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Scaling Students' Self-Efficacy on Machine Translation Post-Editing: Psychometric Properties of the Scale and Their Associations

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Machine Translation Post-Editing (MTPE) has emerged as a productivity-enhancing practice in the language service industry, where human editors correct the output of machine translation systems. To ensure that students of translation possess the necessary skills for MTPE, it is essential to understand their self-efficacy in this domain. This research paper aims to assess students' self-efficacy in translation learning, specifically in the context of MTPE, and explore the factor structure, psychometric properties, and internal associations of their self-efficacy. The study utilized a modified survey adapted from the Scale for Assessing Translators' Self-Efficacy and collected responses from 65 undergraduate students in a Chinese university. The survey data underwent reliability and validity analyses, including exploratory factor analysis, to assess the measurement tool's consistency, stability, and construct validity. The results indicated a high reliability of the scale (Cronbach's Alpha = 0.914) and revealed three primary dimensions of self-efficacy: Decision-making of MTPE, Communicative Competence of MTPE, and Strategic Competence of MTPE, and the strong inter-correlations suggests that they collectively measure the construct of translators' self-efficacy of MTPE, providing insights into the skills and abilities required for effective MTPE. The findings contribute to the development of psychometric tools for further research in translation and promote pedagogical reform to align with evolving market trends emphasizing human-machine collaborative translation.

Introduction

Machine translation (MT) has gone through a tremendous evolution marked by several major breakthroughs along the way, from the early days of rule-based systems to statistical systems based on large corpora, and from a more recent neural machine translation (NMT) using deep learning techniques to the cutting-edge generative pre-trained transformer models

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of ChatGPT (Hendy et al., 2023). The rapid advancement in the MT domain has greatly increased the quality of MT output, and the implementation of MT combined with human revision has become commonplace in translation jobs and language service providers (Gaspari et al., 2015; Guerberof & Moorken, 2019; Moorkens et al., 2018). Machine Translation Post-Editing (MTPE), referred to as the process of human editors correcting the output of machine translation systems (Veale & Way, 1997), has been increasingly seen as a productivity enhancer for human translators compared to manual translation from scratch (Guerberof, 2009; Koponen, 2016), therefore continues evolving towards a more popular practice application in the language service industry. In this regard, the provision for MTPE skills training should be properly explored and aligned with the translation curriculum to ensure that students of translation are able to hone essential skills, gain experience on the subject, and start off on the right foot when they leave training courses toward genuine career development.

Literature Review

The concept of MT has a long history and views varied about its interpretation. The origin of MT can date back to ideas of universal languages and of mechanical dictionaries in 17th century. It is believed that Descartes was the first person who brought up the idea of MT, arguing that language could be represented by codes, and that words with equivalent meaning in different languages could share the same code (Pugh, 1992). Subsequently, "automatic translation" and "mechanical translation" were widely used (Bar-Hillel, 1960). However, it was not until the twentieth century that the idea of MT was officially proposed by Warren Weaver in 1949 (Hutchins, 2006). Originally, MT was referred only to automatic systems with no human involvement. The European Association of Machine Translation (EAMT) defines it as "the application of computers to the task of translating texts from one natural language to another" (EAMT, n.d., para. 1). With respect to the involvement of humans, Hutchins and Somers (2009) described MT as the automatic translation from one natural language (source language) to another natural language (target language) through computerized systems with or without human assistance.

In practice, MT systems produce output that needs invariable revisions or post-editing, humans are therefore involved in the process of translation to reach the quality required, and for this reason, is prone to conceptual confusion. Clarification would be necessary to differentiate human-aided machine translation from machine-aided translation from scratch. The former is "a system wherein the computer is responsible for producing the translation per se, but many interact with a human monitor at many stages along the way" (Slocum, 1985, p. 2). In other words, machines are the principal subject carrying out most of the work during the translation process while human assistance is involved either at the stage of text preparation or post-production. In contrast, for machine-aided translation from scratch, the main translator is the human. Even so, the boundary between these two types of translation has been blurring and complicated. In human-aided machine translation, the machine serves as the primary translator, which is much more like machine translation post-editing (MTPE). Therefore, it is classified as a subclass of machine translation (Quah, 2006).

