



Development and validation of machine translation literacy scale for translation education

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Abstract

The rise of machine translation demands a fundamental shift in both translators' roles and educational approaches. However, translation education research and practice have struggled to keep pace with the latest developments. To bridge the pedagogical gap, this study conceptualises machine translation literacy within the context of translation education and develops a diagnostic scale to assess students' proficiency in machine translation literacy. Drawing on a review of existing literature and case studies on machine translation literacy applications in translation pedagogy and related disciplines, this study establishes an initial framework for machine translation literacy. To validate the structure and reliability of a proposed model for machine translation (MT) literacy, data were collected from 389 undergraduate and graduate translation students in South Korea and analysed using Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA). The analysis yielded a robust six-factor model encompassing risk management, verification and correction, basic knowledge, operational knowledge, flexibility, and transparency. This study provides a reliable assessment model for evaluating students' machine translation literacy and lays the groundwork for the translation education planning at both macro and micro levels. Additionally, it positions machine translation literacy as an essential component within the broader theoretical framework of translation education research and serves as a foundation for expanding research into interdisciplinary domains.

Keywords: Machine translation, machine translation literacy, translation education, assessment tool, EFA, CFA

Introduction

With the rapid advancement of information and communication technologies, the generation of digital data has grown at an unprecedented rate. In 2020 alone, it was estimated that humanity produced nearly 300,000 terabytes of data daily (DePalma, 2020, pp. 28–29). This immense volume and the diverse nature of the content have made it increasingly difficult to address translation needs through human effort alone or by relying solely on machine translation. As a result, there is an urgent necessity for effective collaboration between human expertise and machine capabilities.

At the same time, advancements in machine translation and the automation of translation workflows have established machine translation post-editing (MTPE) as a dominant pillar in the global translation market. Consequently, the industry has undergone noticeable bipolarization. According to recent studies (Bowker, 2021; Olohan, 2021; Pym & Torres-Simón, 2021), translation services are increasingly divided between the bulk market, driven by MTPE and Computer-Assisted Translation (CAT), and the premium market, where human creativity and linguistic artistry remain indispensable. This shift is further evidenced by the growing reliance on machine translation among Language Service Providers (LSPs). In Europe, for instance, the majority of LSPs were already utilising machine translation by 2018 (ELIS Report, 2018), with adoption rates rising to over 70% by 2024 (ELIS Report, 2024). Reflecting this evolution, European Master's in Translation—tasked with overseeing the master's programme in translation for European Union member states—has identified proficiency in machine translation as a critical element of modern translation curricula (EMT Competence Framework, 2022). However, machine translation has been sometimes regarded as “elephant in the room.” Students use it and trainers know that students use it. Yet, neither specific training nor even discussions ever take place (Loock et al., 2022).

Given the increasing integration of machine translation technologies into both professional and everyday translation contexts, there is a pressing need to implement structured user training and develop targeted educational programmes. In the broader context, the development of an AI literacy-implemented curriculum organised based on teachers' perspectives and students' needs has been underlined as an important approach (Aravantinos et al., 2024). This pedagogical reorientation necessitates a reconceptualisation of translation education rather than focusing only on linguistic proficiency. Moreover, in light of the rapid and ongoing evolution of MT technologies, training should focus not merely on the functionalities of specific tools, but on cultivating an understanding of the fundamental principles and shared mechanisms underlying these systems. Educators must prepare future translators to manage MT-integrated workflows, critically assess outputs, and make contextually informed decisions regarding their use.

This means future translators should be able to integrate technological, strategic, and ethical dimensions of machine translation competence. Within this evolving paradigm, the concept of Machine Translation Literacy (Bowker & Buitrago-Ciro, 2019) provides a valuable framework for equipping students with the knowledge and critical awareness needed to engage effectively with machine translation technology. However, existing MT literacy educational initiatives have largely been designed for non-translation majors and the general public—particularly in countries such as Canada and Switzerland.

Despite growing academic consensus on the importance of MT and MT literacy in translator training (Dorst et al., 2024), there is limited evidence to suggest that MT literacy and relevant competencies have been systematically implemented in educational practice. Krüger (2022) suggested professional MT literacy into five key subcomponents. Krüger and Hackenbuchner

(2022) proposed a didactic framework for integrating data literacy and MT literacy into translation education. However, few empirical studies have investigated how these frameworks are being operationalised in real-world translation educational contexts.

This gap appears even more pronounced in the South Korean context, where a noticeable disconnect exists between theoretical developments and educational practice in MT training. Although translation technologies are occasionally included in curricula, they are typically limited to isolated, standalone courses and rarely integrated into domain-specific or genre-oriented translation instruction. As Song (2024) reports, there is a widespread reluctance among instructors to incorporate MT tools into classroom practice. Many instructors remain sceptical of the pedagogical value of MT and demonstrate limited familiarity with the concept of Machine Translation Literacy. These findings underscore an urgent need for pedagogical reform—particularly in South Korea—to ensure that translation education fosters a more comprehensive understanding of technical realities and challenges posed by machine translation.

Therefore, it is necessary to systematically examine translation students' attitudes and perceptions—at both undergraduate and graduate levels—toward the use of MT tools. Only through such examination can effective educational strategies for fostering MT literacy be developed. Moreover, the successful implementation of MT literacy education requires the development of reliable tools to assess students' levels of literacy. However, little research was conducted on the development of an MT literacy scale, and none in South Korea.

In the broader domain of digital literacy education, however, various assessment scales have already been developed both domestically and internationally. Methodological approaches employed in scale development across other disciplines offer valuable frameworks that can inform the design of a context-specific machine translation literacy scale for translation students.

Accordingly, this study aims to address the research gap concerning the integration of MT literacy into translator training, as well as the lack of an MT literacy scale specifically designed for undergraduate and graduate students in translation programmes. First, it outlines the development of the initial item pool and the structuring of factors, which were informed by a comprehensive review of existing literature. Second, it describes the application of Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA), based on data collected from 389 students, to identify the most representative dimensions of students' MT literacy and to validate the reliability and effectiveness of the proposed assessment scale. Finally, the study examines the potential integration of the scale into translation education and provides recommendations for future-oriented research and pedagogical strategies.

