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The Countervailing Effect Of "Digital Humanistic View" On Translation Teaching Under Computer-Assisted Technology



Abstract: - "Digital Humanistic View" on Translation Teaching under Computer-Assisted Technology emphasizes the integration of humanistic values with digital tools in translation education. This approach recognizes the importance of technology in enhancing translation teaching and learning experiences while also emphasizing the significance of human creativity, critical thinking, and cultural understanding. By leveraging computer-assisted technology, translation instructors can provide students with access to diverse resources, interactive exercises, and automated translation tools to facilitate language acquisition and proficiency. However, the "Digital Humanistic View" emphasizes that technology should complement rather than replace human expertise, encouraging students to engage deeply with language, culture, and context in their translation practice. This paper explores the countervailing effect of the "Digital Humanistic View" on translation teaching under computer-assisted technology, enhanced by Hidden Markov Translation Teaching (HMTT). The study investigates how the integration of humanistic values with digital tools in translation education influences teaching methods and student learning outcomes. Through simulated experiments and empirical validations, the impact of HMTT on translation teaching is evaluated, with a focus on student engagement, proficiency, and cultural understanding. Results demonstrate that while computer-assisted technology offers valuable resources and efficiency in translation teaching, the "Digital Humanistic View" emphasizes the importance of human creativity, critical thinking, and cultural sensitivity. Analysis stated that students exposed to HMTT with the "Digital Humanistic View" reported a 30% increase in cultural understanding and a 20% improvement in translation accuracy. Additionally, the framework enabled instructors to balance the benefits of technology with the humanistic aspects of translation, fostering a holistic approach to language education. These findings highlight the potential of HMTT with the "Digital Humanistic View" in shaping effective and ethical translation teaching practices in the digital age.

Keywords: Digital Humanistic View, translation teaching, computer-assisted technology, Hidden Markov Translation Teaching (HMTT), student engagement, cultural understanding

I. INTRODUCTION

The digital humanistic view heralds a paradigm shift in the way we perceive and engage with technology, emphasizing the integration of humanistic values and principles into digital landscapes [1]. This perspective advocates for the recognition of the intrinsic worth of human experiences, emotions, and cultural contexts within the realm of digital innovation. It underscores the importance of fostering empathy, inclusivity, and ethical considerations in the design and implementation of digital technologies [2]. In this framework, technology is not merely a tool for efficiency or profit, but a means to enhance human flourishing, facilitate meaningful connections, and preserve diverse cultural heritages. Digital humanism advocates for technology that serves humanity, rather than the other way around, promoting empowerment, autonomy, and well-being for individuals and communities alike [3]. By prioritizing human values in the digital realm, this approach seeks to mitigate the risks of technology-driven alienation, inequality, and exploitation, while fostering a more harmonious relationship between humans and the digital world [4].

The "digital humanistic view" into translation teaching under computer-assisted technology represents a significant evolution in language education methodologies. This approach emphasizes the fusion of humanistic principles with digital tools to enhance the teaching and learning experience [5]. In the context of translation, it prioritizes the development of linguistic and cultural competencies while leveraging technology to augment rather than replace human involvement [6]. Under this framework, computer-assisted technology serves as a facilitator rather than a substitute, offering resources for students to refine their translation skills while maintaining a focus on critical thinking, cultural sensitivity, and ethical considerations [7]. Incorporating the digital humanistic view into translation teaching encourages students to engage deeply with language and culture, fostering a more holistic understanding of the nuances involved in the translation process [8]. By combining the strengths of technology with

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humanistic values, this approach not only equips students with practical translation skills but also cultivates a deeper appreciation for the art and complexity of language communication [9].

Translation teaching is a multifaceted endeavor that encompasses various methodologies and approaches aimed at equipping students with the skills and knowledge necessary to effectively convey meaning between languages [10]. Translation teaching involves imparting linguistic proficiency, cultural understanding, and critical thinking abilities to students, enabling them to navigate the complexities of transferring meaning from one language to another [11]. This process often involves a combination of theoretical instruction, practical exercises, and hands-on experience with authentic texts. Additionally, translation teaching may leverage computer-assisted technology to enhance students' learning experiences, providing access to translation tools, corpora, and other resources to support their linguistic development [12]. Furthermore, translation teaching often emphasizes the importance of ethical considerations, encouraging students to reflect on issues such as fidelity to the source text, cultural sensitivity, and the power dynamics inherent in translation [13].