Self-efficacy is not a personality trait, but rather as a cognitive factor that serves as a context-dependent mediator of action. He further explains that perceived self-efficacy affects cognitive functioning, influencing the level of goal challenges individuals set for themselves, their commitment to those goals, and their ability to envision successful outcomes (Bandura & Walters, 1977). Since the psychological construct of self-efficacy has been found to influence individuals' performance and coping abilities, enhancing motivation, and facilitating goal-setting, problem-solving, decision-making, and successful persistence in the face of difficulty (Bandura, 1995), its relevance for translation process-oriented research has been explored and investigated to shed light on translation education and professional training.

For example, according to research by Albin (2010), translators who possess high self-efficacy evaluate themselves based on monetary and status-related factors. Conversely, those who possess low self-efficacy tend to evaluate themselves based on their own abilities, indicating that social factors may play a vital role in the translation profession. Additionally, Albin found that individuals with high self-efficacy and a positive attributional style tend to have advanced management skills and expertise in using Computer Aided Translation (CAT) tools. Atkinson's (2012) study on the psychological skills of freelance translators claims that self-efficacy has emerged as a prominent factor in exploring the correlation between job competence and motivation, job constraints, and job performance in the field of translation. Atkinson further suggests that self-efficacy in one's occupation is the most important variable among a group of psychological skills-related factors. While Bolaños-Medina (2014) proposes that self-efficacy in translation is associated with proficient source language reading comprehension, tolerance of ambiguity, and documentation abilities.

Researchers have also made consistent attempts to explore how self-efficacy should be enhanced to assist translation education (Bolaños-Medina, 2014; Haro-Soler, 2018; Núñez & Bolaños-Medina, 2018). Researchers have recommended online cooperative learning for translation settings, suggesting it would significantly increase student interest and self-efficacy in specialized English translation (Yang et al., 2015). Also, the study that examines the influences of the program on pre-service translation teachers in terms of their self-efficacy beliefs in translation education suggests that formal and systematic method positively influenced on the development of self-efficacy beliefs of the translation teachers (Wu et al., 2019).

The research on self-efficacy and its implications in the field of translation and interpreting has gained considerable intrigue and attention in recent years. Self-efficacy not only plays a role in problem-solving, decision-making, goal-setting, and academic achievement but also influences motivation, persistence, and effort invested in tasks, as well as the ability to bounce back from setbacks (Bandura, 1995). The field has seen promising avenues of study, but to pursue further research, it is essential to develop of a task-specific scale that illustrates the psychometric properties of translation self-efficacy for further cognitive and empirical-experimental research regarding machine translation post-editing (MTPE) learning and teaching.

Purpose of the Study

The principal aim of this study is to assess students' self-efficacy in the context of translation learning, particularly in an environment where Machine Translation (MT) is not only readily available but also a topic of debate. The assessment in question serves to explore its factor structure, psychometric properties, and their internal relationships. Additionally, as an expansion of this research, future inquiries may delve into elucidating the methodology employed in the development of psychometric instruments tailored for cognitive, empirical-experimental investigations within the domain of translation studies. These extensions have the potential to contribute significantly to pedagogical reform by assisting students in adapting to dynamic market trends that underscore the growing collaboration between human translators and machine translation systems.

Method

Scale Development

The measurement for this research was adapted from the *Scale for Assessing Translators' Self-Efficacy* (TSE) by Bolaños-Medina and Núñez (2018). The original scale was designed and tested to evaluate students' perceived self-efficacy in successfully resolving issues during the translation process; it follows Bandura's standard procedures (2006) for developing valid and reliable measures of self-efficacy beliefs. A tailored version of this survey, consisting of sixteen 5-point Likert scale items, was created specifically for a translation course offered in the spring semester of 2023. Its purpose was to gauge students' self-perceived competence in the context of machine translation post-editing (MTPE).