The findings of this study could enhance our understanding of translation students' attitudes towards and comprehension of machine translation, offering valuable insights for the improvement of translator education. These insights may inform the development of pedagogical strategies and academic applications that respond to the evolving demands of a technology-driven translation landscape. Furthermore, the results may serve as a foundation for faculty members to design more effective teaching and learning plans, ensuring that future translators are better equipped to navigate MT-integrated professional environments.

Theoretical Background and Review of Previous Studies

The Concept and Components of Machine Translation Literacy

One of the pioneering studies introducing the concept of Machine Translation Literacy was by Bowker and Buitrago-Ciro (2019). Their study examined the use of online machine translation

for scholarly communication, underscoring the necessity of establishing a well-defined framework for machine translation literacy. They conceptualised Machine Translation Literacy as the user's ability to understand how machine translation systems operate and can be utilised, assess the machine translatability of specific texts, and effectively post-edit machine translation outputs (Bowker & Buitrago-Ciro, 2019, p. 88).

Bowker (2019) emphasised the growing necessity of Machine Translation Literacy, asserting that machine translation is easily accessible, easy to use, and produces a quality of output that is reasonable for some purposes, however, users do not know instinctively how to use it wisely in a given context (p. 105). In a subsequent publication, Bowker (2020) positioned Machine Translation Literacy as an emergent component of digital literacy—one that transitions the focus from technical skill acquisition to critical reflection on technology use.

This perspective underscores that Machine Translation Literacy extends beyond the mere technical operation of translation tools; it encompasses a cognitive understanding of whether, when, where, why, and how such tools should be used effectively. Significantly, the dimension of “how” is not limited to mechanical functionality but includes a deeper, strategic awareness of how users can interact with MT systems to enhance both the quality and relevance of the resulting translations. As a result, acquiring Machine Translation Literacy empowers users to become informed critical users who are capable of evaluating and leveraging translation tools and outputs effectively (Bowker, 2020, p. 28). In contrast, a lack of Machine Translation Literacy can lead to an oversimplified view of translation's complexity and an overestimation of machine translation's capabilities due to its speed and convenience. Such misperceptions can lead to inappropriate or ineffective use of MT (Vieira, 2020, pp. 98–99). In this vein, it is critical to introduce a means of measuring MT literacy to help users, particularly translation students, recognise and reflect on their own knowledge and attitudes towards the use of MT technologies.

Since the introduction of the concept of Machine Translation Literacy by Bowker and Buitrago (2019), much of the subsequent research has drawn upon this foundational idea. However, much of the existing research has focused on equipping lay users—individuals with varying levels of familiarity with translation tasks—with the skills and attitudes necessary to use MT effectively and responsibly. Consequently, limited attention has been given to the specific needs of translation students or professional translators. Among the few exceptions, Krüger (2022) argued that MT literacy should be regarded as a core component of translation competence in professional contexts. He emphasised that the linguistic, economic, and social implications of MT within professional translation workflows are substantial, thereby necessitating the development of specific skills to critically engage with and effectively integrate MT technologies. Expanding on this premise, he introduced the concept of Professional Machine Translation Literacy, which he defined as the comprehensive set of MT-related competencies required by professional translators and language practitioners to competently navigate and contribute to all phases of MT-assisted translation processes (p. 249).

Furthermore, Krüger subdivided Professional Machine Translation Literacy into five distinct subcomponents. The first is technical machine translation literacy, which refers to foundational technical knowledge of machine translation systems. The second is linguistic machine translation literacy, which involves skills in processing, evaluating, and adapting machine-generated texts. The third is economic machine translation literacy, focusing on project management skills for optimising workflows involving machine translation. The fourth is societal machine translation literacy, which encompasses the ability to address ethical and societal issues related to machine translation. Finally, cognitive machine translation literacy refers to the capacity to manage cognitive load effectively during machine translation processes (Krüger, 2022,

pp. 250–262). This nuanced framework broadens the scope of machine translation literacy by addressing the specific competencies required by professionals to navigate the increasingly complex translation landscape.

Subsequently, Krüger and Hackenbuchner (2022) proposed a didactic framework that integrates theoretical insights from machine translation literature with the authors' pedagogical experience in teaching MT to translation students. This framework offers a comprehensive mapping of the intersections between data literacy and machine translation literacy, identifying five core dimensions and 23 sub-dimensions. These elements serve as a foundational structure for designing and implementing machine translation literacy education in translator training programmes.

Among the limited Korean papers on MT literacy, Choi (2024) advanced machine translation literacy education and research in South Korea by developing and evaluating materials specifically designed for teaching MT literacy to undergraduate international students learning Korean. Choi's (2024) MT literacy education materials consist of four sections: the history of machine translation development, why translation is challenging, pre-editing skill, and post-editing skill (Choi, 2024, pp. 338–339). However, these materials predominantly focus on the functional aspects of using machine translation and do not fully align with Bowker's concept of Machine Translation Literacy, which places greater emphasis on critical thinking.

As discussed, although a small number of studies have made meaningful contributions to incorporating MT literacy into translation education, the concept remains relatively underexplored. In particular, there is a notable absence of a reliable and validated tool for measuring MT literacy, which presents a significant obstacle to the systematic and pedagogically sound implementation of literacy-based education. Therefore, there is a pressing need for empirical research to define the underlying constructs of MT literacy and to develop measurable factors and their items.

Current Status of Machine Translation Literacy Education

Though there have been numerous educational efforts to incorporate machine translation (MT) into language learning (Jiang et al., 2024; Lo, 2025; Niño, 2024, 2025), machine translation literacy has not been extensively explored or utilised in empirical studies.

