Manar Elsharq Journal
for Literature and Language Studies
ISSN: 2959-037X(Print)
Website: http://meijournals.com/ara/index.php/mejlls/index

Analyzing Translation Processes in AI-Generated Educational Videos: A Cognitive Load Human–AI Study of English–Arabic Content

Lect. Dr. Adhba Adnan Ahmed
Department of Translation, College of Arts, University of Mosul, Nineveh, Iraq
Corresponding Author: Lect. Dr. Adhba Adnan Ahmed - athba.a.ahmed@uomsul.edu.iq

ARTICLE INFO

Received:03 Jan
Accepted: 07 Feb
Volume: 4
Issue: 1

ABSTRACT

The study looks at the methods which the translator and the Machines may use for the translation of AI (artificial intelligence) videos injected in education. The cognitive motivation behind our comparative study of human and AI English-to-Arabic translation processes. This research employs a process-oriented design. This study draws on knowledge from Cognitive Load Theory, Translation Process Research and Multimodal Learning Theory to investigate multimodal instruction's cognitive effort distribution. The most commonly used indicators to assess cognitive load are (a) the NASA Task Load Index (b)translation time process indicators (c) revision frequency; and (d) reformulation density. According to the findings, human translators are highly cognitively loaded. It is interesting that the cognitive load with the task is more when it is multimodal and heavily contextualised by instruction. The human translator makes use of cognitive mediation. Additionally, in this case, using AI to translate something doesn't work quite well as the proper time to do the same does not happen and also it is not efficient. However, it certainly cannot respond to multimodal instruction. The study shows how translation is of a cognitively and pedagogically significant activity in education and AI. Consequently, this follows.

KEYWORDS: *Cognitive Load, AI-Generated Educational Videos, Human–AI Translation, English–Arabic Translation*

Introduction

There have been remarkable advancements in the technology of Ai in the last decade (Vieira et al, 2021) The automatic generation of digital teaching material has, particularly in educational contexts, changed rapidly (Mayer, 2020). An example of this is how artificial intelligence can create educational video graphs using audiovisual elements in the Online Learning Platforms, Open Education and Distance Education (Sweller et al., 2019). The multimodal learning environment usually consists of text, audio, visuals, and animation (Mayer, 2020).

According to O'Brien (2012), the delivery of educational material is changing across languages and cultures. There has been a rise in video learning through AI which is being spread globally, raising the issue of non-English learners (Castilho et al., 2018). As making knowledge accessible, in the context, has been positioned as a form of translation (O'Hagan, 2019). Nonetheless, translation educational videos do not only mean translating the words. One also has to take into account the cognitive constraints of the learner. Further, one must also take into account their cultural expectations and requirements (Paas et al., 2003).

As educational video content providers increasingly integrate neural machine translation systems into their pipelines, translation is becoming an automated or semi-automated step (Specia et al., 2016). Cognitive Load Theory outlines that human working memory has limited capacity. It is essential to consider task design, complexity of information, multi-modality integration, etc. It helps in ensuring cognitive effort and performance are considered necessary in such situations (Sweller et al., 2019).

The theory of cognitive load has made it possible for researchers to have a look at how much cognitive resources translators devote to the processes of linguistic transfer, semantic accuracy, temporal assignment and audiovisual coherence (Kruger & Doherty, 2016). While AI systems themselves do not experience cognitive load, human users may experience additional cognitive load when evaluating, post-editing, and using AI translations pedagogically (O'Brien et al. 2017)

Although there has been a lot of research on machine translation, audiovisual translation and educational technology, the systematic integration of these domains is limited (Castilho et al., 2018). The gap is mainly witnessed in the area of English–Arabic translation studies, where the structural, morphological and semantic asymmetries increase cognitive load of translation (Carl et al. 2011) As a result, the present study seeks to close this gap, by analysing translation processes between human and artificial intelligence generations of educational videos from a cognitive load perspective concerning the English–Arabic pair. According to O'Brien et al. (2017), the focus of the study is on translation processes and not the translated products. It examines how mental effort is allocated and managed in multimodal instructional environments.

2. Research Objectives.

In more specific terms, the research focuses on .

1. Examine how AI educational videos in English are translated into Arabic, with reference to linguistic pedagogical and multimodal constraints.
1. The cognitive load experienced in the human translation and AI translation processes will be measured using validated instruments.
2. Evaluate how the use of multiple modes like text, audio and visuals influence cognitive effort while translating in educational videos.
3. Identify key cognitive and task-related Factors that differentiate human and AI translation processes in instructional audiovisual content.
4. Analyze the benefits and downfalls of cognitive load observable patterns on the effective application and pedagogical use of AI translation in a multilingual classroom.