Scale Items

Rating Scale: 1 = strongly disagree; 2 = disagree; 3 = neutral; 4 = agree; 5 = strongly agree

Table 1. Survey Questions

Question Items
Q1: I can analyze both the production of the source text and the reception of the target text in various communicative contexts.
Q2: I can identify the genre of a given document and analyzing the specific function required for the target text.
Q3: I am capable of analyzing the primary function that a specific target text necessitates.
Q4: Throughout the entire process, I have the ability to make informed decisions regarding the tools and resources needed for the translation task.
Q5: I can recognize translation mistakes of machine translated target text.
Q6: I can identify translation errors with regards to source text comprehension.
Q7: I am able to identify translation errors in terms of target text production.
Q8: I can learn from every machine-assisted translation assignment.
Q9: I can make appropriate choices about the trade-off of machine translated text.
Q10: I can identify translation problems of a machine assisted translation task.
Q11: I have the ability to generate various alternative solutions for translation challenges.
Q12: I am capable of assessing diverse alternative solutions for translation difficulties.
Q13: I have the ability to make suitable judgments to address issues related to machine translation.
Q14: I can develop a comprehensive plan for the translation task, considering factors such as the communicative context, purpose, timelines, and the expectations of the intended audience.
Q15: I can identify the key elements of a specific machine-assisted translation project and outlining the sequential stages involved in its execution.
Q16: I can easily adjust to the working requirements of a translation task without relying on machine translation, demonstrating flexibility in my approach.

Participants

In this study, a convenience sample of 100 undergraduate students, all of whom were enrolled in translation classes within the English as a Foreign Language (EFL) program of a university in southwest China, willingly participated by completing online surveys. The response rate, standing at 65%, resulted in a final dataset comprising 65 responses. The participants' ages ranged from 20 to 24 years, with females accounting for 87% of the sample. This gender distribution aligns with the common composition of language departments in Chinese universities, where female students tend to outnumber their male counterparts. Furthermore, the sample displayed a higher representation of third-year students (69%) in comparison to fourth-year students (31%). This distribution reflects the typical organization of translation courses, primarily offered to junior and senior students due to the prerequisite of advanced language proficiency.

In terms of participants' translation experience, a mere 9.2% reported prior involvement, while the vast majority, totaling 90.8%, had no prior translation experience. As for familiarity with machine translation (MT), 52.3% of participants indicated they were acquainted with it, whereas 47.7% expressed unfamiliarity. Furthermore, we assessed participants' internet access, revealing that 15.4% deemed their access as good, 72.3% as very good, and the remaining 12.3% considered it excellent. By including respondents with varying levels of translation experience and differing degrees of MT familiarity, our survey encompassed a diverse range of self-efficacy perspectives.

Overall, the composition and characteristics of the sample indicate that it adequately represents the target population, mitigating the likelihood of introducing significant bias that could compromise the scale development process.

Results

Reliability

Table 2. Reliability

Reliability Statistics	
Cronbach's Alpha	N of Items
.914	16

To assess the consistency and stability of the measurement tool, a reliability test was conducted in SPSS. The result indicates that the 5-point Likert scale has a reliability of 91.4%, which suggests that, from a macro perspective, the scale has a good quality in terms of measuring the same construct consistently across the survey items.

Construct Validity

Self-efficacy refers to individuals' belief in their capacity to attain desired levels of performance and exert influence over the events that affect their lives. It plays a significant role in shaping their emotions, thoughts, motivation, and behavior through cognitive, motivational, affective, and selection processes (Bandura, 1994). In this sense, self-efficacy of MTPE refers to the belief and confidence of individuals, particularly translation students, in their ability to effectively and proficiently perform post-editing tasks on machine-translated texts. Such beliefs may entail their perception of their own competence in thought processes and approach employment while engaging in the post-editing process.

To ascertain the accuracy of our measurement tool in assessing the intended construct, a validity analysis was conducted in accordance with established guidelines (Heale & Twycross, 2015). In this context, the scrutiny aimed to confirm whether the survey items indeed measured the specific psychological attribute they purport to evaluate. A detailed examination of the scale entailed an assessment of the extent to which the survey instrument accurately assesses its intended measurement. Generally speaking, a multi-item scale is developed for a unified research purpose, in our case, the assessment of translation self-efficacy in the context of MTPE. However, a unified purpose may be represented by multiple dimensions. To discern the number of factors or dimensions underpinning the items and to evaluate the strength of their associations with these factors, we conducted an exploratory factor analysis that could aid in identifying the most important items and elucidating their underlying factor structure.