Bowker was among the first to develop MT literacy guidelines, encapsulated by the slogan, “using machine translation is easy, but using it critically requires some thought” (Bowker, 2019, p. 105). These guidelines were specifically designed to assist undergraduate students and academic researchers, whose first language is not English, in making more informed decisions about the use of machine translation technology and maximising its effectiveness.

In Canada, Lynne Bowker has spearheaded workshops as part of the Machine Translation Literacy Project, aimed at academic researchers whose first language is not English and undergraduate students from non-translation disciplines. Furthermore, she has explored incorporating machine translation literacy education as a submodule within broader information literacy lectures. Similarly, universities in Switzerland have collaborated to introduce machine translation literacy education through the DigLit Project, demonstrating an institutional commitment to equipping students with machine translation literacy skills. These initiatives reflect a growing recognition of the importance of Machine Translation Literacy in higher education. In addition, Looock and Léchauguette (2021) conducted a study that adopted the concept of MT literacy to examine how undergraduate students in applied languages programmes engage with MT tools in practice. Their findings highlighted the need to enhance students' critical thinking and effective usage skills related to machine translation.

In Korea, Bowker's concept of Machine Translation Literacy was introduced in 2021 through a paper by Lee (2021), who sought to apply it to Korean composition education for Chinese learners. Since then, the concept has primarily been applied in the context of teaching Korean as a foreign language, focusing on ways to incorporate machine translation into language education. In other cases, MT literacy has been intermittently addressed in studies examining the use of machine translation as a supplementary tool in undergraduate Korean-to-English translation courses (Sung, 2023), as well as in approaches aimed at enhancing machine translation proficiency among high school English learners (Jung & Kim, 2024). While the research discussed above offers relevant and valuable insights, none of the studies focused on students majoring in translation, thereby limiting their direct relevance and applicability to translator training contexts.

Meanwhile, Ehrensberger-Dow et al. (2023) argued that professional translators and translation educators with advanced machine translation literacy are uniquely positioned to offer valuable consultation services to clients who lack foundational knowledge and linguistic expertise. These services can help clients identify the optimal balance between post-edited machine translation and professional human translation to meet their multilingual content requirements. As a result, aspiring translators must not only develop machine translation literacy to keep pace with advancements in artificial intelligence but also acquire post-editing skills to effectively support clients with limited time and resources who are unable to access premium professional translation services (Ehrensberger-Dow et al., 2023, p. 394).

In addition, Dorst et al. (2024) investigated how university students in Finland, Belgium, and the Netherlands enrolled in translation, language, and AI courses conceptualise machine translation (MT) in comparison to human translation. The findings revealed that about 60% of students viewed MT and human translation as distinct, while approximately 30% acknowledged both similarities and differences. Based on these findings, the study highlights a pedagogical need to systematically integrate data and AI literacy into MT-related curriculum so that such education should address students' preconceptions and promote a critical understanding of MT technology (Dorst et al., 2024).

Studies discussed above align with the argument that translation education should move beyond traditional, standalone, tool-centred, and language-focused classes by integrating technology throughout the curriculum and fostering comprehensive competencies (Melinger, 2017; Venkatesan, 2023). In this context, Machine Translation Literacy can serve as a foundational step toward a more integrated approach to machine translation education.

In summary, although the integration of MT literacy into translator training remains limited, the concept itself is emerging as a significant area of interest within translation studies. Recognising this gap, the present study aims to investigate how MT literacy can be effectively incorporated into translation education by exploring translation students' perceptions of, and engagement with, its key subcomponents. Additionally, this study seeks to establish a foundation for the development of future curricula that can more effectively prepare translation professionals for the dynamic and increasingly technology-driven nature of the field.

Research Method

Data Collection and Subject Selection

The aim of this study is to develop a scale to measure the level of machine translation literacy among translation majors and to validate the scale. To achieve this objective, exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) were employed, with data collected through two rounds of surveys. The surveys targeted undergraduate and graduate students enrolled in translation and interpreting programmes at eight universities in Korea.

Based on the collected data, the validity of the theoretical model was assessed through statistical factor analysis. With the cooperation of 13 translation and interpreting programmes that agreed to participate, the first survey was conducted online over 2.5 weeks, from September 12 to September 30, 2024, and the second survey was conducted online over two weeks, from October 14 to October 28, 2024. The collected data were used as two independent samples for EFA and CFA. The first sample, consisting of 217 participants, was allocated for EFA, while the second sample, comprising 176 participants, was initially allocated for CFA. Responses deemed incomplete or insincere were excluded from the analysis. Ultimately, a total of 389 valid responses (217 from the first survey and 172 from the second, all of whom consented to participate in the study) were included in the final analysis. The demographic characteristics of the 389 participants in this study are presented in Table 1.

Table 1. Demographic characteristics of participants.

	Round 1 (n = 217)	Round 2 (n = 172)
Age	25.93	27.31
Male	64	39
Female	153	133
Freshman	0	24
Sophomore	18	32
Junior	58	17
Senior	64	16
Master 1st year	39	35
Master 2nd year	38	42
MA course completed	0	3
Ph.D. Course	0	3

An intriguing aspect of the study participants’ characteristics is the relatively low frequency of machine translation usage. The data collected from the two surveys reveal that only 24.2% (94 participants) reported using machine translation more than once per day. Additionally, 45.2% (176 participants) had never taken a course related to machine translation; when including those who had taken only a single course during their entire academic programme, this figure rises to 91.5%. Notably, as undergraduates progress through their studies, the number of machine translation-related courses they have taken increases rather slowly, with seniors averaging 0.87 courses. This suggests that systematic curricula related to machine translation are available only in certain universities or programmes. Conversely, in master’s programmes, which are expected to offer more specialised translation and interpreting courses, first-year students took an average of only 0.53 courses, while second-year students averaged 0.65 courses, underscoring the need to expand machine translation education at the master’s level. The most frequently used machine translation tool among respondents was Papago, a local

Korean service, which was mentioned 230 times as a preferred machine translation tool, followed by ChatGPT (223 mentions) and DeepL (158 mentions). These findings indicate that both machine translation courses and their utilisation are still in the early stages. However, a significant number of participants are employing new technologies, including neural machine translation and generative AI, without having received systematic education on their use. This underscores the high necessity for education on MT literacy to guide proper usage and suggests that the scale developed in this study could serve as a foundational tool for long-term curriculum development.

