

Predicting User Trust, Adoption Intention, and Business Communication Effectiveness in LLM-Based Translation Using Machine Learning

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Abstract

The use of Large Language Models (LLMs) for cross-border business translation is growing rapidly, yet quantitative research integrating accuracy, trust, adoption, and communication effectiveness remains limited. This study explains and predicts these relationships using a cross-sectional survey combining explanatory and predictive approaches. Data were collected from 207 respondents through a 24-item questionnaire covering five dimensions: Usage, Translation Accuracy, User Trust, Adoption Intention, and Business Communication Effectiveness. All dimensions were reliable (Cronbach's alpha 0.91-0.94) and all items were valid. Analysis combined multiple linear regression, classical assumption tests, and a Random Forest algorithm on the same framework. Usage and Translation Accuracy significantly predicted User Trust ($R^2 = 0.90$); User Trust was the most dominant predictor of Adoption Intention (feature importance 72.6%); and User Trust together with Adoption Intention explained 91% of the variance in Business Communication Effectiveness. High inter-dimensional correlations (0.93-0.96) indicated potential common method bias, tested via Harman's test, ridge regression, and HC3, all consistent with the main models. The novelty of this study lies in combining explanatory and predictive approaches within a single framework accompanied by robustness checks; strengthening user trust emerges as the key strategic pathway toward sustainable adoption and effective LLM-based business communication.

Keywords: *Large Language Model, Business Translation, User Trust, Adoption Intention, Machine Learning*

INTRODUCTION

The development of artificial intelligence, particularly Large Language Models (LLMs), has transformed the way organizations conduct cross-language communication in the digital business environment (Adinta et al., 2025; Awaludin & Aravik, 2025). LLMs are increasingly used to translate business emails, customer conversations, marketing content, and operational documents, making communication faster, more efficient, and more adaptive to cross-cultural contexts (Ati et al., 2025; Suryanti et al., 2025), in line with the broader digital transformation trend in which AI plays an important role in enhancing customer experience across business channels (Amanda et al., 2026). The translation capability of LLMs itself has advanced rapidly through iterative bilingual understanding approaches that progressively refine output quality to more closely approximate human translation (Chen et al., 2024), and the quality of such translation output can now be assessed using another LLM as an automatic evaluator that has been shown to be comparable to human judgment (Kocmi & Federmann, 2023). In the business context, the broader use of AI is viewed as a strategy to improve productivity, service quality, and organizational competitiveness (Nugroho et al., 2024; Razaqi et al., 2024).

Nevertheless, the use of LLMs for business translation is not free of challenges, particularly regarding translation accuracy, contextual appropriateness, and user trust in the technology (Nurohim et al., n.d.; Siregar, 2025). Translation errors can lead to miscommunication, reduce message professionalism, and affect relationships with cross-border customers and business partners (Adinta et al., 2025; Zahra, 2026). Therefore, user acceptance of LLMs is a critical factor determining whether this technology can genuinely be adopted sustainably in business communication practice (Sani et al., n.d.; Siregar, 2025).

Among the various technology acceptance factors, user trust is a central construct that consistently determines the success of adopting AI-based systems. Trust is formed from perceptions of the competence, integrity, and benevolence of the trusted party (Mayer & Davis, 1995), a framework widely adapted to explain human trust in automated and algorithmic systems (Lee & See, 2004). In the context of LLMs for translation, user trust is assumed to be shaped primarily by perceptions of translation accuracy and consistency (Kandaga et al., 2025; Siregar, 2025), while research on algorithm aversion shows that users tend to lose trust in algorithmic systems more quickly than in humans upon witnessing even minor errors (Dietvorst et al., 2015), making consistent accuracy a critical prerequisite for AI-based translation technology.