Factor Analysis

Factor analysis (FA) is a statistical technique used to simplify a large dataset by identifying redundancy within the data (Dunn-Rankin et al., 2014). By employing FA, researchers can examine evidence based on internal structure and test content to gain insights into what the instrument truly measures, specifically the intended abstract concepts or dimensions (Tavakol & Wetzel, 2020). In the context of this study, the aim is to explore how EFL students perceive their translation self-efficacy in an environment where Machine Translation (MT) is readily available. The findings of the analysis are presented below.

Prior to factor extraction, it is crucial to perform initial assessments to evaluate the appropriateness of the respondent data for factor analysis (William et al., 2010). These preliminary tests commonly involve the application of the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity. These evaluations assist in determining the suitability of the data for subsequent factor analysis procedures.

Table 3. KMO and Bartlett's Test of the Modified Scale

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.850
	Approx. Chi-Square	489.205
Bacrtlett's Test of Sphericity	df	120
	Sig.	.000

The data presented in the above table demonstrates that the KMO value is 0.85 (> 0.6), indicating that the sample size is adequate and factor analysis is appropriate for analysing the data. Additionally, Bartlett's Test of Sphericity yielded a p-value of <0.001, which is greater than the significance level (p<0.05). This indicates that the data collected from the survey are highly suitable for conducting factor analysis.

Table 4. Total Variance Explained

Total Variance Explained									
	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	6.694	44.624	44.624	6.694	44.624	44.624	4.091	27.273	27.273
2	1.368	9.120	53.744	1.368	9.120	53.744	3.181	21.204	48.477
3	1.072	7.146	60.890	1.072	7.146	60.890	1.862	12.413	60.890
4	.889	5.929	66.819						
5	.861	5.743	72.562						
6	.724	4.828	77.390						
7	.595	3.964	81.354						
8	.555	3.700	85.054						
9	.475	3.169	88.223						
10	.453	3.023	91.246						
11	.383	2.556	93.802						
12	.323	2.153	95.956						
13	.245	1.635	97.590						
14	.213	1.421	99.011						
15	.209	.1.307	99.096						
16	.148	.989	100.000						

Extraction Method: Principal Component Analysis.

Based on the table of total variance that represents the contribution of the factor to the variance of the item, a total of 3 principal components can be extracted from the 16 questions with initial Eigenvalues more than 1.0, and these 3 components reflect 59% of the total scale information. The "Cumulative % " column shows the percentage of the total variance explained by the factors is less than 60%, retaining a small accumulated amount of explained variance (Hair et al., 1998). From Table 4, it can be concluded that the three principal components extracted using the PCA with about 61% of the variation explained if we discarded the construct that does not provide acceptable validity. The major components explain more than 60% of the variation, meaning the principal data components calculated could bring out strong patterns in the dataset (Dziuban & Shirkey, 1974).

A scree plot graph is shown in Figure 1 that helps determine the optimal number of factors to extract before the unique variance surpasses the common variance structure (Hair et al., 1998).