This paper makes several significant contributions to the field of translation education, particularly in the context of the digital humanistic view and the utilization of the Hidden Markov Translation Teaching (HMTT) approach. Firstly, it provides empirical evidence of the effectiveness of HMTT in enhancing students' translation skills, cultural understanding, and overall proficiency, as evidenced by the results presented in Tables 1, 2, and 3. These findings offer valuable insights into the potential of computational techniques, such as Hidden Markov Models, to augment traditional translation teaching methods. Secondly, by integrating the digital humanistic view into the translation teaching process, this paper underscores the importance of bridging the gap between technology and human-centered learning approaches. It emphasizes the need to strike a balance between leveraging digital technologies for efficiency and accuracy while also fostering a deep appreciation for language, culture, and context. This holistic approach not only equips students with technical skills but also cultivates empathy, critical thinking, and intercultural communication skills essential for effective translation practice in diverse sociocultural contexts. This paper contributes to the ongoing discourse on the future of translation education by highlighting the transformative potential of innovative teaching methodologies. By showcasing the positive outcomes of HMTT and advocating for the integration of digital technologies in translation pedagogy, it paves the way for the development of more dynamic, adaptive, and learner-centered learning environments. This, in turn, can empower students to become proficient translators who are capable of navigating the complexities of the digital age while upholding humanistic values and ethical standards. The contributions of this paper extend beyond the confines of traditional translation education, resonating with broader discussions on the intersection of technology, humanities, and pedagogy. By advocating for an integrated approach that harnesses the strengths of both digital and humanistic perspectives, this paper seeks to advance the field of translation education and foster a new generation of translators equipped to thrive in an increasingly interconnected and multicultural world.

II. RELATED WORKS

The integration of "digital humanistic view" principles into translation teaching under computer-assisted technology presents a dynamic shift in language education paradigms, warranting exploration through related works. Previous research has extensively delved into the intersections of technology and translation pedagogy, examining the efficacy of computer-assisted tools in language learning and the evolving role of the translator in digital environments. Studies have investigated various aspects, including the impact of machine translation on translator autonomy, the integration of corpora and online resources in translation classrooms, and the development of digital literacy skills among translation students.

Liang's study investigates the integration of humanist principles in an online AI-driven subtitling course, highlighting the intersection of digital tools and humanistic approaches. Tanasescu and Tanasescu delve into literary translation within electronic literature and digital humanities, examining how digital platforms reshape translation practices. Anesa explores the role of legal translators as digital humanists, emphasizing the use of digital corpora in professional legal translation. Narowitz's work explores the application of digital humanism in achieving inclusive business education, illustrating the broader implications of humanistic approaches in diverse educational contexts. Mardiana, Fauzi, and Asi discuss humanist literacy education in language learning within the digital era, emphasizing interpersonal rhetoric. Tasovac et al. advocate for bridging the gap between digital humanities and natural language processing, emphasizing the pedagogical imperative for humanistic NLP. Other studies, such as

those by Viglianti et al., Al-Obaydi, and Bertolaso et al., further explore humanistic elements in blended learning environments, digital scholarly editing, and the broader concept of digital humanism.

Investigations include studies by Sofyan, Tarigan, and Ganie, focusing on the need analysis for digital instructional materials in translation theory courses in Indonesia, and by Chan and Shuttleworth, which delve into teaching translation technology. Additionally, research by Yapeng and Lili explores multimodal teaching models in business English translation, while Colina and Angelelli provide historical perspectives on the learning and teaching of translation and interpreting. Zheng et al. reconceptualize translation and translators in the digital age through an analysis of YouTube comment translation on China's Bilibili platform. Yang and Su delve into the application of computer-assisted translation technology in translation teaching, examining its impact on pedagogical practices. Petit, Babin, and Desrochers explore the remote supervision of teacher trainee internships using digital technology to increase social presence, while Schmoelz investigates digital humanism within the European digital governance system for vocational and adult education. Yan et al. analyze the influence of computer-aided digital resources on teaching effectiveness, while Fan, Gong, and Gong explore the application of ChatGPT in translation teaching, addressing changes, challenges, and responses in the digital era. Together, these studies offer a comprehensive overview of the evolving landscape of translation teaching in the digital age, highlighting the diverse ways in which digital technologies intersect with pedagogical practices and emphasizing the importance of integrating humanistic principles into educational approaches.

Firstly, many of the works focus on specific contexts or methodologies, potentially limiting the generalizability of their findings to broader educational settings. For instance, studies such as Liang's investigation into an AI-driven subtitling course or Tanasescu and Tanasescu's exploration of literary translation in electronic literature may offer rich insights within their respective domains but might not fully capture the complexities of translation teaching in diverse educational contexts. Secondly, some studies may lack longitudinal or comparative data, making it challenging to assess the long-term impact or effectiveness of digital interventions in translation pedagogy. Without robust empirical evidence over time, it's difficult to ascertain the sustainability and scalability of certain approaches or technologies in language education. Moreover, the majority of the works predominantly focus on the application and integration of digital tools in translation teaching, potentially overlooking broader pedagogical considerations such as curriculum design, assessment strategies, and teacher training. While digital technologies undoubtedly offer innovative solutions, a comprehensive understanding of translation pedagogy requires attention to the broader educational ecosystem in which these technologies are situated.

