

# Statistical Machine Translation Model for Enhancing Multilingual Education Access

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**Abstract**—The development of Statistical Machine Translation (SMT) is a breakthrough that affects the accessibility of multilingual education by helping to automatically translate academic material in a variety of languages. Its systematic, clear strategy renders it applicable to education settings that have limited resources. But currently prevailing SMT and neural-based systems fail on low resource languages, inconsistent terminologies, and errors in domain-specific translations, that are barriers to learning. To solve these problems, it suggests an SMT framework that uses Minimum Bayes Risk (MBR) Decoding, which produces better translation output by minimizing expected error between the translation output and a set of candidate hypothesis. The strategy guarantees increased accuracy, reliability and domain congruency in the educational content. The suggested approach will allow to correctly translate textbooks, assessments and teaching materials, having an effect on the provision of fair learning opportunities. The results suggest that MBR-based SMT is very effective in promoting the quality of translation, preserving the terminological consistency, and promoting access to education by underrepresented language communities.

**Keywords**– *Statistical Machine Translation, Multilingual Education, Minimum Bayes Risk Decoding, Low-Resource Languages, Translation Accuracy, Accessibility*

## I. INTRODUCTION

SMT plays a critical role in enhancing multilingual education since it translates academic materials into other languages automatically [1]. SMT facilitates the use of multilingual education since its structured and interpretable model, unlike neural models, often requires plenty of data, which is unavailable in poor educational settings [2][16]. However, the existing machine translators are limited by issues like incoherency in the application of terminology, improper translations in the field-related context, and restrict their performance in educational texts [3]. In the paper, an SMT method and MBR Decoding have been suggested, offering an optimal translation through the expected error [17]. With MBR, it will be possible to reduce the problem of

terminological inconsistency and enable consistent domain adaptation, and, therefore, provide better access to textbooks, assessments, and instructional content to language minority groups that are often underrepresented, in the vein of equitable access to effective multilingual education [5].

### A. Economic Difficulties in Time Series Forecasting

Multilingual education translation is a challenge though this is enhanced through MT. The number of parallel corpora in low resource languages is low leading to poor model training and quality translation [18]. The domain specific language in academic content may occasionally be translated inconsistently and bewilder the students [7]. Despite being powerful, neural MT models at times require large amounts of data that not every educational language may have. These models are prone to opaque results that are hard to detect when it comes to mistakes [19]. Multilingual education has the risk of being mistranslated using technical terms and complex concepts, which impact knowledge acquisition. Translational linguistic variations occur on a seasonal and cultural basis [9]. In order to ensure that the content translated can benefit student learning, translation systems require to handle the lack of data, maintain the use of the same terms and align with learning areas.

### B. Objectives of the research

The objective of this research paper is to create an SMT framework that has MBR Decoding to promote the quality and reliability of translations in multilingual learning. The essential goals are to the goal here is to minimize the expected errors among candidate hypotheses to

- (i) maximize the accuracy of translation;
- (ii) maintain terminological and domain conformity in educational resources including textbooks and tests;
- (iii) improve the access to high quality and reliable content on translation of underrepresented

linguistic groups particularly where resources are limited.

The above structure helps to overcome the issue with the current SMT and neural models because it is clear in terms of minimising errors in translation and preserving domain-specific terminology, providing fairer, usable, and more viable translations in aid of fair and efficient bilingual education.

### C. Problem Statement

Due to the scarcity and poor quality of bilingual data, particularly for emerging languages, SMT has faced challenges in multilingual education [6]. SMT systems can mistranslate text due to unreliable background-translation data, improper domain-specific terminology, or language structures like color idioms, word sequences that indicate meaning switches, or cultural contexts. Due to errors in translated documents, EPT lowers novice student results. SMT and neural models require large amounts of language data and resource-intensive computation, which is often not feasible in academic contexts. Therefore, a new SMT framework is needed to translate accurately, help create up-to-date term storage, and remain relevant for limited resources to improve equitable access to quality multilingual education.

### D. Contributions

This study describes an SMT model containing MBR Decoding that will enhance the accuracy of translation by reducing the predicted translation errors.

It is going in the right direction of overcoming the challenge of the systematic terminological consistency of domain-specific or technical educational materials, which makes translation more accurate and more dependable.