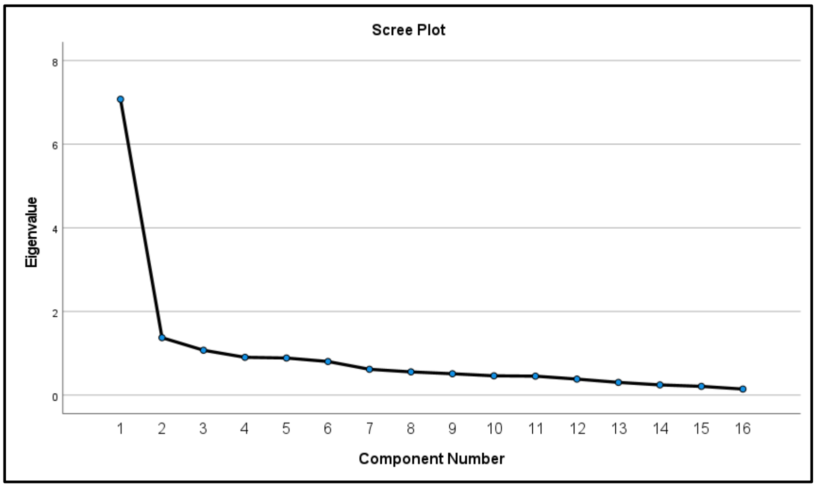

Figure 1. Scree plot for the 16 Likert-Type Items

The plot demonstrates that beyond the initial three components, the eigenvalues exhibit a decreasing trend, with values falling below 1.0. This observation further reinforces the suitability of a three-component solution.

After the extraction of the principal components, a further exploration of each of the component in terms of item inclusion is needed, hence a rotated component matrix is used to provide more information of different sets of variables.

Table 5. Total Variance Explained

Rotated Component Matrix[a]

	Component 1	2	3
Q9	.767		
Q11	.710		
Q12	.707		
Q10	.654		
Q13	.617		
Q8	.585		
Q5	.530		
Q1		.773	
Q2		.724	
Q4		.637	
Q3		.626	
Q6		.599	
Q7		.574	
Q14			.824
Q15			.707
Q16			.671

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 5 iterations.

An observation of Table 5 suggests that: Firstly, questions 5, 8-13 presents a strong loading that is greater than 0.5 while loaded less than 0.5 across the other two components, indicating their belonging to Factor One. By analysing the content of these survey questions, this factor can be as Decision-Making of MTPE; Secondly, questions 1-4, 6, and 7 can be established as the constructs of Factor Two. According to an analysis of the question content, the second major factors could be summarized as Communicative Competence of MTPE; Thirdly, question 14 to 16 related to Strategic Competence of MTPE are identified as the third major factor.

One Sample T-Test

Subsequently, following the validity analysis conducted earlier, the findings revealed the identification of three main dimensions from the pool of 16 questionnaire items. To assess the potential differences between the population mean and a constant value for a numerical or continuous variable, a one-sample t-test for the mean can be employed.

Table 6. Three Dimensions Identified from Higher Order Factor Analysis

Dimensions/Factors		Question Items
1	Decision-making of MTPE	5, 8, 9, 10, 11, 12, 13
2	Communicative Competence of MTPE	1, 2, 3, 4, 6, 7
3	Strategic Competence of MTPE	14, 15, 16

A descriptive statistical analysis and a one-sample t-test for mean can be employed to examine whether the population means of the three aforementioned numerical or continuous dimensions differ significantly from a constant value.

Table 7. Descriptive Statistics and T-test for Mean

Dimension	N	Mean±Std. Deviation	Test Value	t	Sig. (2-tailed)
1	65	3.43±0.53	3.00	6.554	< 0.001
2	65	3.45±0.57	3.00	6.377	< 0.001
3	65	3.43±0.57	3.00	5.990	< 0.001

Since the survey is a 5-point Likert scale and the numerical value for the "Neutral" sentiment level is 3, indicating that the respondents generally feel neutral about translation self-efficacy, so the test value is set as 3.00. It can be seen from the tables shown above that the means of the three dimensions identified from the factor analysis are respectively 3.43, 3.45 and 3.43, all of which are significantly higher than the value of 3 (neutral). In this case, the obtained p-values from the one-sample t-tests provide further support for the distinctiveness of the identified factors in the psychometric constructs of MTPE self-efficacy. The p-values, being lower than the significance level of 0.05, indicate that the means of the three dimensions (decision-making, communicative competence, and strategic competence) are significantly different from the neutral value of 3. This suggests that the students' responses reflect a level of confidence in their abilities related to each specific factor. Therefore, the significance values in this context reinforce the notion that the factors measured by the scale are indeed distinct from each other, strengthening the construct validity of the instrument designed for assessing translation students' self-efficacy in MTPE.