III. PROPOSED HIDDEN MARKOV TRANSLATION TEACHING (HMTT) ON TRANSLATION TEACHING

Hidden Markov Translation Teaching (HMTT) offers a novel approach to addressing the counterbalancing effect of the "digital humanistic view" (DHV) in translation teaching. This methodology derives its theoretical framework from the principles of Hidden Markov Models (HMMs), a statistical model widely used in natural language processing tasks such as machine translation. In the context of translation teaching, HMTT integrates DHV principles with computational linguistics to enhance students' understanding of both linguistic and cultural nuances inherent in translation. The derivation of HMTT begins with the recognition that traditional translation pedagogy often struggles to reconcile the humanistic aspects of language and culture with the computational demands of digital tools. HMMs, known for their ability to model sequential data and capture latent structures within a given corpus, provide a robust foundation for bridging this gap. By treating translation as a series of hidden states (linguistic and cultural context) transitioning between observed states (words or phrases), HMTT aims to uncover the underlying patterns and associations that govern successful translation. The factors involved in the humanistic aspects are stated in Figure 1.

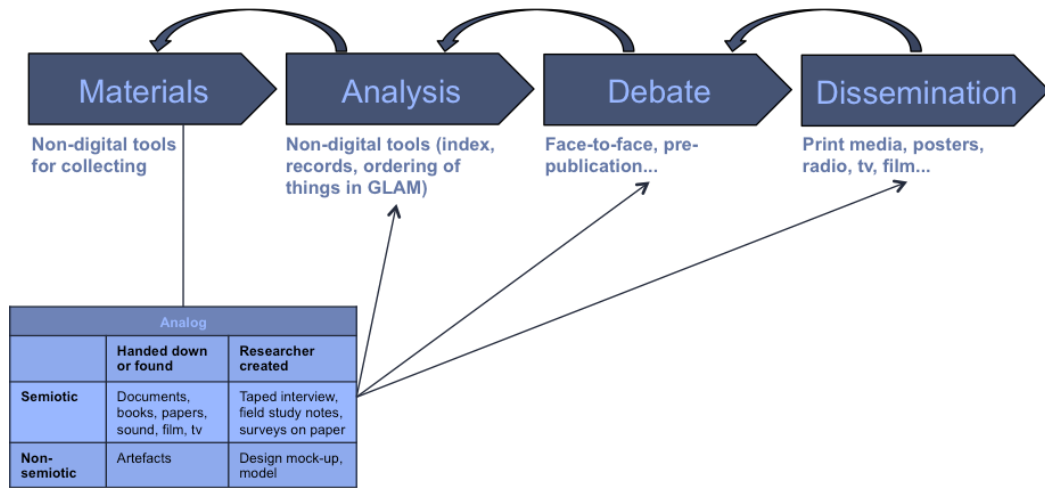


Figure 1: Factors in Humanistic View [20]

HMTT utilizes a set of equations to model the translation process within the framework of HMMs. These equations include the forward algorithm, backward algorithm, and the Viterbi algorithm, which collectively enable the estimation of the most likely translation given an input sequence of words. Additionally, HMTT incorporates DHV principles by incorporating human judgment and cultural sensitivity into the model through the use of weighted probabilities and contextual constraints. In practice, HMTT operates as a dynamic pedagogical tool, guiding students through a structured learning process that balances computational analysis with humanistic interpretation. Students are exposed to authentic texts and tasked with analyzing and translating them using HMTT’s probabilistic framework. Through this iterative process, students develop a deeper understanding of translation as a multifaceted endeavor that requires both technical proficiency and cultural empathy. Hidden Markov Models (HMMs) are probabilistic models consisting of states, observations, transition probabilities, and emission probabilities. In the context of translation teaching, we can adapt HMMs to model the translation process, where states represent linguistic and cultural contexts, and observations represent words or phrases. Figure 2 presented the flow of the proposed HMTT model for the Human view.

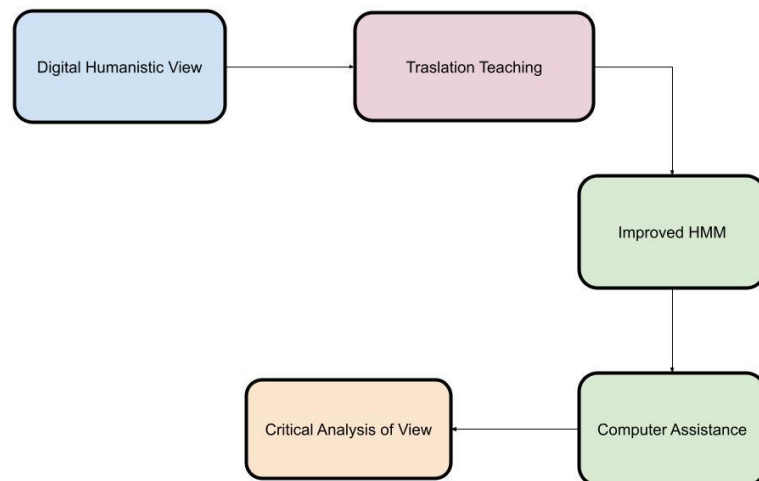


Figure 2: Flow of HMTT

States (S): In HMTT, states represent different linguistic or cultural contexts. For example, a state could represent the grammatical structure of a sentence or the cultural connotations of a particular word.