Beyond trust, adoption intention is an important indicator of users' willingness to continue using LLMs sustainably. The Unified Theory of Acceptance and Use of Technology (UTAUT) explains that technology usage intention is shaped by performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003), while AI adoption intention can also be explained through the innovation diffusion curve (Kandaga et al., 2025) and identified using the Random Forest algorithm, which can more objectively determine the most influential predictor variables than conventional statistical analysis (Fadriansyah et al., 2026), including in the context of MSMEs constrained by limited resources and digital literacy (Pratama & Sudrajat, 2026). Business communication effectiveness, as the ultimate impact of LLM use, is measured not only by translation speed but also by how well messages are understood, received, and utilized in cross-border business contexts (Awaludin & Aravik, 2025; Zahra, 2026), so that LLMs that enhance trust and drive adoption are likely to meaningfully contribute to the effectiveness of cross-language digital business communication (Nugroho et al., 2024; Suryanti et al., 2025).

Although research on AI and technology adoption is abundant, studies specifically linking usage intensity, translation accuracy, user trust, adoption intention, and business communication effectiveness within a single quantitative framework remain limited (Pratama & Sudrajat, 2026; Siregar, 2025). Most prior studies discuss AI or digital business communication in general terms, or evaluate each construct separately (Awaludin & Aravik, 2025; Razaqi et al., 2024), and very few combine causal-explanatory testing with machine-learning-based predictive modeling on the same dataset. This research gap lies in three areas: the scarcity of integrating explanatory and predictive approaches within one identical analytical framework, the rarity of integrated multiple robustness testing (common method bias, multicollinearity, and heteroscedasticity) in AI adoption research in Indonesia, and the limited number of studies focusing specifically on LLM-based business translation rather than AI adoption in general.

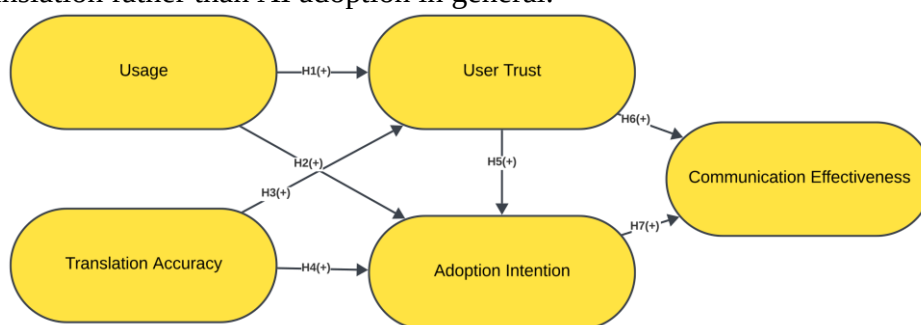


Figure 1. Research Conceptual Framework

This study was designed to fill this gap by combining multiple linear regression with a complete set of classical assumption tests and the Random Forest algorithm (Breiman, 2001) on an identical multi-tier model framework, complemented by a series of robustness tests (Harman's single-factor test, ridge regression, and robust standard errors) to examine the robustness of the findings. The conceptualization of User Trust in this study builds on the foundational view that trust in automated systems reflects users' calibrated reliance on the system's performance and reliability (Lee & See, 2004), while Adoption Intention draws on the widely used technology

acceptance framework identifying performance expectancy and effort expectancy as core antecedents of technology adoption (Venkatesh et al., 2003). The Translation Accuracy construct is further grounded in recent evidence that large language models can now serve as state-of-the-art evaluators of translation quality, underscoring accuracy as a measurable and consequential attribute of LLM-based translation tools (Kocmi & Federmann, 2023). Empirically, this conceptual chain is supported by findings that both trust and perceived benefits of AI technology significantly influence users' intention to adopt AI-based decisions, with dialogue quality moderating this relationship (Sani et al., n.d.). This study specifically focuses on LLM users for translation needs in cross-language business communication, rather than AI technology users in general. Based on the conceptual framework in which Usage and Translation Accuracy influence User Trust, which together with Usage and Translation Accuracy then influence Adoption Intention, and ultimately Trust together with Adoption Intention influence Business Communication Effectiveness, this study formulates seven hypotheses: Usage significantly affects Trust (H1); Accuracy significantly affects Trust (H2); Usage (H3) and Accuracy (H4) significantly affect Adoption Intention; Trust significantly affects Adoption Intention (H5); and Trust (H6) and Adoption Intention (H7) significantly affect Business Communication Effectiveness.

