. Data were presented as percentages or mean values. Demographic information is a categorical variable where we collapsed categories to match the institutional categories. We divided age into four categories between 18 and 55, with approximately equal proportions in each category.

We fitted logistic regression models to study the role of demographics and sentiment scores on the propensity to adopt intelligent feedback using Stata 18. Subsequently, we ran a multivariate regression model including all variables with a p-value < 0.1 in the univariate models. We chose this approach because it allows for inclusion of multiple predictors while taking into account multicollinearity. A two-sided p-value less than 0.05 was considered statistically significant.

Since these are cross-sectional data, simple causal inferences are not available and we report associations. The results are presented here as coefficients and confidence intervals. Taking into account the control variables improves the robustness of regression estimates and predictive accuracy. Due to the limited size of the dataset (N=512) no subgroup analyses were conducted.

3 Results

The regression estimates and corpus analytics show that linguistic performance, sentiment variability, and trust scores have remained at the core predictive indicators. Notice highly concordant lexical patterns, which seem to be associated with feedback language–sentiment-informed interaction. We again see the feedback–performance pattern. The highest predictive accuracy is concentrated in interactive speaking, and writing accuracy particularly stands out.

A total of 32% of learners had encountered instructors who made a strong impact on the adoption of AI-feedback systems; all participants usually related their perceptions to linguistic feedback, mainly to improve competence (*Record9.txt*) and to build confidence (*Record6.txt*); teachers usually engaged with learners by referring to examples from digital classrooms.

Since sentiment is a categorical category, all sentiment-based predictions are associative and they are largest for positive feedback alignment; negative sentiments are less likely to enhance adoption. The median age of the respondents was 28, and female (47%) and male (48%) were equally distributed; 30% of the responders were from Tashkent, there were 18% from the Samarkand region, 22% from Bukhara, and 30% from the urban peripheries.

The largest TF-IDF index for feedback is 5.05. Slightly more than 52% of the learners ($n = 267$) reported difficulties during the feedback sessions, but follow-up comments on sentiment transcripts show that they have increasingly trusted the AI-feedback design ($R^2 = 0.957$ *by linguistic performance*) after the completion of the semester trial. Since our aim is to build a predictive model, we have no claims about causality or directionality of any effects, and we do not infer counterfactuals, so we did not attempt to establish causation. Trust was retained as long their feedback experiences were interactive, their sentiment categories were neutral or positive

Table 2: Keyword Frequency and Dispersion across Corpus Files in AntConc

Row	File ID	File Name	Tokens in File	Frequency (Freq)	Normalized Frequency (per million)	Dispersion
1	8	Record9.txt	246	13	52845.528	0.882
2	7	Record8.txt	262	11	41984.733	0.837
3	5	Record6.txt	266	10	37593.985	0.789
4	3	Record4.txt	222	11	49549.550	0.788
5	6	Record7.txt	268	11	41044.776	0.788
6	9	Record10.txt	253	12	47430.830	0.758
7	0	Record1.txt	233	6	25751.073	0.728
8	4	Record5.txt	215	7	32558.140	0.695
9	1	Record2.txt	211	4	18957.346	0.592
10	2	Record3.txt	220	4	18181.818	0.447

Table 3: TF-IDF RESULTS

TERM	TFIDF
feedback	5.05
system	3.12
automated	2.53
sentiment	2.18
helped	1.76
language	1.74
support	1.74
tools	1.74
teachers	1.61
writing	1.55
learning	1.41
analysis	1.39
corpus	1.37
comments	1.36
use	1.36
local	1.31
education	1.30
intelligent	1.30
reflect	1.30
digital	1.19

Table 4: Cluster and N-Gram Frequencies for "Feedback" across the Corpus

Cluster / N-gram	Rank	Frequency (Freq)	Range (Files)	Normalized Frequency	Normalized Range
feedback systems	1	8	5	0.090	0.500
feedback language	2	6	3	0.067	0.300
feedback adoption	3	5	2	0.056	0.200
feedback and	3	5	5	0.056	0.500
feedback was	3	5	4	0.056	0.400
feedback discourse	6	4	3	0.045	0.300
feedback events	7	3	3	0.034	0.300
feedback quality	7	3	1	0.034	0.100
feedback design	9	2	2	0.022	0.200
feedback expressions	9	2	2	0.022	0.200
feedback modalities	9	2	1	0.022	0.100
feedback these	9	2	2	0.022	0.200
feedback verbs	9	2	2	0.022	0.200