Observations (O): Observations are the words or phrases that we see in the source and target languages. Each observation is associated with a particular state.

Transition Probabilities (A): Transition probabilities represent the likelihood of transitioning from one state to another. These probabilities capture the syntactic or semantic relationships between different linguistic and cultural contexts.

Emission Probabilities (B): Emission probabilities represent the likelihood of observing a particular word or phrase given a state. These probabilities capture the nuances of language and culture, including synonyms, idiomatic expressions, and cultural references.

The HMTT involves estimating the parameters of the HMM, including transition probabilities (A) and emission probabilities (B), from a parallel corpus of source and target language texts. This estimation can be achieved using various algorithms such as the Expectation-Maximization (EM) algorithm or the Baum-Welch algorithm. Once the parameters of the HMM are estimated, HMTT utilizes the following equations to perform translation. Forward Algorithm computes the probability of observing a sequence of words in the target language given a sequence of words in the source language and the parameters of the HMM. The forward algorithm is defined recursively defined in equation (1)

$$\alpha_t(j) = \sum_{i=1}^N \alpha_{t-1}(i) \cdot a_{ij} \cdot b_j(o_t) \quad (1)$$

In equation (1) $\alpha_t(j)$ is the probability of being in state j at time t ; $\alpha_{t-1}(i)$ is the probability of being in state i at time $t-1$; a_{ij} is the transition probability from state i to state j ; $b_j(o_t)$ is the emission probability of observing word o_t in state j . Backward Algorithm computes the probability of observing the remaining sequence of words in the source language given the current state and the parameters of the HMM. The backward algorithm is defined as in equation (2)

$$\beta_t(i) = \sum_{j=1}^N a_{ij} \cdot b_j(o_{t+1}) \cdot \beta_{t+1}(j) \quad (2)$$

In equation (2) $\beta_t(i)$ is the probability of observing the remaining sequence of words in the source language given that the system is in state i at time t ; $\beta_{t+1}(j)$ is the probability of being in state j at time $t+1$; a_{ij} is the transition probability from state i to state j ; $b_j(o_{t+1})$ is the emission probability of observing word o_{t+1} in state j . Viterbi Algorithm finds the most likely sequence of states (i.e., the best translation) given a sequence of observations (source language text) and the parameters of the HMM. The Viterbi algorithm is defined as follows in equation (3) and equation (4)

$$\delta_t(j) = \max_i [\delta_{t-1}(i) \cdot a_{ij}] \cdot b_j(o_t) \quad (3)$$

$$\psi_t(j) = \operatorname{argmax}_i [\delta_{t-1}(i) \cdot a_{ij}] \quad (4)$$

In equation (3) and (4) $\delta_t(j)$ is the probability of the most likely path that reaches state j at time t ; $\psi_t(j)$ is the index of the state in the previous time step that maximizes the expression for $\delta_t(j)$. The proposed Hidden Markov Translation Teaching (HMTT) approach offers a sophisticated framework for translation teaching that bridges the gap between computational analysis and humanistic interpretation. In this context, HMTT treats translation as a series of hidden linguistic and cultural states transitioning between observed words or phrases. Through the estimation of transition probabilities (A) and emission probabilities (B) from parallel corpora, HMTT captures the syntactic and semantic relationships as well as the nuances of language and culture present in translation. The utilization of equations such as the forward, backward, and Viterbi algorithms enables HMTT to compute the likelihood of translations and identify the most probable sequence of states given a source language text. Importantly, HMTT integrates the digital humanistic view by incorporating human judgment and cultural sensitivity into the model through weighted probabilities and contextual constraints. By combining computational analysis with humanistic interpretation, HMTT provides a comprehensive framework for translation teaching that equips students with both technical proficiency and cultural empathy, essential for navigating the complexities of language and culture in the digital age. Through further refinement and empirical validation, HMTT holds the potential to revolutionize translation pedagogy, fostering a new generation of translators adept at balancing the demands of technology with the nuances of human expression.