Measures

The first survey included 30 preliminary items designed to assess machine translation literacy. Based on the results of an exploratory factor analysis conducted on the first survey data, the items were refined for the second survey, which featured 23 revised items.

Preliminary Items for Machine Translation Literacy Scale

To develop a scale for assessing machine translation literacy among translation majors, the first step involved generating initial factors and items for exploratory factor analysis (EFA). In this phase, the research team referred to the case study by Bowker (2020). The six dimensions proposed in her work can be summarised as follows: (1) privacy and confidentiality; (2) academic integrity; (3) potential for algorithmic bias; (4) awareness of different tools; (5) awareness of different translation tasks; and (6) improving MT output by modifying the input. Initially, two items were developed for each of these six factors.

However, to construct a robust scale that could more accurately capture both the ability and attitude of translation majors, it was necessary to conduct an in-depth review of additional domestic and international literature and to generate a larger pool of items. The researchers therefore decided to expand the number of items and, if needed, reorganise them into the original structure suggested by Bowker (2020) or reclassify them under alternative factors as appropriate.

Looock et al. (2022) expanded upon the ideas proposed by Bowker and Buitrago-Ciro (2019) and Bowker (2020), suggesting additional factors such as technical and ethical considerations, and highlighting the importance of ensuring that students understand how machine translation tools function and are able to identify their errors. In addition, the 11 follow-up questions presented by Looock and Léchauguette (2021) provided valuable insights, particularly regarding students' capacity to critically evaluate and correct MT output, which informed the development of further items. Some parts of technical, linguistic, economic, societal, and cognitive literacy, as proposed by Krüger (2022), were also incorporated into the item construction process. Furthermore, as several previous studies initiated broader discussions on MT literacy by drawing on digital literacy frameworks, this study similarly reviewed research on digital literacy to guide the development of items relevant to translation training (Bae et al., 2023; Kang et al., 2014). Through this iterative process, a total of 65 items were developed.

In line with the purpose of this study, the research team operationally defined MT literacy for translation majors as a multifaceted competence encompassing fundamental knowledge and practical use of MT, a nuanced understanding of its strengths and limitations, the ability to identify and resolve issues through revision, effective use of translation technologies, clear communication with collaborators, and the ethical and critical application of these skills within educational contexts. Based on this definition, a follow-up discussion session was conducted to refine the identified factors and items, with particular emphasis on selecting those most appropriate for introducing MT literacy within the translation classroom.

Building on the previously defined constructs, the research team developed an initial conceptual framework comprising eight factors, drawing on the work of Krüger (2022) and Bowker (2020). These factors included: (1) psychological and personal competencies; (2) ethical competencies related to machine translation; (3) general understanding of MT; (4) knowledge of MT engines; (5) proficiency in using MT; (6) familiarity with MT tools; (7) application and communication skills in MT contexts; and (8) critical utilisation of MT.

In the subsequent phase, two experts in translation studies reviewed the 65 generated items to evaluate their validity and ensure alignment with the intended constructs. Items that were conceptually redundant or failed to clearly convey their intended meaning were removed. In addition, items requiring an excessively high level of technical knowledge were excluded. As a result, the following six factors were suggested.

The first factor, basic knowledge, refers to familiarity with machine translation tools and the foundational understanding required to use them effectively, as highlighted in much of the previous research. This includes the ability to systematically analyse the performance and limitations of MT systems and to apply this understanding in appropriate usage. The factor comprises five items, including knowledge of the history and operational mechanisms of MT.

The second factor, basic skills, encompasses the ability to evaluate the quality of machine-translated output and to revise and utilise it appropriately according to the intended purpose. This factor reflects not only the core part of post-editing competencies and quality expectations highlighted by Krüger (2022), but also extends beyond them. Specifically, it includes five items, such as adjusting the style and phraseology of translations and enhancing them through post-editing processes.

The third factor, risk management, refers to the ability to use machine translation tools ethically and to manage the associated risks. This factor was developed based on the ethical considerations emphasised by Loock et al. (2022), as well as privacy concerns highlighted by Bowker (2020). Specifically, it comprises five items, including limiting the use of MT tools to protect user privacy and recognising the potential risk of sensitive information leaks.

The fourth factor, transparency, refers to the clarity and openness of users' actions and communication when utilising machine translation in real-world contexts. This factor reflects the communication skills discussed by Bowker (2019) and the concerns regarding academic integrity raised by Bowker (2020). Transparency contributes to maintaining ethical standards in translation tasks and preventing potential issues during the translation process. It includes five items, such as refraining from the use of MT tools when they conflict with learning objectives, and clearly indicating sources when citing MT outputs.

The fifth factor, flexibility, refers to the ability to distinguish between different machine translation MT engines and to apply them effectively within specific contexts. This factor can be viewed as a simplified aspect of technical and data literacy, as discussed by Krüger (2022). It includes five items, such as recognising performance variations based on factors like the type of training data and the size of the engines' databases.

The sixth factor, credibility, pertains to the degree of trust users place in machine translation outputs and their ability to make informed judgements and decisions based on that trust. This factor was developed as an extension of the concept of critical use of MT output, which is frequently highlighted in previous research, as well as the awareness of different MT tools discussed by Bowker (2020). It comprises five items that assess users' confidence in machine-generated translations and their tendency to verify or rely on these outputs accordingly.

A total of 30 preliminary items were designed and were categorised into six factors as outlined in Table 2.

Table 2. Preliminary items.