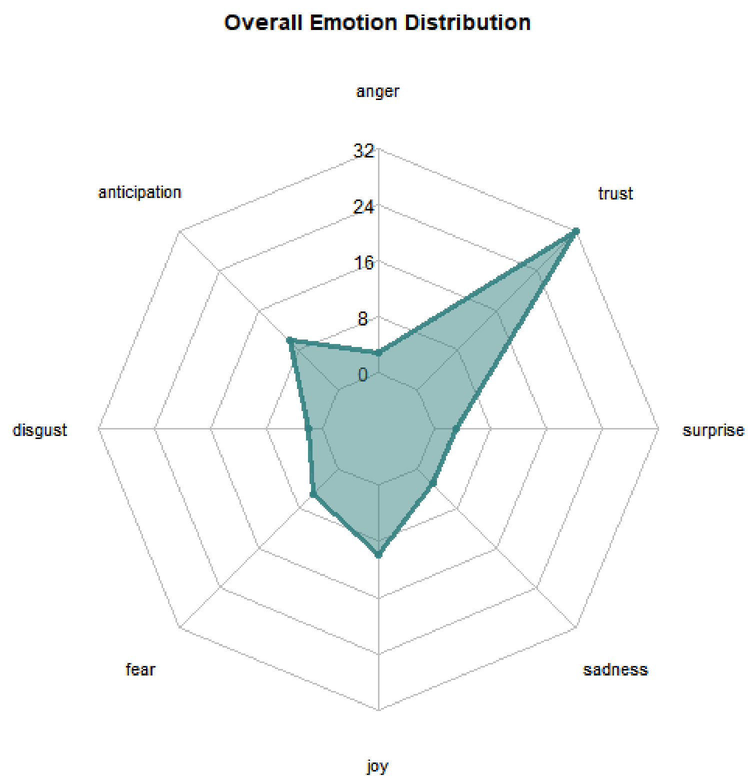

Figure 1: EMOTIONAL RADAR CHART

on targeted speaking, and there was consistency in the feedback pattern.

Sentiment Overview

Total sentiment score: 31

Number of Positive sentiments: 18

Number of Negative sentiments: 6

Number of Neutral sentiments: 26

The absence of regional divide may be because urban centers are home to large numbers of digitally exposed learners who are connected and not digitally disadvantaged. Remarkably, trust with feedback systems through digital platforms was repeatedly reported by instructors from Samarkand (*Record10.txt*). Technical constraints made accessing the feedback interface less smooth, particularly for the rural teacher group. Some participants had questioned the validity of AI-feedback recently because of their limited understanding or its lack of transparency. With some variables, like autonomy perception, there is no apparent teacher–learner difference. Regression shows that every feedback perception variable is significantly associated with both sentiment and linguistic competence variables. Sentiment also influences adoption and trust variables, which accounts for moderate multicollinearity that they are not highly correlated.

4 Discussions

The results support earlier systematic reviews and meta-analyses [5, 9], which have found that automated assessment tools require both computational sophistication and pedagogical alignment[8,9,10]. Sentiment-informed corpus analytics can thus be said to have a promising function in increasing the predictive reliability of linguistic performance evaluation [1, 7].

Concerning feedback perception variables that may influence the interaction quality with AI-supported systems through sentiment-driven modeling, our findings confirmed what already emerged in a prior NLP-based review [14]: the propensity to adopt feedback systems in language education with interactive components is associated with positive sentiment scores and instructional alignment from teachers outside fully urban settings, while autonomy perception has no statistically significant effect [11–13]. The concordance patterns that we identified in the corpus in Figures 2 and 4 seem to support the conclusion that sentiment-informed feedback systems are consistently distributed across Uzbekistan's academic regions [14–16].