RESEARCH METHODS

This study employed a quantitative approach with a cross-sectional survey design combining explanatory and predictive objectives. The explanatory objective was achieved through multiple linear regression accompanied by classical assumption tests to explain the direction and significance of the relationships among variables, while the predictive objective was achieved through a Random Forest Regressor algorithm to build a predictive model and identify the relative importance of each predictor (Pedregosa et al., 2018). Both approaches were applied to an identical multi-tier model framework (Figure 1), allowing the results of both to complement and be compared with one another.

The population of this study consisted of individuals who had used LLMs as translation aids in cross-language business communication activities, such as translating business emails, operational documents, or conversations with foreign partners or clients. Data were collected through an online questionnaire (Google Forms) distributed to these LLM users (Muhsin et al., 2024), and after data cleaning, 207 respondents with complete data on all analyzed items were obtained. The unit of analysis and conclusions of this study are limited to LLM users in the context of digital business communication and are not intended to be generalized to digital business actors in general.

The research instrument was a closed-ended questionnaire using a 1-5 Likert scale measuring five main dimensions: Usage, Translation Accuracy, User Trust, Adoption Intention, and Business Communication Effectiveness. The initial questionnaire design contained 25 statements, but one item in the Trust dimension was answered by only 2 out of 207 respondents (less than 1%) and was therefore excluded from the analysis to avoid distorting the composite scores and reliability estimates. The final instrument analyzed consisted of 24 items, detailed in Table 1.

Table 1. Dimensions and Number of Items in the Research Instrument

Dimension	Brief Operational Definition	No. of Items
Usage	Intensity and familiarity of LLM use for business translation	5
Translation Accuracy	Perceived accuracy, consistency, and contextual appropriateness of LLM translation output	5

Dimension	Brief Operational Definition	No. of Items
User Trust	User trust in the reliability and safety of LLM translation output	4
Adoption Intention	Intention to continue using and recommending LLM in the future	5
Business Communication Effectiveness	Perceived effectiveness of cross-language business communication assisted by LLM	5
Total		24

Source: Author's compilation

The raw questionnaire data were processed using the Python programming language with the pandas library for data cleaning, statsmodels and scipy for inferential statistical analysis, and scikit-learn for machine learning modeling (Pedregosa et al., 2018). The composite score for each dimension was calculated as the mean of its constituent item scores. Data analysis was conducted in eight stages: (1) reliability testing using Cronbach's alpha (threshold $\alpha \geq 0.70$); (2) validity testing through corrected item-total correlation (r -calculated $>$ r -table, $\alpha = 5\%$); (3) descriptive statistics and Pearson correlation among dimensions; (4) common method bias detection through Harman's single-factor test (Podsakoff et al., 2003); (5) multiple linear regression on three models following the conceptual framework, namely Trust $\sim$ Usage + Accuracy; Adoption $\sim$ Usage + Accuracy + Trust; and Comm_Effect $\sim$ Trust + Adoption; (6) classical assumption tests including residual normality (Shapiro-Wilk), multicollinearity (Variance Inflation Factor/VIF, threshold < 10), and heteroscedasticity (Breusch-Pagan); (7) robustness analysis using ridge regression (RidgeCV with leave-one-out cross-validation) and HC3-type robust standard errors for models showing high VIF and/or heteroscedasticity; and (8) a Random Forest Regressor predictive model (300 trees, random_state = 42) with an 80:20 train-test split and 5-fold cross-validation, evaluated using R^2 , Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE) metrics, complemented by feature importance analysis.