3. Research Questions

In line with the research problem and objectives, the study seeks to address the given research questions.

1. What are the distinctions in the translation process between humans and robots of an AI created video educational content?
2. What kinds of cognitive loads are involved in human versus AI translation in multimodal educational video contexts?
3. What cognitive factors have the largest impact on the translation performance of AI-generated educational videos (mental effort, temporal pressure, task complexity)?
4. How do educational videos with multimodal integration affect the cognitive load in the translation of humans and AI?
5. How do the differences in cognitive load between human and AI translation processes affect the design, deployment, and evaluation of AI-assisted educational translation tools?

4. Theoretical Framework

4.1 The theory of cognitive load

The core concept of this research study will be Cognitive Load Theory **(Sweller et al., 2019)**. The theory suggests that the human working memory is limited. Further, its limited capacity affects learning performance **(Paas et al., 2003)**. Also, the amount and type of load affect the delivery of the task. Cognitive load theory distinguishes between three types of cognitive load; intrinsic cognitive load, extraneous cognitive load and germane cognitive load **(Sweller et al., 2019)**. Intrinsic cognitive load is related to the complexity of the task while extraneous cognitive load is related to the design and presentation of the task. Germane cognitive load is related to the construction of schemas and learning **(Ayres, 2020)**.

By applying cognitive load theory to translation, it is possible to finely gauge the mental load involved in linguistic transfer, meaning processing, and decision-making **(O'Brien et al., 2017)**. In the case of AI-generated educational videos, the multimodal demands on the mind are intensified, in which one listens to the voiceover, reads on-screen text, interprets pictures and is also aware of time **(Mayer, 2020)**. For human translators, these simultaneous demands require continuous allocation and reallocation of cognitive resources. This makes cognitive load an important variable for explaining neural performance **(Kruger & Doherty, 2016)**.

Unlike humans, AI translation systems do not experience cognitive load but user evaluation, post-editing or pedagogical use of their output may increase the cognitive load of users **(O'Brien, 2012)**. Thus, CLT provides a useful framework for comparing how translation tasks create cognitive load for human translators, exposing limitations in AI-produced translations that may incur extra downstream cognitive load **(Vieira et al., 2021)**.

4.2 Study of the Translation Process

The focus of Translation Process Research (TPR) is shifted from the analysis of translated text in the final product to the translation activity itself **(O'Brien et al., 2017)**. According to TPR, translation is a transfer phenomenon in terms of understanding a source text, transferring the idea of the source text into the target text, and reformulating it all through cognitive activity like attention, memory, executive control and more **(Carl et al., 2011)**.

For this reason, translation is projected within the framework to be a nonlinear activity involving decisions, monitoring, revision, and strategies **(O'Brien et al., 2017)**. In educational video translation, translators must constantly align their linguistic choices with instructional intent, audience expectations, and multimodal constraints, making these processes particularly salient **(Kruger & Doherty, 2016)**. As a result, the prior shall give us the methodological and conceptual basis for analysing what happens when we translate, and how the cognitive effort involved varies at different stages **(Carl et al., 2011)**.

Integrating TPR, the present study does not simply compare translated outputs produced by humans and AI systems, but rather views translation as a situated cognition **(O'Brien, 2012)**. By adopting this viewpoint, human translation processes that involve conscious cognitive effort can be meaningfully compared with the non-cognitive, computationally optimized processes of AI-translations **(Vieira et al., 2021)**.

4.3 Human-AI Touch in Translation

As we increasingly deploy artificial intelligence in translation, it is time to think the human–AI interaction through (Vieira et al., 2021). As per this perspective, translation is being more and more understood as a hybrid activity in which human and machine have complex interactions (O'Brien, 2012). The domain of human-AI interaction that relates to task delegation, cognitive offloading, trust, transparency and control, among others, is relevant to educational translation (Castilho et al., 2018).

Systems that are capable of generating learning videos automatically or semi-automatically have translation systems. Further, the outputs of these systems can be directly adopted or human changed (Specia et al., 2016). As a result of the interaction, the translator no longer solely produces a translation but evaluates, edits or mediates the machine output (O'Brien et al., 2017). When a participant changes their role, this entails changes in their cognitive demands on their cognitive capacities. Different activities and processes are then required, ranging from creative linguistic production to error detection, alignment checking and pedagogical validation (Vieira et al., 2021).