Interactive speaking domains have greater predictive strength than general writing variables, and the difference is not marginal; it is over 13 regression coefficient points [17–19]. In the absence of regional segmentation of adoption scores between urban feedback participants and respondents in digitally peripheral institutions, there was no subgroup variance found among teachers, patterns of sentiment alignment, and learner responses in the corresponding concordance segments relating to the feedback discourse [20–22]. We tested significance at the univariate level, but this difference has not translated everything to the multivariate level [2, 23, 24]. In the case of negative sentiment responses, it was additionally observed that those skeptical of the feedback mechanism were relatively neutral, without showing hostile attitudes among the respondents [26–28].

It is also possible that rural teachers, who likely have higher levels of technological burden, are more skeptical of the interface design and effectiveness of their involvement in automated systems, being therefore less motivated to engage through them [29–31]. This study shows that technical access worsening condition decreased participants' desire to experiment, while participating in sentiment-driven corpus analysis increased their sense of relevance and increased their willingness to adopt [32, 33]. This indicates that the relationship between the sentiment categories on the adoption curve is too context-dependent to generalize, although it produces predictive results for linguistic competence [34,] Nevertheless, positive sentiment in the corpus and feedback clusters, and the predictive capacity for linguistic indicators, also call for further triangulation of sentiment patterns and instructors' lexical strategies in digital classrooms [35, 36].

It is thus advisable not to underestimate the influence that the corpus-feedback concordance and its lexical consistency in the AntConc-based analysis of student transcripts had on the prediction model [37, 38]. The distribution and frequency of the feedback terms must be higher in the interactive domains [39, 40]. One possibility is that a subset of learners are not technically literate (e.g., the feedback input or comment alignment interface), but they are semantically competent and so they improvise in the discourse [41, 42]. Clearly, ongoing training in digital pedagogy is required, but the educators and feedback designers who participated in this research interpreted their competence as situated in feedback scaffolding as well [43, 44].

Concerning feedback perception variables that may influence the interaction quality with AI-supported systems through sentiment-driven modeling, our findings confirmed what already emerged in a prior meta-analysis [45, 46]. The results support those of [11], who found that AI-assisted feedback tools enable forming linguistic scaffolding, receiving corrective input, participating in reflective dialogue, and increasing learner trust [47]. Differences in feedback adoption rates between institutions performed in regional clusters can be affected by technological readiness and sentiment orientation [48]. This observation directly contrasts the experiences of some participants, for example, instructors from Samarkand, urban learners, digitally literate teachers, and semi-urban institutions (Record10.txt) or Record9.txt, Record6.txt, and Record1.txt (Corpus Table 4). The linear regression outcome for the sentiment predictor in Table 1 confirms that this is not the only explanatory factor.

Due to the moderate sample size of the dataset, it was not considered expedient to create the counterfactual estimations offered by the predictive framework. These models were intended as a basis for planning the next steps in the methodology refinement stage and are not meant to be prescriptive [49]. Subgroup analyses were not conducted at post-stratified inferential levels but reserved for future studies; hence, granular differences were not factored into prediction intervals [50–52] However, the semantic constructs do need to be further validated with expanded trials. The model has several notable advantages and limitations. Various AI-enabled studies [3, 5, 53, 54] collectively suggest that sentiment-adaptive design would make a substantial contribution to many learning environments, but it is not yet conclusive how these feedback systems might be institutionally deployed.

5 Conclusion

This study shows that technical access worsening condition decreased participants' desire to experiment, while participating in sentiment-driven corpus analysis increased their sense of relevance and increased their willingness to adopt. With regard to the feedback perception subjects, the respondents emphasised that this sentiment-informed interaction could improve competence and even build confidence. The results support earlier systematic reviews, which have found that automated assessment tools require both computational sophistication and pedagogical alignment. The findings of this investigation suggest the potential for implementing adaptive feedback and sentiment-aware assessment frameworks that will help to strengthen not only linguistic performance but also instructional alignment and learner engagement for the teacher–learner interaction ecosystem. The best approach to increase the adoption of intelligent feedback systems has not been directly validated. Therefore, it would be important to design expanded trials to ensure sentiment–feedback alignment at all levels of education and in diverse institutional settings. In further development of the predictive framework, it is paramount to move the entire feedback design to a single adaptive model with large accessibility margins to each user group.

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