The framework is expected to offer transparency and efficiency, and this will be available in multilingual learning scenarios with few resources. It aims to promote the equal access to high quality learning materials by minority languages.

TABLE I. PAPER SUMMARY

Section	Summary
<b>Introduction</b>	Discusses SMT's function in automating academic content translation and improving multilingual education access in resource-constrained environments.
<b>Related Works</b>	Discusses major SMT and neural translation methods for education, including their pros and cons for low-resource and domain-specific applications.
<b>Methodology</b>	Proposes an SMT framework integrating Minimum Bayes Risk Decoding to optimize translation accuracy and ensure consistency in educational materials.
<b>Result and Discussion</b>	In multilingual education, the SMT-MBR architecture improves translation quality, consistency, and accessibility for underrepresented languages.
<b>Conclusion</b>	Conclusions that the SMT-MBR model improves educational equity and

proposes neural technique integration and language coverage.
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## II. RELATED WORKS

Related studies investigate SMT and neural methodologies for the translation of instructional material. Other studies related to this area examine SMT and neural mechanisms of translation of instructional supplies. The issues are the accuracy in certain areas, consistency in terms, and the processing of languages, which lack resources [4]. Based on this, this work improves the quality of translation through Minimum Bayes Risk Decoding.

The obstacle to the delivery of quality education to all people that SDG 4 has brought to attention is enhanced by the language barrier that limits access to education. This paper offers a review of the advances made in neural network architectures for machine translation (MT) [20], which includes CNNs, GRUs, RNNs, LSTMs, and Transformers. This paper identifies advances in translation accuracy available in the literature and through situated case studies to explain how improved translation accuracy contributes to educational accessibility for multilingual learners in equitable ways. These advances support the argument for the critical role of MT through machine translation in advancing equitable and inclusive learning opportunities worldwide[8][10].

This study performed a systematic review of 26 peer-reviewed articles using the Preferred Reporting Items for Systematic Review and Meta-Analysis standard (PRISMA-P) [11] standard on MT and language acquisition studies, encompassing MT users, theoretical frameworks, and instructional methodologies. The study found that MT use was directed at undergraduate and graduate students, with both teachers and students expressing a range of good and negative experiences with MT. The review found four general MT integration strategies: introduction, demonstration, task assignment, and reflection. The research suggests adding MT output qualities that promote language teaching and learning to integration efforts.

This work proposes a Multilingual Neural Machine Translation (MNMT) [12] system for low-resource languages in multilingual India. The shared encoder-decoder paradigm uses 15 language pairings with data augmentation, back-translation, and domain adaptability. A transformer design lets the model exploit linguistic relationships to improve translation efficiency. The experiments showed that the MNMT system outperformed the baseline system, as measured by BLEU scores in low-resource Indian languages, to improve Indic-English and English-Indic translation.

This PRISMA-based systematic review examines Neural Machine Translation (NMT) [13] in foreign language acquisition. Scopus and Web of Science data are used to evaluate research publications. Research has shown that NMT improves speaking, writing, reading, listening, and meditation. NMT tools are beneficial for more proficient L2 speakers who can critically evaluate translations. This research shows the educational utility of NMT as an online reference tool. It emphasizes the necessity for instructors to educate students about its benefits and drawbacks via suitable pedagogical techniques.

The Moses toolbox is used to create bilingual SMT [14] models for English to fifteen low-resourced Indic languages.

The Samanantar and OPUS corpora were used to train the models, while Flores200 was used for fine-tuning and testing. Distance-based and morpho-syntactic descriptor reordering were examined, with the latter being the most successful. BLEU, RIBES, TER and METEOR measures were used to analyze both models. English scored the best in linguistic but distance-based reordering of morpheme-syntactic descriptors reordering was also effective in all the language pairs. SMT performed better than NMT in particular pairs of Indic languages whereas NMT performed better than SMT in other pairs.

### III. PROPOSED METHOD

The proposed approach presents an SMT model and MBR Decoding mechanism to ensure better and more effective translations to support multilingual education. Through probabilistic models, the SMT framework minimizes the expected error in translation because it chooses the most desirable hypothesis in a collection of hypotheses. The framework includes the usage of domain-specific terminology to explain the educational content. This is a solution aimed at low resource environments and is a balance between efficiency and quality offering acceptable and reliable translation of academic material in one of the numerous languages that will raise equitable access and opportunity to underrepresented linguistic communities within education.