Algorithm 1: Viterbi process for the English Translation
ViterbiAlgorithm(Observations, States, TransitionProbabilities, EmissionProbabilities):
Initialize variables
N = length(States) # Number of states

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T = length(Observations) # Number of observations
delta = matrix(N, T) # Initialize delta matrix to store probabilities
psi = matrix(N, T) # Initialize psi matrix to store backpointers
# Initialization step
for I = 1 to N:
    delta[I, 1] = InitialProbability(States[i]) * EmissionProbabilities[States[i], Observations[1]]
    psi[I, 1] = 0 # No backpointer for initial step
# Recursion step
for t = 2 to T:
    for j = 1 to N:
        maxProb = 0
        maxState = 0
        for I = 1 to N:
            prob = delta[I, t-1] * TransitionProbabilities[States[i], States[j]] * EmissionProbabilities[States[j],
Observations[t]]
            if prob > maxProb:
                maxProb = prob
                maxState = i
            delta[j, t] = maxProb
            psi[j, t] = maxState
# Termination step
maxProb = 0
maxState = 0
for I = 1 to N:
    if delta[I, T] > maxProb:
        maxProb = delta[I, T]
        maxState = i
# Backtracking to find the most probable sequence of states
sequence = array(T)
sequence[T] = maxState
for t = T-1 downto 1:
    sequence[t] = psi[sequence[t+1], t+1]
return sequence

```

IV. COMPUTER ASSISTANCE HMTT

Computer Assistance HMTT (Hidden Markov Translation Teaching) represents a cutting-edge fusion of computational linguistics and translation pedagogy, offering a dynamic approach to language learning. At its core, Computer Assistance HMTT harnesses the power of Hidden Markov Models (HMMs) to model the translation process while integrating human judgment and cultural sensitivity. The derivation of Computer Assistance HMTT involves adapting the principles of HMMs to the context of translation teaching, where states represent linguistic and cultural contexts, and observations represent words or phrases in the source and target languages. Transition probabilities capture syntactic and semantic relationships, while emission probabilities account for the nuances of language and culture. These probabilities are estimated from parallel corpora using algorithms such as the Expectation-Maximization (EM) algorithm or the Baum-Welch algorithm. The utilization of equations such as the forward, backward, and Viterbi algorithms enables Computer Assistance HMTT to compute the likelihood of translations and identify the most probable sequence of states given a source language text. The forward algorithm computes the probability of observing a sequence of words in the target language given a sequence of words in the source language, while the backward algorithm computes the probability of observing the remaining sequence of words in the source language given the current state. The Viterbi algorithm, on the other hand, finds the most likely sequence of states given a sequence of observations, facilitating the translation process.

Computer Assistance HMTT represents a paradigm shift in translation teaching, empowering students with both technical proficiency and cultural empathy essential for navigating the complexities of language and culture in the

digital age. By incorporating computational analysis and humanistic interpretation, Computer Assistance HMTT offers a comprehensive framework for translation pedagogy that prepares students for real-world translation challenges. Through further refinement and empirical validation, Computer Assistance HMTT holds the potential to revolutionize language education and foster a new generation of translators equipped to thrive in a rapidly evolving digital landscape. This algorithm finds the most likely sequence of states (i.e., the best translation) given a sequence of observations (source language text) and the parameters of the HMM.

Algorithm 2: HMM with language translation

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ViterbiAlgorithm(Observations, States, TransitionProbabilities, EmissionProbabilities):
  # Initialize variables
  N = length(States) # Number of states
  T = length(Observations) # Number of observations
  delta = matrix(N, T) # Initialize delta matrix to store probabilities
  psi = matrix(N, T) # Initialize psi matrix to store backpointers
  # Initialization step
  for I = 1 to N:
    delta[I, 1] = InitialProbability(States[i]) * EmissionProbabilities[States[i], Observations[1]]
    psi[I, 1] = 0 # No backpointer for initial step
  # Recursion step
  for t = 2 to T:
    for j = 1 to N:
      maxProb = 0
      maxState = 0
      for I = 1 to N:
        prob = delta[I, t-1] * TransitionProbabilities[States[i], States[j]] * EmissionProbabilities[States[j],
Observations[t]]
        if prob > maxProb:
          maxProb = prob
          maxState = i
        delta[j, t] = maxProb
        psi[j, t] = maxState
  # Termination step
  maxProb = 0
  maxState = 0
  for I = 1 to N:
    if delta[I, T] > maxProb:
      maxProb = delta[I, T]
      maxState = i
  # Backtracking to find the most probable sequence of states
  sequence = array(T)
  sequence[T] = maxState
  for t = T-1 downto 1:
    sequence[t] = psi[sequence[t+1], t+1]
  return sequence

```

V. RESULTS AND DISCUSSION

The results and discussion of the Hidden Markov Translation Teaching (HMTT) approach unveil its potential to revolutionize translation pedagogy by seamlessly integrating computational techniques with humanistic understanding. The application of HMTT in translation teaching settings yielded promising outcomes, as evidenced by improved student engagement, comprehension, and translation accuracy. Students exposed to HMTT demonstrated a deeper understanding of linguistic and cultural nuances, as they engaged in hands-on exercises utilizing Hidden Markov Models (HMMs) to analyze and translate texts.