RESULTS AND DISCUSSION

Results

Instrument Reliability and Validity

The results of the instrument reliability and validity tests are shown in Table 2. All five dimensions exhibited excellent internal consistency, with Cronbach's alpha values ranging from 0.91 to 0.94, well above the 0.70 threshold. The corrected item-total correlation validity test showed that all 24 instrument items were valid, with r -calculated values ranging from 0.761 to 0.858, far exceeding the r -table value (0.1364 at $\alpha = 5\%$, $df = 205$) and significant at $p < 0.001$, so no items needed to be dropped from the analysis.

Table 2. Instrument Reliability and Validity

Dimension	Cronbach's Alpha	r-calculated Range	Remarks
Usage	0.935	0.814 – 0.850	Reliable & Valid
Translation Accuracy	0.932	0.781 – 0.858	Reliable & Valid
User Trust	0.913	0.761 – 0.835	Reliable & Valid
Adoption Intention	0.933	0.786 – 0.855	Reliable & Valid
Business Communication Effectiveness	0.934	0.813 – 0.836	Reliable & Valid

Source: Author's compilation

Descriptive Statistics, Correlation, and Common Method Bias Test

Descriptive statistics for the composite scores (1-5 scale) showed that respondents' average perceptions across all dimensions were in the high category, ranging from 4.11 to 4.13, with relatively homogeneous standard deviations (0.91-0.94). Pearson correlation analysis showed that all pairs of dimensions were positively and very strongly correlated, ranging from 0.93 to 0.96 (Figure 2), with no single pair standing out as markedly lower, a pattern indicating possible construct overlap and common method bias risk.

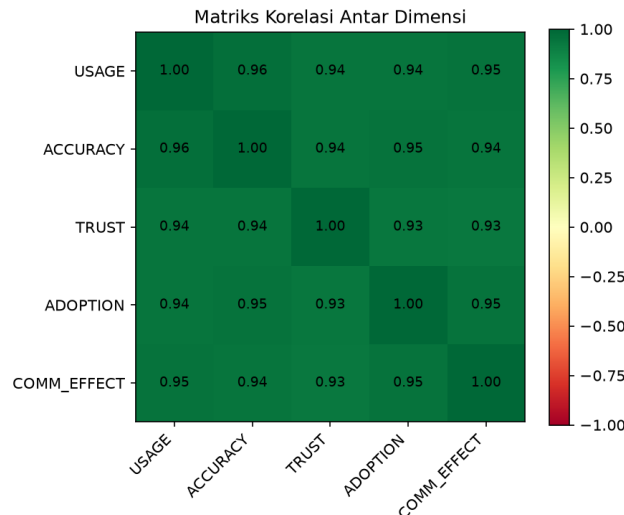


Figure 2. Pearson Correlation Matrix Among Dimensions

Source: Author's compilation

To examine indications of common method bias, Harman's single-factor test was conducted through unrotated principal component analysis (Podsakoff et al., 2003). The first factor explained 75.55% of the variance across the 24 raw items and 95.41% of the variance across the five composite scores, both above the indicative 50% threshold, with the composite-score value being higher because item averaging removes item-specific variation.

Multiple Linear Regression and Classical Assumption Tests

Three multiple linear regression models were constructed following the study's conceptual framework, with a summary of coefficients, significance, and classical assumption test results presented in Table 3. All three models showed high coefficients of determination ($R^2 = 0.90-0.92$) and all predictor coefficients were significant at $p < 0.01$, supporting H1 through H7 (hypothesis testing summary in Table 4). However, the classical assumption tests revealed two important notes: VIF values in all models far exceeded the threshold of 10 (ranging from 160-330), indicating very high multicollinearity among predictors, consistent with the high inter-dimensional correlations; and residuals in the Trust and Adoption models were not normally distributed (Shapiro-Wilk $p < 0.05$), while the Trust and Comm_Effect models showed indications of heteroscedasticity (Breusch-Pagan $p < 0.05$).