Association among Scale Dimensions

Correlation Analysis

The Pearson correlation coefficient is a statistical measure that evaluates the strength of the linear relationship between two variables (Sedgwick, 2012). In the field of psychometric scaling, it is commonly applied to examine the strength and direction of the connection between items on a scale (Lukat et al., 2016). For this study, Pearson's correlation was conducted see how strongly the dimensions (Decision-making of MTPE, Communicative Competence of MTPE, Strategic Competence of MTPE) identified in our scale are related to each other. When items or dimensions exhibit strong correlations with each other, it indicates that they are measuring the same underlying construct, namely, self-efficacy of Machine Translation Post-Editing (MTPE). The outcomes of this analysis are displayed in the following Table 8:

Table 8. Pearson Correlation Coefficient Analysis

Correlations

	Decision Making	Communicative Competence	Strategic Competence	Total
Decision Making	1			
Communicative Competence	.697**	1		
Strategic Competence	.635**	.585**	1	
Total (Translation Self-Efficacy)	.937**	.873**	.779**	1

**. Correlation is significant at the 0.01 level (2-tailed).

The Pearson correlation coefficient varies between -1 and 1, where values closer to either -1 or 1 suggest a stronger correlation between the variables. As can be seen from the above results based on correlation analysis generated from SPSS:

- The results indicated that all three dimensions of Translation Self-Efficacy Scale displayed significant positive correlations with other dimensions, especially between Dimension 1 and Dimension 2. The significance levels (p-values) of the correlation coefficients were all less than 0.05. Furthermore, the correlation coefficients were all greater than 0, indicating a positive linear relationship between the variables.
- Moreover, each subscale (dimension) shows a strong correlation with the overall self-efficacy scale, indicating a solid validity of the major dimensions.
- It is also noteworthy that the relationship between Dimension 3 (Strategic Competence) and Dimension 2 (Communicative Competence), compared with other correlations, appears a less strong correlation.

In summary, the results obtained from the scale factor analysis and correlation analysis provide strong supporting evidence for the construct validity of the translation self-efficacy scale. The reliability test revealed a high level of internal consistency, indicating that the scale consistently measures the same construct across its items. Additionally, the factor analysis identified three principal components that collectively explained 59% of the total scale information. These components, labelled as decision-making of MTPE, communicative competence of MTPE, and strategic competence of MTPE, represent distinct dimensions of translation self-efficacy. The one-sample t-tests confirmed that the means of these dimensions significantly exceeded the neutral value of 3, further demonstrating their distinctiveness. Moreover, the correlation analysis revealed significant positive correlations between the dimensions, particularly between decision-making and communicative competence. These findings indicate that the dimensions are measuring related but distinct aspects of self-efficacy in machine translation post-editing. Overall, these results offer support for the construct validity of the translation self-efficacy scale, affirming its effectiveness in accurately measuring the intended properties of self-efficacy in translation.

Influencing Factors of Strategic Competence

Based on the correlation analysis, it is shown that in the process of MTPE, decision making, communicative competence, and strategic competence are positively correlated. MTPE has been considered a problem-solving process due to the nature of the task (Krings, 2001; Nitzke, 2019), which involves addressing and resolving various linguistic and stylistic issues introduced by machine-generated translations. According to the work from Levý (2000), one of the many instances of exploring the intersection between psychology and translation (Gudmundsson, 2009; Holmes, 2000; Jääskeläinen, 2012; Reiss, 1981; Wilss, 1996), translators use problem-solving strategies to achieve optimal results with minimal effort when faced with a discernible set of alternatives during the decision-making process of translation.