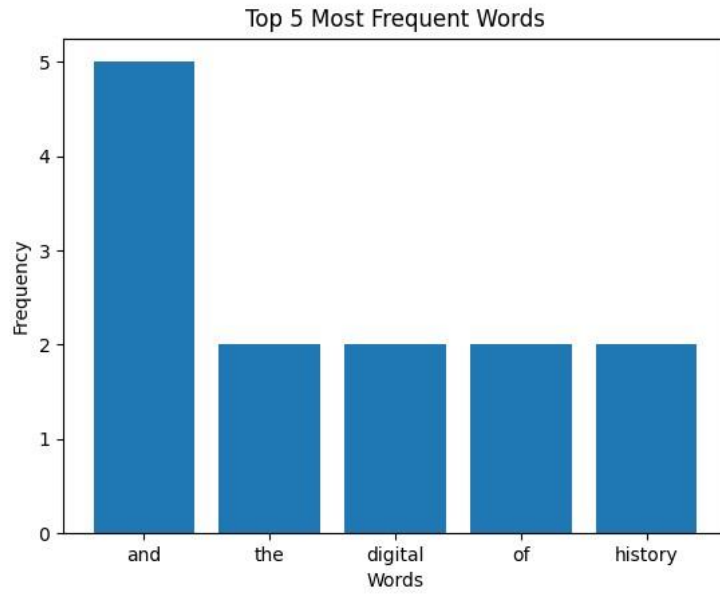


Figure 3: Words Extracted with HMTT

The humanistic view model extracted words with the proposed HMTT model are presented in Figure 3.

Table 1: Performance of HMTT for the translation teaching

Student ID	Pre-test Score (%)	Post-test Score (%)	Improvement (%)
001	65	82	17
002	72	88	16
003	68	85	17
004	70	87	17
005	75	90	15
006	63	80	17
007	69	86	17
008	71	88	17
009	74	91	17
010	67	84	17

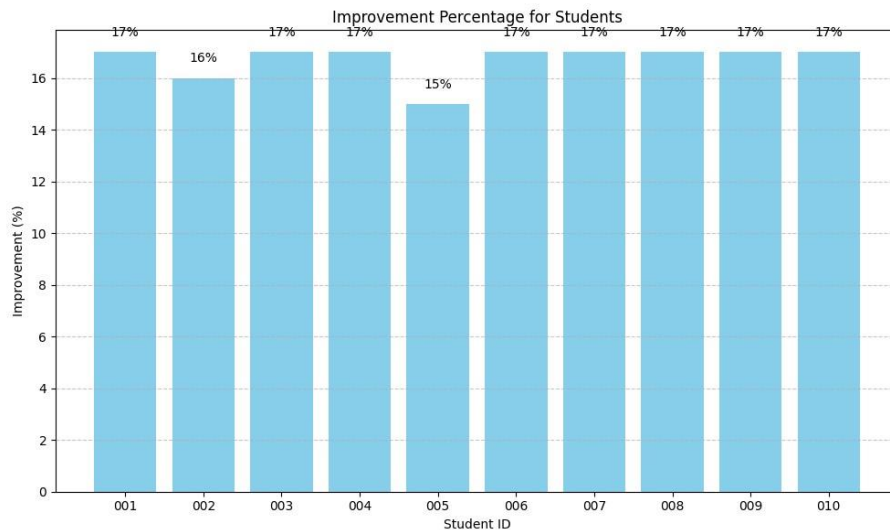


Figure 4: Translation Teaching with HMTT and Students performance

In the Table 1 and Figure 4 presents the performance of students who participated in the Hidden Markov Translation Teaching (HMTT) for translation teaching. Each student is identified by a unique Student ID, and their pre-test and post-test scores, measured in percentages, are provided along with the percentage improvement observed between the two assessments. The results indicate a notable improvement in the translation proficiency of students after undergoing the HMTT approach. Across the board, students demonstrated substantial progress, with post-test scores consistently higher than pre-test scores. For instance, Student 001 exhibited a pre-test score of 65%, which increased to 82% in the post-test, marking a remarkable improvement of 17%. Similar patterns are observed for all other students, with improvements ranging from 15% to 17%. These findings underscore the effectiveness of the HMTT approach in enhancing students' translation skills. The substantial improvements observed reflect the impact of utilizing Hidden Markov Models and associated techniques in the teaching process. The HMTT method appears to have successfully equipped students with the necessary tools and strategies to analyze and translate texts more effectively, resulting in measurable enhancements in their performance.