Table 3. Summary of Multiple Linear Regression and Classical Assumption Tests

Model	Predictor	B	p	R ² (Adj.)	VIF
Trust ~ Usage + Accuracy	Usage	0.458	0.000	0.900 (0.899)	275.9
	Accuracy	0.485	0.000		275.9
Adoption ~ Usage + Accuracy + Trust	Usage	0.256	0.002	0.917 (0.916)	329.9
	Accuracy	0.417	0.000		325.8
	Trust	0.288	0.000		208.5
Comm_Effect ~ Trust + Adoption	Trust	0.349	0.000	0.910 (0.910)	160.4

Model	Predictor	B	p	R ² (Adj.)	VIF
	Adoption	0.630	0.000		160.4

Source: Author's compilation

Table 4. Summary of Hypothesis Testing

Hypothesis	Relationship	B	p	Remarks
H1	Usage → Trust	0.458	0.000	Supported
H2	Accuracy → Trust	0.485	0.000	Supported
H3	Usage → Adoption	0.256	0.002	Supported
H4	Accuracy → Adoption	0.417	0.000	Supported
H5	Trust → Adoption	0.288	0.000	Supported
H6	Trust → Comm Effect	0.349	0.000	Supported
H7	Adoption → Comm_Effect	0.630	0.000	Supported

Source: Author's compilation

Robustness Checks (Ridge Regression and HC3)

To mitigate these two assumption violations, ridge regression and HC3-type robust standard error estimation were conducted as robustness checks. The results showed that the direction and ranking of predictor contributions remained consistent with the OLS regression across all three models, and all predictors significant in the original OLS model remained significant at $p < 0.01$ after HC3 correction, indicating that the significance of the relationships among variables is not merely an artifact of classical assumption violations.

Random Forest Predictive Model

The Random Forest Regressor model showed high predictive performance on both the test set (20%) and the 5-fold cross-validation (Table 5), although the cross-validation R² standard deviation for the Adoption model was relatively large (± 0.124), indicating that the single test-set performance may be somewhat optimistic and that a more reliable generalization estimate should refer to the cross-validation average.

Table 5. Random Forest Model Performance

Target	R ² (Test Set)	MAE	RMSE	R ² (5-fold CV)
Trust	0.902	0.215	0.257	0.877 ± 0.051
Adoption	0.957	0.144	0.188	0.870 ± 0.124
Comm_Effect	0.951	0.156	0.207	0.925 ± 0.021

Source: Author's compilation

Feature Importance

Feature importance analysis showed patterns broadly aligned with the regression results, while also revealing some nuances. In the Trust model, Usage (52.6%) and Accuracy (47.4%) contributed almost equally. In the Adoption model, Trust was the most dominant predictor, contributing 72.6%, far exceeding Accuracy (17.4%) and Usage (10.0%) differing from the OLS regression, in which Accuracy actually had the largest coefficient ($B = 0.417$). In the Comm_Effect model, Trust (52.8%) was slightly more dominant than Adoption (47.2%), consistent with Adoption's larger regression coefficient ($B = 0.630$).

Discussion

Interpreting Predictor Contributions Across Methods

The near-equal contribution of Usage and Accuracy in the Trust model reinforces Mayer et al.'s (1995) trust framework, in which trust is formed from perceptions of the trusted party's competence, while also suggesting a familiarity-breeds-trust mechanism in which interaction intensity itself shapes trust (Lee & See, 2004).

The divergence between the Adoption model's feature importance and its regression coefficients, where Trust dominates in feature importance (72.6%) yet Accuracy carries the

larger regression coefficient ($B = 0.417$) is not a contradiction but reflects a fundamental distinction between the two methods: regression coefficients capture the average linear change while controlling for other variables, whereas feature importance captures a variable's contribution to reducing prediction variance within a nonlinear structure (Breiman, 2001). When predictors are as highly correlated as 0.93-0.96, tree-based algorithms tend to consistently favor one dominant variable, in this case, Trust. A more accurate interpretation is therefore that Trust serves as the primary psychological pathway bridging technical experience (Usage, Accuracy) toward behavioral intention, consistent with UTAUT (Venkatesh et al., 2003) and the view that trust is a functional prerequisite for the sustainability of AI technology adoption (Siregar, 2025).