Factor	Item
Basic Knowledge	1. I know how machine translation tools operate.
	2. I know the historical development of machine translation tools.
	3. I am aware that machine translation can be performed not only on text but also on images and files.
	4. I understand that it is necessary to input clear text with minimal semantic ambiguity when using machine translation tools.
	5. I am aware that machine translation tools do not fully address the contextual ambiguity and complexity of human language.
Basic Skills	1. I know how to adjust the style and tone of machine translation output according to its intended use.
	2. When accuracy issues are identified in machine translation outputs, I know how to improve the results through post-editing.
	3. I can judge whether post-editing meets the quality requirement or if it needs to be retranslated by a human.
	4. I know how to configure data processing and sharing settings when using machine translation tools.
	5. I know how to convert machine translation outputs into different file formats for use.
Risk Management	1. I refrain from inputting privacy-related information into machine translation tools.
	2. I am aware that using machine translation tools could lead to the leakage of sensitive information, such as personal data.
	3. I can assess whether to use a machine translation tool based on the sensitivity of the information contained in the text.
	4. I am aware of the risk that data used to train machine translation tools may be influenced by bias or prejudice.
	5. I am aware that indiscriminate use of machine translation tools can contribute to the spread of bias or prejudice.
Transparency	1. I do not use machine translation tools when they conflict with the learning objectives of the class.
	2. I provide proper attribution to the original source when translating academic papers and books using machine translation and citing the ideas from the original work.
	3. I am aware that using machine translation outputs for commercial purposes may lead to copyright issues.

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Factor	Item
Transparency	4. I understand that the user of a machine translation tool is responsible if issues arise due to errors in the machine translation output.
	5. I am aware that when translation tasks are completed using machine translation, this fact should be disclosed to the client.
	1. I am aware that different machine translation tools may produce different results because they are trained on different data.
Flexibility	2. I am aware that the quality of machine translation output may vary depending on the extent of the database used for its development.
	3. I try to use different machine translation tools for work and assignments and compare their outputs.
	4. I know that machine translation tools may work more effectively in specific fields depending on the type of data they are trained on.
Credibility	5. I make an effort to use different machine translation tools for each translation task to evaluate how each tool performs with specific texts.
	1. I trust machine translation results in languages I do not know.
	2. I try to review and verify machine translation results in languages I am familiar with.
	3. I am aware that machine translation outputs may contain errors.
	4. I trust machine translation output in emergency and urgent situations.
	5. I understand that professional translators' outputs contribute to maintaining and improving the quality of machine translation tools.

Analysis Method

In the first survey, an exploratory factor analysis was conducted using SPSS 29.0 to examine the construct and factors of the preliminary scale, which consisted of 30 items. Factor extraction was performed using maximum likelihood estimation, and factor rotation was done using direct oblimin (Kim et al., 2009). To assess whether the machine translation literacy scale, refined to 23 items through exploratory factor analysis, can retain its six-factor structure when applied to new data, additional data (n = 176) were collected through a second survey. A confirmatory factor analysis (CFA) was subsequently conducted using AMOS 29. Prior to the analysis, responses that were insincere or had missing values (4 cases) were excluded, and maximum likelihood estimation was employed for the model estimation.

Although there is no universally agreed standard for sample size in factor analysis, Hair et al. (2006) suggests that the sample size should exceed 100 or be at least five times the number of survey items. In this study, with 30 preliminary items and 23 main items, both the first and second surveys met these minimum sample size criteria for factor analysis. Finally, SPSS 29.0 was used to assess the reliability of items and to examine the validity of the scale.

Results

Exploratory Factor Analysis

To assess the suitability of the collected data for factor analysis, we used the Kaiser-Meyer-Olkin (KMO) measure to test sampling adequacy and Bartlett's test to examine sphericity. The KMO value was .806, which is considered acceptable (Kaiser, 1974). Bartlett's test of sphericity was significant, $\chi^2(435) = 2,297.084$ ($p < .001$), indicating this data set was acceptable for factor analysis.

Initially, a seven-factor model was considered, as there were seven factors with eigenvalues greater than one and the inflection point in the scree plot (see Figure 1) also supported this structure. However, when the items were organised according to the seven-factor model, some factors seemed a bit fragmented, and the interpretability of the factors was not clear-cut. Consequently, the six-factor model was adopted, as it was deemed more theoretically grounded and practically meaningful for the objectives of this study.

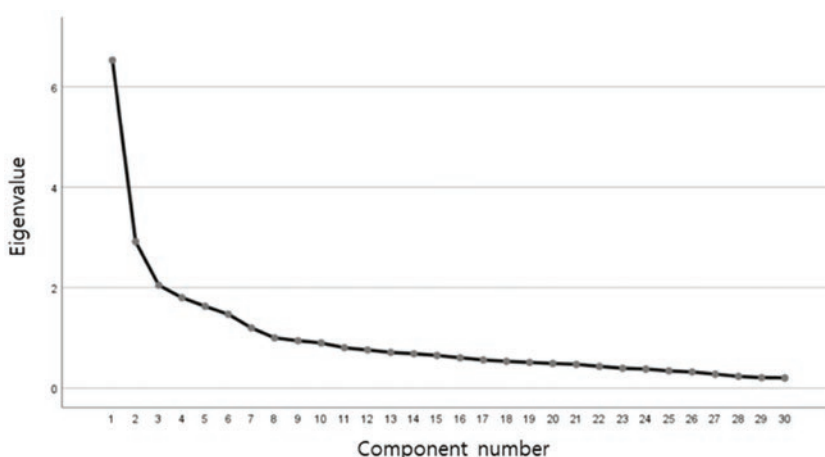


Figure 1. Scree plot

This model demonstrated a good fit ($\chi^2(270) = 420.14$, $p < .001$, Root Mean Square Error of Approximation (RMSEA) = .05¹), and the total variance explained was 54.63%. As a preliminary screening, any items with factor loadings below .4, which are commonly considered marginal, were removed (Tabachnick & Fidell, 2013). As a result, seven items were removed in total. In addition, some items were grouped differently than initially anticipated, leading to renaming factors based on the contents of the items.