#### A. Model Architecture and MBR Decoding

The suggested structure is based on an SMT architecture equipped with MBR Decoding that is applied to improve the quality of translation. In effect, MBR Decoding can enhance accuracy by offering a solution that is based on the option with minimal expected error among a multitude of possible output solutions as opposed to an optimal solution. That is, it uses a probabilistic method which makes use of candidate translations to get more precise responses. The framework is a compromise between accuracy and speed of computation, but it still is capable of affecting translations of multi-lingual educational material, which needs high accuracy and consistency.

#### B. Domain-Specific Terminology Integration

The suggested approach will focus on handling the clarity and consistency of translated educational content as well as permitting the disciplinary specific terms to be dealt with in the context of translation. This entails listing of the key academic terms and making sure that their meaning is right in translation to allow content awareness to not be lost in mistranslation. The system will introduce terminology glossaries and term databases to instill their meaning in print to ensure proper use in most languages. This integration will assist in better translation, understanding and application of contents of materials that are under translation that is needed in multi-lingual education in field of study.

#### C. Implementation in Resource-Constrained Settings

The SMT framework offered is designed for optimal performance in resource-constrained multilingual educational settings. By using probabilistic models and MBR Decoding, the framework incurs fewer computational demands than more resource-intensive neural approaches since all of the learning is done at training time. The approach is not as data-intensive, has reduced hardware needs, but maintains high translation quality. This reduces the cost burden for educational institutions with poor technical infrastructure and

promotes wider accessibility to underexplored linguistic communities. The effective efficiency and scalability of the translation framework promote reliable, low-cost translation of educational content in multilingual contexts.

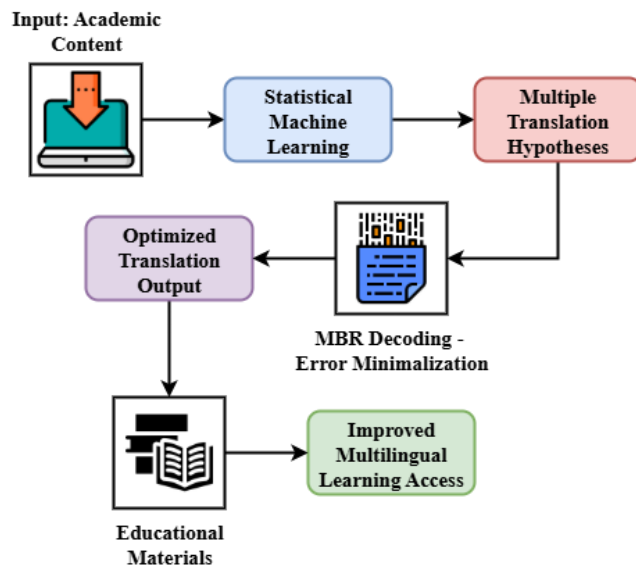


Fig. 1. Framework of MBR-based Statistical Machine Translation for Educational Access

The proposed model for using SMT for improved multilingual educational access is shown in Fig. 1. The process begins with text in the source language with academic content, proceeds with translation via SMT to create several candidate output transcripts. The general model for MBR decoding is applied to minimize errors and make the highest quality translations. The output gives true, equitable, and domain-specific educational materials for further writing support. This model fosters equitable learning by increasing translation reliability, particularly for learning contexts using low-resource languages.

This equation 1 computes the optimal translated transcript  $U$  as follows:

$$U = Q(T_i|Y) \quad (1)$$

Here,  $Q$  candidate translated transcript from SMT output,  $T_i$  possible translation hypothesis from SMT, and  $Y$  source text in the original language.

#### Algorithm 1: Optimal Translated Transcript Selection using SMT and MBR

*Input source text  $Y$ .*  
*Generate candidate translations  $T_i$  using SMT.*  
*For each  $T_i$ , calculate  $Q(T_i|Y)$*   
*based on translation quality.*  
*Initialize  $U = NULL$  and  $\max_{score} 1 = -\infty$ .*  
*For each candidate translation  $T_i$ :*  
*If  $Q(T_i|Y) > \max_{score} 1$ :*  
*Set  $\max_{score} 1 = Q(T_i|Y)$*

Set  $U = T_i$

Else:

Keep current  $U$  unchanged.