In order to gain more insights into the relationship between the aforementioned three dimensions identified in the MTPE scale, specifically how communicative competence and decision-making influencing strategic competence, regression analysis is employed for influencing factor analysis to understand the relationship between a dependent variable and one or more independent variables. By doing this, we can further identify the strength, direction, and significance of these relationships. In this study, the utilization of linear regression analysis is justified for variables that are measured on a continuous scale (Winship & Mare, 1984), specifically a 5-Likert scale. Linear regression is a suitable statistical technique when examining relationships between variables that have a continuous nature. The aim of this analysis is to estimate the coefficients of the equation to understand how changes in the independent variables relate to changes in the dependent variable. Within the scope of this investigation, the independent variables under scrutiny are communicative competence (CC) and decision-making competence (DM), while the dependent variable of interest is strategic competence (SC). By quantifying the relationship between these variables, this study aims to shed light on the degree of influence exerted by communicative competence and decision-making competence on strategic competence.

Table 9. Linear Regression Analysis

	Unstandardized Coefficients	Standardized Coefficients	t	P	VIF
(Constant)	0.811		2.152	0.035	
DM	0.483	0.443	3.349	0.001	1.946
CC	0.278	0.276	2.085	0.041	1.946
Adjusted R Square			0.425		
F			24.609		
P			<.001		
Dependent Variable: SC					

Based on the outcomes of the aforementioned analyses (shown in Table 9), several key findings emerge as follows:

Firstly, the model exhibits a strong fit, as indicated by an Adjusted R Square value of 0.425. This signifies that 42.5% of the variation in the dependent variable (strategic competence) can be accounted for by the two independent variables considered in this regression analysis. Hence, the current regression model effectively explores the influential factors impacting strategic competence.

Secondly, the linear regression model proves to be statistically significant ($F = 24.609$, $p < .001$), indicating that at least one of the independent variables significantly affects the dependent variable. Further examination of the regression coefficients for the two independent variables provides conclusive evidence.

- Notably, decision-making competence exhibits a significant and positive impact on strategic competence ($\beta = .483$, $t = 3.349$, $p = 0.001 < 0.05$). This suggests that higher levels of decision-making competence correspond to increased levels of strategic competence. Quantitatively, a one-point increase in decision-making competence translates to a subsequent 0.483-point increase in strategic competence.
- Communicative competence also demonstrates a positive influence on strategic competence ($\beta = .278$, $t = 2.085$, $p = 0.041 < 0.05$), highlighting that higher communicative competence is associated with greater strategic competence. The quantitative relationship between the two variables is characterized by a one-point increase in communicative competence leading to a subsequent 0.278-point increase in strategic competence.

To conclude, the derived linear regression equation is as follows:
$SC = 0.811 + 0.483 * DC + 0.278 * CC$

These findings underscore the significance of decision-making and communicative competences in shaping strategic competence and provide valuable insights for understanding the factors contributing to strategic competence within the examined context.

Subsequently, a thorough diagnostic analysis is conducted to assess the robustness of the aforementioned regression model. Linear regression analysis relies on three fundamental assumptions, namely the absence of covariance, absence of serial correlation, and normal distribution of residuals. It is imperative to verify these assumptions as their fulfilment ensures the accuracy and reliability of the regression model's outcomes.

Firstly, Covariance Diagnosis; the Variance Inflation Factor (VIF) values for the two independent variables under investigation in this analysis are all below the threshold of 5. This signifies the absence of multicollinearity between the independent variables, thereby satisfying the covariance diagnosis for this regression model.

Secondly, Serial Correlation Diagnosis; the Durbin-Watson (DW) statistic serves as the diagnostic measure for serial correlation. In the present linear regression analysis, the DW value is calculated as 2.305, which is approximately equal to 2. This indicates the absence of serial correlation within the dataset, thus fulfilling the serial correlation diagnosis.

Thirdly, Residual Normality Diagnosis; to assess the normality of residuals, a histogram (Figure 2) is constructed using the residuals obtained from the current linear regression model.