The exploratory factor analysis (EFA) regrouped the items. The results largely supported the originally proposed constructs of risk management and transparency, with each factor retaining all but one item. In the case of flexibility, two items were retained. For the basic skill factor, three items remained, and one item originally categorized under credibility was grouped together with basic skill. As this cluster primarily addressed the evaluation and revision of machine

¹ It essentially quantifies the discrepancy between the data and the model's implied covariance matrix. A smaller RMSEA value indicates a better model fit.

translation outputs, the factor was renamed verification and correction to better reflect its conceptual focus. Furthermore, items from the flexibility, credibility, and basic knowledge factors were clustered together to form a revised basic knowledge factor. This factor reflects awareness of variations in translation quality, recognition of mistranslations, and an understanding of the inherent limitations of machine translation. Finally, a subset of items from the original basic knowledge and basic skill factors were clustered together to form a new factor concerned with understanding how machine translation systems are developed and operated, as well as general knowledge related to their use. This factor was renamed operational knowledge to more accurately represent the theme of the items.

As a result, the final factors were risk management, flexibility, verification and correction, basic knowledge, operational knowledge, and transparency. Table 3 presents the factor loadings and the internal consistency (Cronbach’s α coefficients) of each factor and their corresponding items. The internal consistency across the 23 items was .83, and the internal consistency for each factor exceeded .6, indicating that the overall reliability of the scale was acceptable.

Table 3. Exploratory factor analysis results.

Factor	Item	Factor loading ¹	Cronbach’s α^2
Risk Management (RM)	1. I am aware that using machine translation tools could lead to the leakage of sensitive information, such as personal data.	.76	.80
	2. I can assess whether to use a machine translation tool based on the sensitivity of the information contained in the text.	.72	
	3. I am aware of the risk that data used to train machine translation tools may be influenced by bias or prejudice.	.58	
	4. I am aware that indiscriminate use of machine translation tools can contribute to the spread of bias or prejudice.	.57	
	5. I make an effort to use different machine translation tools for each translation task to evaluate how each tool performs with specific texts	.82	
Flexibility (FLX)	6. I try to use different machine translation tools for work and assignments and compare their outputs	.81	.79
	7. I know how to adjust the style and tone of machine translation output according to its intended use.	.83	

(Continue)

Table 3. (Continued)

Factor	Item	Factor loading ¹	Cronbach's α ²
Verification & Correction (V & C)	8. When issues are identified in machine translation outputs, I know how to improve the results through post-editing.	.64	.76
	9. I can judge whether post-editing meets the quality requirement or if it needs to be retranslated by a human.	.62	
	10. I review and verify machine translation results in languages I am familiar with.	.43	
Basic Knowledge (BK)	11. I am aware that different machine translation tools may produce different results because they are trained on different data.	-.72	.79
	12. I am aware that the quality of machine translation output may vary depending on the extent of the database used for its development.	-.67	
Basic Knowledge (BK)	13. I am aware that machine translation outputs may contain errors.	-.50	.79
	14. I am aware that machine translation tools cannot fully address the contextual ambiguity and complexity of human language.	-.45	
	15. I know how machine translation tools operate.	-.66	
Operational Knowledge (OR)	16. I know the historical development of machine translation tools.	-.56	.71
	17. I am aware that machine translation can be performed not only on text but also on images and files.	-.54	
	18. I know how to configure data processing and sharing settings when using machine translation tools.	-.45	
	19. I know how to convert machine translation outputs into different file formats for use.	-.42	
Transparency (TRS)	20. I am aware that using machine translation outputs for commercial purposes may lead to copyright issues.	.55	.64

(Continue)

Table 3. (Continued)

Factor	Item	Factor loading ¹	Cronbach's α ²
Transparency (TRS)	21. I understand that the user of a machine translation tool is responsible if issues arise due to errors in the machine translation output.	.51	.64
	22. I am aware that when translation tasks are completed using machine translation, this fact should be disclosed to the client.	.51	
	23. I provide proper attribution to the original source when translating academic papers and books using machine translation and citing the ideas from the original work.	.49	

¹In the context of factor analysis, a factor loading is a correlation coefficient that quantifies the relationship between a variable and a factor. It indicates how strongly a variable is associated with a specific latent (underlying) variable, known as a factor.

²Cronbach's alpha is a way of assessing reliability by comparing the amount of shared variance, or covariance, among the items making up an instrument to the amount of overall variance.

Confirmatory Factor Analysis

To validate the six-factor, 23-item scale derived from the exploratory factor analysis, a confirmatory factor analysis (CFA) was conducted using data from the second survey. Model fit was evaluated using key indices, including the Tucker-Lewis Index (TLI; Bentler & Bonett, 1980), Comparative Fit Index (CFI; Bentler, 1990), and RMSEA (Steiger & Lind, 1980). As shown in Table 4, the initial six-factor model exhibited suboptimal fit indices. Based on modification indices and the item structure, an alternative model was developed by incorporating correlated errors, as illustrated in Figure 2 (Kim et al., 2009). As a result, this modification improved the model fit. Although the TLI (.852) and CFI (.876) did not meet the conventional threshold of .90 (Bentler, 1990), the RMSEA value was .066 (90% CI [.055, .077]), indicating an acceptable level of fit (Browne & Cudeck, 1992). Additionally, as shown in Table 5, all items loaded significantly on their designated constructs ($p < .001$). These results demonstrate that the six-factor, 23-item machine translation literacy scale has acceptable construct validity and explanatory power.

Table 4. CFA results.