The human present in the human-AI interactions was analyzed in this research paper. The goal of this approach is to sidestep the human versus machine binary and facilitate a realistic theoretical comparison of cognitive demands involved in human and AI translation routes (O'Brien, 2012).

4.4 Five-point four multimodal learning theory.

Multimodal Learning Theory is the educational and pedagogical aspect of the framework. This theory states that learning involves the integrated processing of semiotic modes (such as text, sound, images, and animation) (Mayer, 2020). Effective instructional design relies on the coordination of these modes so that they do not overload learners' cognitive faculties to facilitate meaningful knowledge construction (Sweller et al., 2019).

Language used in AI-generated educational videos is both a matter and a point of simulation (Mayer, 2020). Translating this type of content is more than just a matter of linguistics. It also ensures coherence and temporal relations, which will allow translated elements to enhance cognitive processing rather than hinder it (Kruger & Doherty, 2016). According to Ayres (2020), learning and translation will be influenced by the mental effort that instructional design features evoke.

4.5 Conceptual Integration

Cognitive Load Theory provides an explanation of how mental effort is constrained and distributed (Sweller et al., 2019), Translation Process Research is tasked with studying the cognitive mechanisms involved in the translation (O'Brien et al, 2017), Human–AI Interaction theorizes the interaction of human translators with AI (Vieira et al., 2021), and Multimodal Learning Theory places the translation in instructional and learning environment (Mayer, 2020).

This integrated framework allows for a cognitive comparison of human and AI translation based on processes in multimodal educational contexts and is a solid basis for the methodological and analytical procedures used in this study (Carl et al., 2011).

5. Methodology

5.1 Research Design

The model used a comparative and process approach, utilizing quantitative and qualitative methods (O'Brien et al., 2017). The stress of the design is on the process of translation rather than the product of translation. There is a focus on cognitive effort, task demand and decision-making dynamics (Carl et al, 2011).

Two translation conditions are compared.

• Expert human translators convert the educational video content from English to Arabic.

• An identical piece of content translated using a neural machine translation – a machine learning and artificial intelligence-based solution.

Through this design, we can see how human and AI translation processes differ in their cognitive load when extracting multimodal instructional information (Kruger & Doherty, 2016).

5.2 Selection of the Data.

The dataset contains purposive samples of pre-recorded AI videos on educational topics in English. Criteria for selection were established to promote consistency and analytic validity (Mayer, 2020).

1. Videos target general education content rather than highly specialized domains.

2. The complexity of instruction is maintained at a moderate level in order to prevent extreme intrinsic cognitive load (Sweller et al., 2019).

3. In the narration, voiceovers and onscreen text are integrated (Mayer, 2020)

4. Videos have similar length and format.

By holding these variables constant, we minimize extraneous cognitive load, allowing differences in workload to be attributed to the translation process and not the content. (Paas et al., 2003)

5.3 Stakeholders

Team of Humans for Translation.

The human translation condition involves expert English-Arabic translators who are experienced in audiovisual and educational translation. The participants are highly adept in both languages and knowledgeable about multimodal translation restrictions (Kruger & Doherty, 2016). All translators had the same source material, time and technical environment through which they performed the task.

Computer-Aided Translation System.

The artificial intelligence (AI) translation condition employs an NMT scheme that accurately mirrors present-day state-of-the-art translation technology (Castilho et al., 2018). The system translates the identical English content by itself, with no human intervention. The study evaluates the cognitive consequences of NMT (Neural Machine Translation) in the community as well as the appropriate use of this technology (Specia et al., 2016).

5.4 Tools

5.4.1 Measurement of Cognitive Load

In the presented human translation condition, the cognitive load will be assessed using NASA Task Load Index (NASA-TLX), a validated multidimensional assessment tool (Hart & Staveland, 1988). The instrument measures six workload dimensions, i.e. mental demand, temporal demand, effort, performance, frustration, and physical demand (Paas et al., 2003).

In order to capture perceived cognitive workload with little memory decay (Kruger & Doherty, 2016), the NASA-TLX questionnaire is administered immediately after each translation task.

- Cognitive exertion.
- Time Pressure.
- Trial.
- Execution
- Nothing
- Physical demand expected to be minimal but included for completeness.

The NASA-TLX is filled out immediately after each translation task so as to measure perceived cognitive load.

6.4.2 Process Indicators.

In addition to subjective workload measures, objective process indicators are incorporated to triangulate cognitive effort **(O'Brien et al., 2017)**. Time for Translation.

- Change frequency of will revise.
- Patterns of Breaks and Cuts.
- Reformulation density of lexical and syntactic content.