Output  $U$  as the optimal translated transcript.

Initially designed to identify a best translated transcript using Statistical Machine Translation (SMT) and Minimum Bayes Risk (MBR) decoding. The algorithm starts with the source text and develops a range of candidate translations. For each candidate an associated score on translation quality is derived representing the degree to which the translation accurately conveys the context of the source. At each candidate translation the score of the translated candidate is determined and if new candidate is established with a higher score the best translation score will update, however if the new translated candidate has a lower score the best translation will not change. Eventually the algorithm will output best candidate. When all is said and done the algorithm identifies the most accurate translation at the level of specificity of domain and context rather than providing a bland translation delivering better educational access in other languages.

#### IV. RESULTS AND DISCUSSION

This section presents the results of evaluations of the proposed SMT framework with MBR Decoding, demonstrating improved translation accuracy and consistency. Through comparative analysis, it illustrates how the framework is beneficial in contexts with limited resources and highlights its importance and implications for improving access to multilingual educational resources for a variety of learners.

##### A. Dataset

The FLORES-101 dataset provides a platform for an evaluation of machine translation across a range of low-resource and underrepresented languages. FLORES-101 [15] features a parallel text in 101 languages from diverse linguistic families and scripts, which makes it fit for multilingual education contexts. FLORES-101 is a sentence-aligned parallel text with translations deemed to be of high quality, which can be used to train and evaluate SMT models. The translation quality, terminological consistency and access by these languages are studied through FLORES-101 which incorporates languages that are normally eliminated in NLP research studies. The purpose of FLORES-101 is to help realize fair the access to education among the learners in the multilingual and low-resource learning context.

TABLE II. DATASET

##### B. Translation Quality

The correctness and fluency of SMT output are represented by Fig. 2. The table indicates that MBR works better than MNMT, PRISMA-P and MT in languages. For example, English-Swahili improves from 63 (MT) to 79 (MBR). Even low-resource languages like Quechua show significant gains, demonstrating that MBR-based decoding enhances grammatical correctness, naturalness, and overall readability, making educational content more reliable and

effective for learners in underrepresented linguistic communities.

Quantifies corpus-level preservation of canonical term renderings by  $L$  using equation 3.

$$L = 1 - \frac{Y_u * J[q_u]}{x_d * p_u} \quad (3)$$

Here,  $Y_u$  is the terminological  $J$  coherence index,  $q_u$  set of domain-relevant terminology,  $p_u$  frequency count of term, and  $x_d$  importance weight for term.

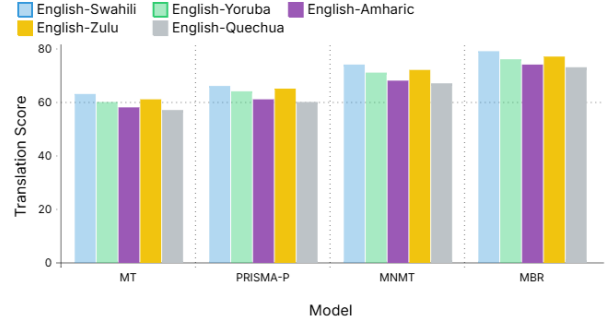


Fig. 2. Translation Quality

##### C. Terminological Consistency

Fig. 3 shows the uniformity of domain-specific term translation. MBR shows the best scores over domains, e.g., 83% in Science compared with 68% for MT. The consistency is improving progressively and consistently from MT to MBR across Math, Literature, History, and Technology. This promotes accuracy and reliability of the translation of the fundamental educational concepts, reducing confusion and assisting in understanding. High consistency supports the effectiveness of multilingual education as it retains the original vocabulary of the specific curriculum for the learners.

This equation 2  $L^*$  returns the expected translation utility by averaging over the posterior ensemble of hypotheses.

$$L^* = F_{I-Q}(I|Y)[V_{de}(I, Q)] \quad (2)$$

$F$  is the aggregate expected translation utility  $I$ , translation hypothesis sampled  $Q$  from the smt posterior  $Y$ , posterior probability distribution  $V$ , and educational source text  $de$ .