Model	Models validated	χ ² (df)	TLI	CFI	RMSEA
Model 1	Initial 6 factors	471.009 (215)***	.762	.815	.082
Model 2	v1-v2, v13-v14, v15-v16 correlated errors added	369.383 (212)***	.852	.876	.066

*** $p < .001$.

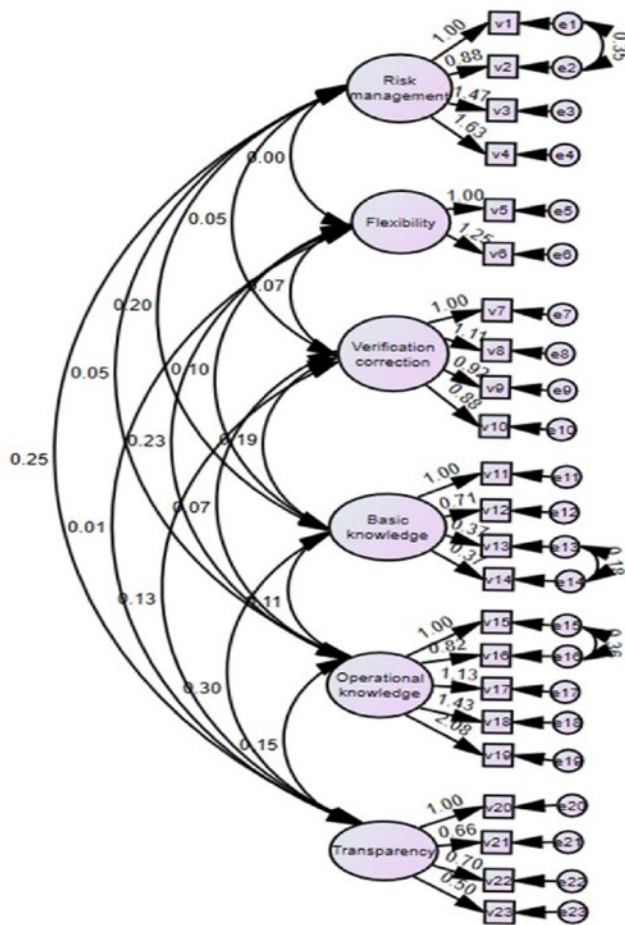


Figure 2. Six-factor machine translation literacy scale CFA model

Reliability and Validity of the Final Scale

To evaluate the reliability of the six-factor scale, internal consistency was assessed using Cronbach’s alpha, alongside a review of composite reliability. As shown in Table 5, all factors, except transparency (.538), demonstrated Cronbach’s alpha values above .70. Similarly, composite reliability values exceeded the generally accepted threshold of .6 for all factors, with the exception of transparency (.537). These results indicate that the scale exhibits acceptable internal consistency overall (Nunnally & Bernstein, 1994). The lower Cronbach’s alpha of .538 for transparency may be attributed to the diverse range of aspects it encompasses, including copyright issues, translators’ responsibility for errors, disclosure of machine translation usage, and proper citation practices when using machine translation.

In assessing the scale’s validity, convergent validity is considered adequate when standardised coefficients are above .70 and the Average Variance Extracted (AVE) exceeds .50 (Bagozzi et al., 1991; Fornell & Larcker, 1981). As shown in Table 5, the standardised coefficients ranged from .35 to .90, and the AVE values ranged from .23 to .80, indicating that some variables did not reach the desired levels. To assess the discriminant validity, the Heterotrait-Monotrait ratio

Table 5. CFA results for machine translation literacy scale.

Pathway Item ← Factor	Estimation				CR1	AVE	CR2	Cronbach's α
	Unstandardised Coefficients	Standardised Coefficients	Stan- dard Error					
v1 ← RM	1.000	.462***						
v2 ← RM	.879***	.459***	.163	5.409		.460	.758	.763
v3 ← RM	1.472***	.816***	.256	5.739				
v4 ← RM	1.633***	.866***	.284	5.742				
v5 ← FLX	1.000	.798***				.757	.861	.856
v6 ← FLX	1.248***	.937***	.164	7.615				
v7 ← V & C	1.000	.762***						
v8 ← V & C	1.109***	.748***	.123	9.045		.540	.823	.820
v9 ← V & C	.919***	.796***	.097	9.469				
v10 ← V & C	.881***	.620***	.117	7.543				
v11 ← BK	1.000	.881***						
v12 ← BK	.713***	.735***	.085	8.391				
v13 ← BK	.374***	.432***	.072	5.219		.413	.716	.733
v14 ← BK	.372***	.387***	.080	4.668				
v15 ← OK	1.000	.462***						
v16 ← OK	.818***	.376***	.165	4.945				
v17 ← OK	1.132***	.467***	.269	4.200				
v18 ← OK	1.429***	.630***	.291	4.901		.318	.685	.705
v19 ← OK	2.078***	.789***	.400	5.195				
v20 ← TRS	1.000	.620***						
v21 ← TRS	.659***	.467***	.148	4.457		.232	.537	.538
v22 ← TRS	.697***	.439***	.164	4.250				
v23 ← TRS	.502***	.363***	.138	3.647				

***p < .001, CR1: Critical Ratio, CR2: Composite Reliability.

(HTMT) was employed. As shown in Table 6, all HTMT values were below the conservative threshold of .85, indicating that the proposed scale exhibits adequate discriminant validity (Clark & Watson, 1995).

These findings suggest that, while most factors of the six-factor scale exhibit acceptable reliability and validity, the transparency factor may require further refinement to improve its internal consistency and convergent validity.

Table 6. HTMT (Heterotrait-Monotrait ratio) results.

	Risk Management	Verification & Correction	Basic Knowledge	Operational Knowledge	Flexibility
Verification & Correction	0.203				
Basic Knowledge	0.442	0.527			
Operational Knowledge	0.364	0.293	0.452		
Flexibility	0.006	0.137	0.202	0.476	
Transparency	0.728	0.348	0.563	0.565	0.088

As presented in Table 7, the inter-correlations among the factors of the machine translation literacy scale revealed that risk management and transparency exhibited the highest correlation ($r = .475, p < .001$). All factors, except flexibility, showed significant positive correlations with other factors. Meanwhile, flexibility demonstrated significant positive correlations only with basic knowledge and operational knowledge. Overall, most correlations between the subscales are positive, suggesting that the MT literacy scale has logical consistency.

Table 7. Correlation coefficient of MTL scale (n = 172).