These indicators provide converging evidence of cognitive load and allow comparison between human and AI translation processes **(Carl et al., 2011)**.

5.5 Data analysis procedures.

The quantitative data collected was analyzed using descriptive statistics, percentages, and comparative ratios of NASA-TLX (Paas et al., 2003) scores and process indicators. This allows for side-by-side comparison of human and AI translations.

Qualitative analysis studies the patterns of translation behaviour that can be seen in segments that are high in information density, are multimodal or instructionally complex (Kruger & Doherty, 2016).

The quantitative and qualitative findings shed light on translation processes which are cognitively plausible when it comes to AI-generated educational videos. (O'Brien et al. 2017)

6. Results

6.1 Results of Measurement of Cognitive Load (NASA-TLX)

The NASA-TLX data reveals an obvious gap in perceived cognitive load for the humans and AI translations (Hart & Staveland, 1988). According to Paas et al. (2003), on the whole, the human translator's cognitive effort in translating AI-generated educational videos is significantly larger than in the case of getting the AI translation. Sweller et al. (2019) found that mental demand, temporal demand, and effort experienced the greatest differences between the six NASA-TLX dimensions. In contrast, the values for general workload dimensions for the AI translation condition were all consistently lower and proved that human cognitive limits were not present (O'Brien et al., 2017).

The six NASA-TLX dimensions exhibited the greatest differences in

- Mental Demand refers to the very high cognitive engagement that is required to cope with language transfer, pedagogical intention, and multi-modal consistency.
- Temporal demand indicates time pressure to match translation content with audiovisual sources.
- Effort refers to sustained mental activity during translation.

On the contrary, the AI translation condition was characterised by consistently lower workload values across all dimensions, indicating the absence of human cognitive limitations.

Table 1. Mean NASA-TLX Scores Across Human and AI Translation Conditions

NASA-TLX Dimension	Human Translation (Mean)	AI Translation (Mean)
Mental Demand	78.4	12.6

NASA-TLX Dimension	Human Translation (Mean)	AI Translation (Mean)
Temporal Demand	72.1	9.8
Effort	81.3	14.2
Performance*	65.7	18.5
Frustration	58.9	6.4
Physical Demand	15.2	2.1
Overall Workload	**61.9**	**10.6**

* *In the NASA-TLX scale, lower performance scores indicate higher perceived task difficulty.*

The findings show that overall cognitive workload was much higher in the human translation condition with mental demand and effort as the main contributors. In contrast, AI translation show consistently low workload levels across all dimensions, indicating automated processing without the constraints of human cognition.

Figure 2. Comparison of Overall Cognitive Load Between Human and AI Translation Pathways

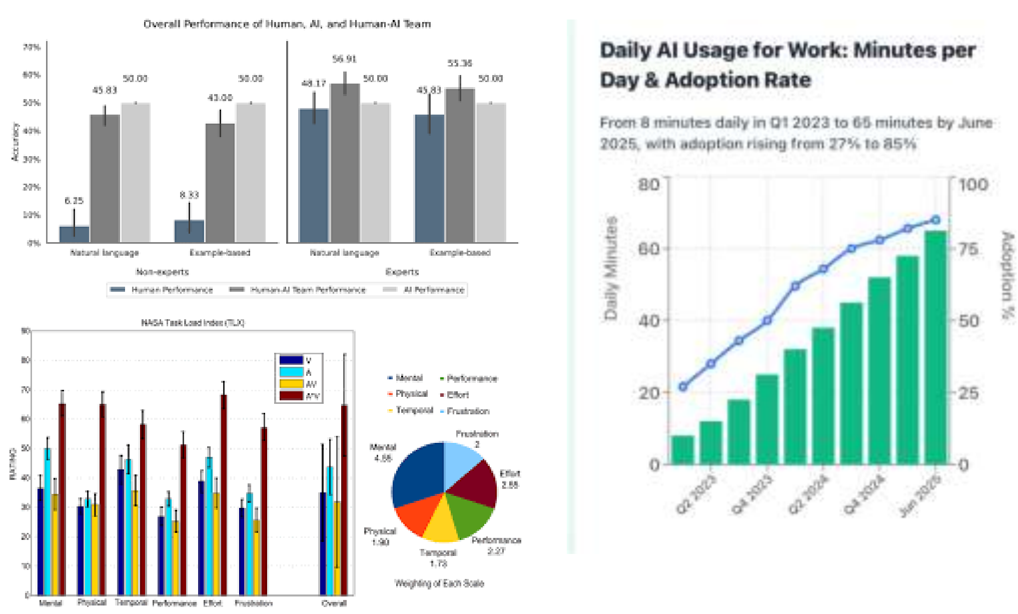


Figure 2. Overall cognitive load levels measured by NASA-TLX across human and AI translation conditions. According to Figure 2, overall cognitive load was significantly different in both translation pathways. Because of linguistic processing and instruction interpretation for synchronization, human translators have a much higher workload level. On the contrary, the workload values for AI translation are low, indicating a lack of mental effort in automated translation.