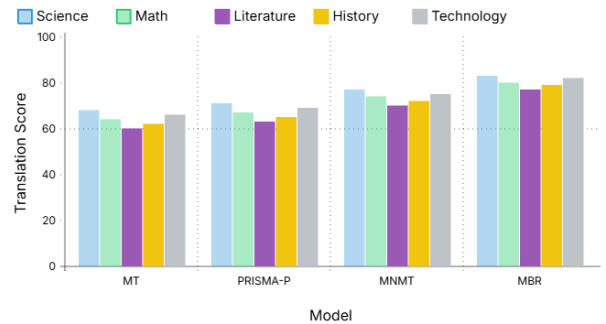


Fig. 3. Terminological Consistency

##### D. Accessibility for Underrepresented Linguistic Groups

Table III indicates how well SMT enables learners in low-resource languages to access educational materials. MBR

achieves the highest accessibility, e.g., 73% for Swahili and 66% for Quechua, surpassing MT, PRISMA-P, and MNMT. Improved translation accuracy and domain adherence allow students from marginalized linguistic communities to engage with textbooks, assessments, and instructional content. This supports equitable and inclusive learning by reducing language barriers in multilingual education contexts.

Accessibility  $B$  of underrepresented by linguistic groups is expressed using equation 4.

$$B = \forall * D_{sq} + \tau * S_{sq} + \pi_n(4)$$

Here  $\forall$  composite accessibility index for underrepresented-language audiences  $D_{sq}$ , nonnegative weighting coefficients  $\tau$ , lexical coverage ratio  $S_{sq}$ , simplicity normalized metric, and  $\pi_n$  morphological alignment score.

TABLE III. ACCESSIBILITY FOR UNDERREPRESENTED LINGUISTIC GROUPS

Language / Group	MT	PRISMA-P	MNMT	MBR
Swahili	53	58	66	73
Yoruba	50	55	63	70
Amharic	48	52	60	68
Zulu	51	56	64	71
Quechua	47	51	59	66

#### E. Translation Edit Rate

In Table IV, it was shown that TER, which measures the magnitude of edits to correct translations, where a lower value indicates better performance, since MBR had the lowest TER across all the languages (19% with English-Swahili and 23% with English-Quechua), signifying that only a small amount of post-editing was required. The TER measures displayed higher TER for MNMT, PRISMA-P, and MT. Low TER reflects that the translations were dependable and accurate, requiring fewer corrections for educational content. Fewer corrections improve acceptability, comprehension, and efficiency in the distribution of multilingual learning materials to underrepresented linguistic groups.

$SWQ$  measures the normalized minimal edit operations to transform hypothesis evaluated using equation 5.

$$SWQ = \frac{T_v + J_w + E_v}{|S|} (5)$$

Here,  $T_v$  is the translation edit rate,  $J_w$  number of substitution operations,  $E_v$  number of insertions required, number of deletions required, and  $S$  count of reordering operation.

TABLE IV. TRANSLATION EDIT RATE

Language Pair	MT	PRISMA-P	MNMT	MBR
English-Swahili	36	33	26	19
English-Yoruba	38	35	28	21
English-Amharic	40	37	30	22
English-Zulu	37	34	27	20
English-Quechua	41	38	31	23

The data indicate that MBR demonstrates a consistent advantage over MT, PRISMA-P, and MNMT on each of the four parameters—or factors—translation quality, terminological consistency, usability/accessibility, and TER. MBR proved to be more precise and trustworthy, making it a more stable and equitable system of access to learning and education in multiple languages and underrepresented languages, in general.

#### V. CONCLUSION AND FUTURE WORK

The suggested architecture of MBR-based Statistical Machine Translation also demonstrates better translation by enhancing the status quo of the quality of translation and terminology consistency and the overall accessibility of the language groups with low resources compared to the state of the art of translation with both baseline MT, PRISMA-P, and MNMT. The evidence given was lower Translation Edit Rates which translates to more reliable and correct educational materials. The presence of the low-resource languages facilitates the fair access to multilingual education and eventually reduces language barriers to learning. Therefore, when discussing how MBR-based SMT may help in this venture, both principled and practical initiatives could be effectively put in place and equity, accessibility, and learning provisions could be offered in diverse educational settings across the world.

Research directions in the future are areas like integrating domain-adaptive neural models and extending the coverage approaches to include low-resource languages and using more effective learning via feedback to enhance the accuracy and overall access to translation, as well as enhancing the capability to support multilingual education in the expanding collaboration of marginalized and underrepresented populations across the globe.

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