	Risk Management	Verification & Correction	Basic Knowledge	Operational Knowledge	Flexibility
Verification & Correction	.160*				
Basic Knowledge	.340**	.414**			
Operational Knowledge	.266**	.230**	.335**		
Flexibility	.006	.113	.161*	.380**	
Transparency	.475**	.231**	.352**	.348**	.057

Discussion and Conclusion

The scale developed in this study can serve a dual purpose: it provides a reliable framework for evaluating the ability of translation majors to critically understand and effectively utilise machine translation, while also offering essential groundwork for systematically shaping machine translation education. The following discussion highlights its academic and practical significance.

First, as the use of machine translation continues to grow rapidly, users are increasingly likely to encounter new challenges. To address these effectively, machine translation literacy should be established as an independent subfield within translation studies, with its theoretical and practical foundations further developed through sustained research in translation studies and related disciplines.

Second, this study aimed to establish the concept of MT literacy within the broader context of translation education planning and systematically integrate it into translation education. To that end, this paper suggested a statistically validated model with six factors and 23 items. This model covers a comprehensive and multifaceted concept beyond just technical skillset. It encompasses basic and operational knowledge of MT, critical use of MT, ethical awareness, and collaborative competencies. This signifies a shift from traditional translation education, which has primarily emphasised technical proficiency, tool mastery, or linguistic fluency in isolated courses, towards a more holistic approach. Hence, the set of factors and items presented in this study can serve as a foundation for designing new translation courses.

Third, from a micro-level perspective on translation education design, this study examined the relationship between educational background and machine translation literacy. The analysis revealed that as students progressed to higher academic levels, their risk management competencies tended to improve. Additionally, learners who had taken more courses related to machine translation demonstrated relatively higher levels of flexibility and operational knowledge. A significant difference in basic knowledge was also observed between those who had taken machine translation-related courses and those who had not. These findings suggest that a more systematic and comprehensive approach to machine translation education can contribute to enhancing machine translation literacy. Therefore, it is essential to integrate translation technologies holistically throughout the curriculum.

More specifically, the proposed scale can serve as a practical resource for designing targeted educational content for translation majors. The assessment results indicate that the overall average score across all items was approximately 3.6, suggesting a level slightly above the mid-range. However, areas related to the development of machine translation, data processing settings, and the evaluation and comparison of MT outputs showed relatively lower scores, averaging in the 2-point range. This approach can help identify areas in need of improvement within machine translation education and suggests that incorporating these insights into future curriculum design may support the development of more systematic and effective instructional content.

Most notably, this study is one of the few to develop an MT literacy scale specifically for translation majors. It distinguishes itself through its model development and data collection methodology. While previous research often drew on limited samples from a single institution, this study conducted a large-scale survey involving approximately 400 students across eight universities and 13 translation and interpreting programmes. Exploratory and confirmatory factor analyses were used to rigorously evaluate the scale's structural validity and reliability. The breadth and diversity of the dataset further strengthen the robustness of the proposed scale.

This study has pioneered a new research domain in machine translation literacy, laying the foundation for its integration into translation education. While it has not yet addressed all aspects comprehensively, it offers considerable potential for further exploration in future research.

First, conducting a comparative study between universities using the machine translation literacy assessment tool would enable a more comprehensive evaluation of the level and effectiveness of MT literacy education across different regions or institutions.

Second, by integrating the assessment tool developed in this study with other assessment instruments, it is possible to conduct a more precise analysis of the learning experiences and

academic performance of translation students. This would enable a systematic examination of the impact of specific learning programmes or educational experiences on the improvement of MT literacy. Notably, existing studies have primarily focused on assessing literacy levels at a single point in time, lacking analysis of how individual competencies evolve over time. Therefore, further research is needed to investigate the long-term learning effects of machine translation literacy.

Third, it is necessary to analyse the gap between the technological literacy skills required by the industry and those taught in academic curricula. There may be discrepancies between the machine translation competencies demanded in professional settings and the instructional content provided by educational institutions. Empirically examining the impact of these discrepancies on students' attitudes and practical competencies is crucial. Such an analysis would contribute to the development of a more practical and industry-aligned machine translation education curriculum.

Fourth, since this study was conducted with a specific sample population, its findings have limitations. Future research should include a more diverse range of learners, particularly non-specialists and interdisciplinary professionals. Additionally, research on machine translation literacy should be expanded to multilingual settings. While existing studies have primarily focused on specific language pairs, future research should explore the applicability of machine translation literacy across various language pairs.

Furthermore, by tracking the developmental trajectory of machine translation literacy across various educational settings, effective instructional strategies can be derived for diverse learner groups, including international students. This approach is expected to enhance the effectiveness of machine translation literacy education in global educational contexts and provide practical insights for the development of more sophisticated training programmes.

Despite its contributions, this study has several limitations. First, since the research was conducted with a limited sample, specifically among translation majors in Korea, future studies should include a more diverse and expanded sample to enhance the generalisability of the findings. In addition, all findings and implications discussed in this study are based on data specific to the Korean context. Therefore, caution should be exercised when applying the results to other settings.

Second, although the factors and items discussed in this study were carefully developed by researchers, they may not comprehensively capture all aspects of MT literacy. In addition, given the rapid pace of AI development, it is uncertain whether the proposed scale will maintain its validity in the future. Therefore, subsequent research should continue to validate and refine the proposed model and factors to ensure their robustness.

Furthermore, the relationship between the machine translation literacy scale developed in this study and the professional machine translation literacy module proposed by Krüger (2022) remains an open question. It may be argued that Krüger's five subcomponents of machine translation literacy are overly specialised for application in undergraduate and graduate translation education in South Korea and are too granular for effective scale development. Moreover, given the current state of machine translation use in the Korean translation industry, the level of literacy Krüger proposes may be considered overly detailed and impractically demanding. However, as the domestic translation industry continues to evolve, the need for a more specialised literacy scale is likely to emerge.

Finally, to help the scale serve as a more sophisticated and solid assessment framework, we encourage other researchers to engage in critical discussions and provide recommendations for additional factors and items that may enhance its comprehensiveness and applicability.

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