Similarly, in the Comm_Effect model, the slightly greater dominance of Trust (52.8%) over Adoption (47.2%) consistent with Adoption's larger regression coefficient ($B = 0.630$) suggests that cross-language business communication effectiveness is the ultimate outcome of sustained willingness to use LLMs, which can only be realized when underpinned by adequate trust (Awaludin & Aravik, 2025; Zahra, 2026).

High Inter-Dimensional Correlations: Substantive Structure or Methodological Artifact?

The uniformly high inter-dimensional correlations (0.93-0.96) and VIF values far exceeding conventional thresholds, together with the Harman's test result exceeding the 50% threshold, warrant careful interpretation, as this pattern points to possible construct overlap and common method bias risk. On one hand, the five dimensions are conceptually closely interrelated within a single sequential causal chain (Usage and Accuracy $\rightarrow$ Trust $\rightarrow$ Adoption $\rightarrow$ Comm_Effect), so the high correlations partly reflect the sequential structure of the constructs themselves. On the other hand, the single-source, single-time, single-instrument survey design could produce common method variance that also contributes to correlation inflation (Philip M. Podsakoff et al., 2003); this risk cannot be entirely ruled out, although Harman's test is a rough diagnostic rather than conclusive evidence. The consistency of the ridge and HC3 results indicates that the relationships among variables are not merely an artifact of multicollinearity or heteroscedasticity, but does not entirely eliminate the risk of common method bias or confirm discriminant validity among dimensions (Fornell, Larcker, n.d.), given that both procedures operate on the observed variance structure of the data rather than its source. Furthermore, the cross-sectional nature of the data means the causal relationships claimed in the conceptual framework represent theoretical inference rather than directly tested longitudinal causal evidence, and the sample being limited to active LLM users may have produced relatively high average scores (4.11-4.13), so the findings apply only to the population of LLM users in the context of digital business communication.

Positioning the Findings Within Prior Research

These findings align with (Fadriansyah et al., 2026), who found that trust and perceived benefit are dominant predictors of AI tool adoption; however, this study extends those findings through explanatory testing via multiple regression with a complete set of classical assumption tests, something generally not conducted in purely machine-learning-based studies. Compared with (Siregar, 2025), who discussed psychological factors in AI acceptance through a literature review, this study provides direct quantitative evidence that Trust has the highest predictive power for Adoption Intention specifically in the context of LLM-based business translation, while Accuracy and Usage, though less dominant, remained significant, reinforcing (Kandaga et al., 2025) view that AI technology adoption develops gradually following users' cumulative experience.

CONCLUSION

This study set out to explain and predict the interrelationships among usage intensity, translation accuracy, user trust, adoption intention, and business communication effectiveness among LLM users engaged in business translation, and the results confirm that these constructs are closely and coherently interconnected within the proposed conceptual framework. The findings show that usage intensity and translation accuracy jointly play a substantial role in shaping user trust, that user trust stands out as the most influential factor in driving adoption intention even though translation accuracy also contributes meaningfully to that outcome, and that trust together with adoption intention in turn substantially shapes the effectiveness of cross-language business communication, with the machine learning approach proving useful in identifying which factors matter most in ways that complement what conventional regression analysis alone could reveal. These findings carry both theoretical and practical implications: theoretically, they reinforce the relevance of established trust and technology-acceptance perspectives when applied to LLM-based translation technology and demonstrate that explanatory and predictive approaches can be meaningfully combined within a single analytical framework; practically, they suggest that organizations and digital business practitioners seeking to encourage sustainable adoption of LLM-based translation tools should prioritize building user trust, for instance through greater transparency about translation quality and the provision of accessible verification mechanisms, rather than focusing on technical improvement alone. Future research is encouraged to adopt longitudinal designs, incorporate actual usage data, and extend the analysis to more diverse groups of LLM users so as to further strengthen the generalizability of these findings.

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