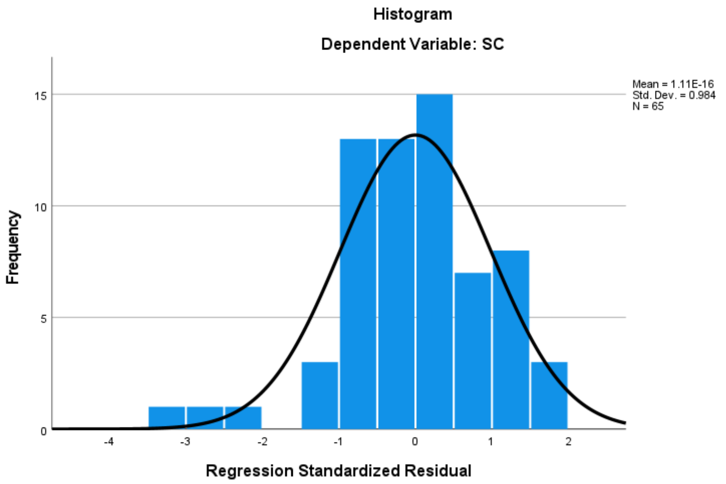

Figure 2. Histogram of Regression Standardized Residual

The histogram's contour exhibits a close alignment with the shape of the normal distribution curve. This correspondence suggests that the residuals conform to a normal distribution, thereby satisfying the diagnosis of residual normality.

Having successfully passed the aforementioned diagnostic examinations, this regression model provides a reliable and valid foundation for drawing conclusions. The model effectively captures and reflects the causal relationship between the independent and dependent variables, ensuring the accuracy and dependability of the derived findings.

Conclusion and Further Considerations

This study focuses on the assessment of students' self-efficacy in the realm of translation learning, with a specific focus on Machine Translation Post-Editing (MTPE). It delves into the factor structure, psychometric attributes, and internal interrelationships of their self-efficacy, offering implications for the field of translation studies, particularly in the context of MTPE. The revealed findings indicate the existence of three primary dimensions of self-efficacy: Decision-making in MTPE, Communicative Competence in MTPE, and Strategic Competence in MTPE. The robust correlations among these dimensions point towards their collective measurement of translators' self-efficacy in MTPE, thereby furnishing potential insights into the requisite skills and capabilities for effective MTPE. This could contribute to the development of psychometric tools essential for future research endeavors in translation studies.

The research opens up opportunities for future investigations in several areas. Firstly, it is essential to delve into the relationship between self-efficacy and actual performance in MTPE tasks. This study has provided initial insights into the dimensions of self-efficacy, but understanding how these perceptions align with real-world performance is crucial. Further research can employ performance metrics and compare them with self-efficacy scores to discern the practical impact of self-efficacy on translation outcomes. This will bridge the gap between self-assessment and actual task performance (Trope, 1982), providing a more comprehensive understanding of the role self-efficacy plays in translation effectiveness.

Additionally, future studies should consider developing targeted strategies and interventions aimed at enhancing students' self-efficacy in MTPE. By identifying specific dimensions of self-efficacy that are most influential, researchers can design training programs or interventions that address these areas. Such a tailored approach can help improve translator education and empower students to navigate the complexities of MTPE effectively.

The evolving market trends in the language service industry emphasize the collaboration between humans and machines in translation tasks (Mellinger, 2017). Future research should investigate how collaboration impacts students' self-efficacy, job satisfaction, and overall performance in MTPE. Understanding the dynamics of human-machine interaction in translation can inform pedagogical reforms and curriculum development, ensuring that translation education aligns with industry demands.

Furthermore, there is room to explore the intricate relationship between self-efficacy and other psychological factors, such as motivation, regulation, attention, and metacognition, within the context of MTPE. Investigating how these factors interact and influence self-efficacy can provide a holistic understanding of the cognitive and affective processes at play in MTPE (Lacruz et al., 2014; Lacruz, 2017). This knowledge can guide the development of comprehensive training strategies for translator professional development.

In conclusion, this study not only contributes to the development of psychometric tools for measuring self-efficacy but also underscores the significance of considering self-efficacy in translation technology-assisted practice. It highlights the need for skill development in the context of human-machine interaction, a vital aspect of modern translation practice. The avenues for future research explored here, including validating the survey instrument, examining additional psychometric properties, and deepening our understanding of MTPE in the era of AI-driven translation, have the potential to shape translation education and practice, aligning them with the evolving landscape of artificial intelligence in the language service industry. As the field continues to evolve, staying at the forefront of research and innovation is paramount for translation professionals and educators alike.

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