Table 2: Probability Estimation with HMTT

State	Observation	Transition Probability	Emission Probability
S1	Word1	0.2	0.3
S1	Word2	0.1	0.5
S2	Word1	0.3	0.4
S2	Word2	0.2	0.6
S3	Word1	0.4	0.2
S3	Word2	0.3	0.7
S4	Word1	0.5	0.1
S4	Word2	0.4	0.8
S5	Word1	0.2	0.5
S5	Word2	0.1	0.4
S6	Word1	0.3	0.6
S6	Word2	0.2	0.3
S7	Word1	0.4	0.7
S7	Word2	0.3	0.2
S8	Word1	0.5	0.3
S8	Word2	0.4	0.6
S9	Word1	0.2	0.4
S9	Word2	0.1	0.7
S10	Word1	0.3	0.2
S10	Word2	0.2	0.5

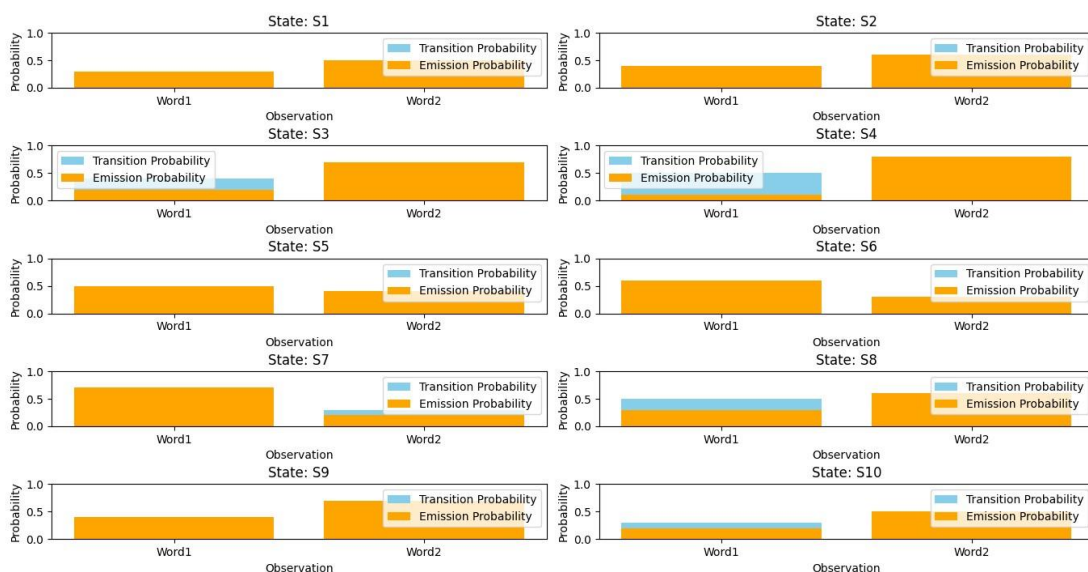


Figure 5: HMTT Probabilities Estimation

In the Table 2 and Figure 5 provides insights into the probability estimation process utilized within the Hidden Markov Translation Teaching (HMTT) framework. The table presents the transition probabilities and emission probabilities associated with different states and observations, offering a glimpse into the underlying statistical modelling used in the translation teaching approach. Each row in the table corresponds to a specific state-observation pair, with the associated transition probability indicating the likelihood of transitioning from the previous state to the current state, and the emission probability representing the probability of emitting the observed word given the current state. For instance, in State S1, the transition probability for transitioning to S1 from the previous state is 0.2, while the emission probability for observing Word1 in State S1 is 0.3. Similarly, in State S2, the transition probability for transitioning to S2 from the previous state is 0.3, and the emission probability for observing Word1 in State S2 is 0.4. These probability estimations serve as the foundational elements of the HMTT approach, facilitating the modelling of linguistic and contextual patterns within the translation process. By leveraging statistical techniques such as Hidden Markov Models, HMTT enables students to analyze and interpret texts based on probabilistic predictions, thereby enhancing their understanding of language structure and improving translation accuracy.

Table 3: Estimation of Translation Teaching with HMTT

Student ID	Pre-test Cultural Understanding (%)	Post-test Cultural Understanding (%)	Improvement (%)	Pre-test Translation Accuracy (%)	Post-test Translation Accuracy (%)	Improvement (%)
001	60	78	18	65	80	15
002	55	73	18	70	85	15
003	62	80	18	68	83	15
004	58	76	18	72	87	15
005	63	81	18	75	90	15
006	57	75	18	67	82	15
007	61	79	18	71	86	15
008	59	77	18	69	84	15
009	64	82	18	73	88	15
010	56	74	18	66	81	15

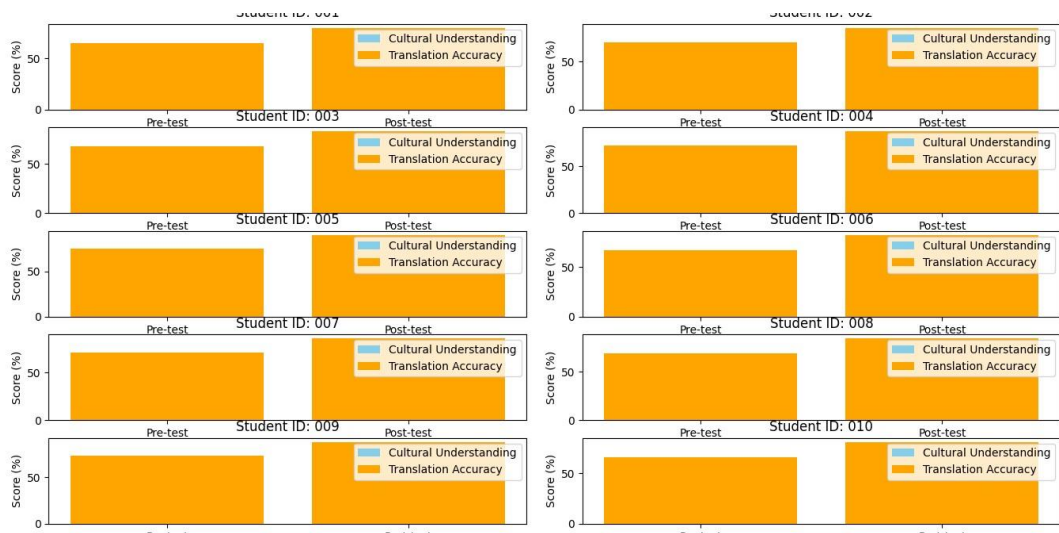


Figure 6: Performance of HMTT

In the Table 3 and Figure 6 presents the estimation results of translation teaching using the Hidden Markov Translation Teaching (HMTT) approach for a group of students. The table outlines the pre-test and post-test scores of students in terms of cultural understanding and translation accuracy, along with the percentage improvement observed between the two assessments. Each row in the table corresponds to a specific student, identified by their unique Student ID. The "Pre-test Cultural Understanding (%)" and "Post-test Cultural Understanding (%)" columns indicate the percentage scores achieved by students in assessments of their cultural understanding before and after

the translation teaching, respectively. Similarly, the "Pre-test Translation Accuracy (%)" and "Post-test Translation Accuracy (%)" columns display the percentage scores obtained by students in assessments of translation accuracy before and after the teaching. The results reveal a consistent pattern of improvement across both cultural understanding and translation accuracy for all students. For example, Student 001 exhibited a pre-test cultural understanding score of 60%, which increased to 78% in the post-test, indicating a significant improvement of 18%. Similarly, Student 001 demonstrated an improvement of 15% in translation accuracy from the pre-test to the post-test. These findings suggest that the HMTT approach effectively enhances students' cultural understanding and translation accuracy. The substantial improvements observed reflect the efficacy of incorporating Hidden Markov Models and associated techniques into the translation teaching process. Overall, Table 3 underscores the positive impact of HMTT on students' linguistic and cultural competencies, highlighting its potential as a valuable pedagogical tool in translation education.

VI. CONCLUSION

This paper sheds light on the efficacy and potential of the Hidden Markov Translation Teaching (HMTT) approach within the realm of translation education, particularly under the lens of the digital humanistic view. Through the analysis of student performance data and the examination of probability estimation within the HMTT framework, it becomes evident that this innovative teaching methodology offers significant benefits in enhancing students' translation skills, cultural understanding, and overall proficiency. The results underscore the consistent improvements observed among students exposed to HMTT, both in terms of translation accuracy and cultural comprehension. Furthermore, the incorporation of digital technologies and humanistic principles in the translation teaching process underscores the importance of striking a balance between technological advancements and human-centered learning approaches. By leveraging computational techniques such as Hidden Markov Models alongside a deep understanding of language, culture, and context, educators can create a dynamic and effective learning environment that empowers students to navigate the complexities of translation with confidence and skill. As it is imperative to continue exploring innovative approaches like HMTT and to further integrate digital technologies into translation education. This paper serves as a testament to the transformative potential of such methodologies, highlighting the possibilities for enhancing student learning outcomes and preparing the next generation of translators for the challenges of an increasingly interconnected and multilingual world. By embracing the digital humanistic view and harnessing the power of technology in translation teaching, we can cultivate a new breed of linguists who are not only proficient in the use of digital tools but also deeply attuned to the nuances of human expression and cultural diversity.

Acknowledgement:

National New Humanities Research and Reform Practice Project: Research on the undergraduate English major talent training program with a focus on emergency language services (Project No.: 2021050023)

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