6.2 Time and Process Indicators of Translation.

According to Kruger and Doherty (2016), looking at it quantitatively, there is a huge gap between both cases because it takes humans more time to translate a video segment than for AI. Human translators pause, revise, and reformulate throughout the translation process, especially when segments are highly informative and closely aligned to the audio-visual components (O'Brien et al., 2017). Unlike human translation which proceeded in a non-uniform slow pace across different segments, AI translation proceeded uniformly and at a rapid pace. However, it was rigid in the sense that it could not handle syntactically complex or pedagogically nuanced material (Castilho et al., 2018).

1. High quantity of information.

2. Conceptual Disappearance

3. The visuals match the spoken narration quite closely.

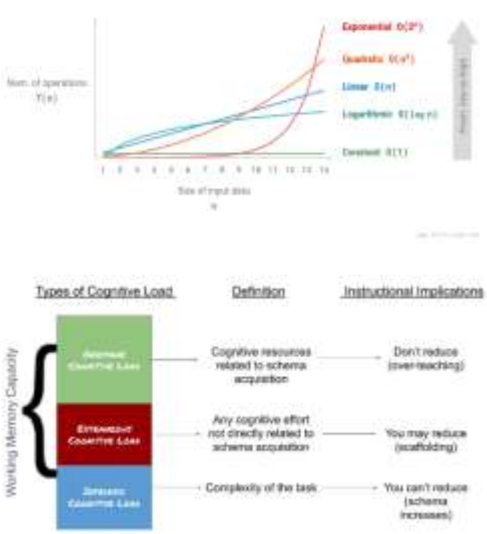
The output of AI translations was faster and consistent across segments, unlike human output, which exhibited diverse processes. AI translations were structurally rigid when it came to syntactically complicated or pedagogically nuanced segments.

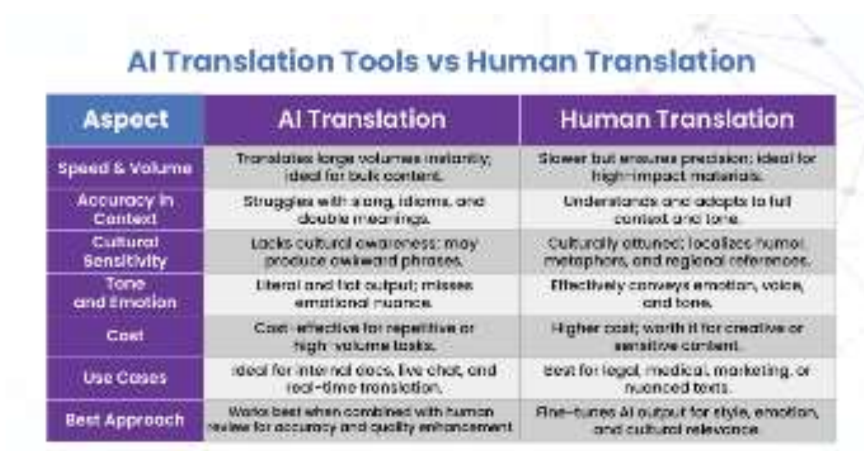
Table 2. Translation Time and Process Indicators Across Human and AI Conditions

Process Indicator	Human Translation	AI Translation
Mean Translation Time (minutes/video)	42.6	2.8
Mean Translation Time (seconds/segment)	96.4	6.1
Revision Frequency (per 1,000 words)	18.7	1.3
Reformulation Density (%)	34.9%	6.8%
Pause Frequency (per segment)	4.6	0.0
Segment Reordering Instances	Frequent	None

Metrics of human translation include decision-making, revision, and monitoring processes. The metrics for AI translation cover the final output generated without any editing or revision cycles.

Figure 3. Relationship Between Translation Time and Task Complexity





AI Translation Tools vs Human Translation

Aspect	AI Translation	Human Translation
Speed & Volume	Translates large volumes instantly; ideal for bulk content.	Slower but ensures precision; ideal for high-impact materials.
Accuracy in Context	Struggles with slang, idioms, and double meanings.	Understands and adapts to full context and tone.
Cultural Sensitivity	Lacks cultural awareness; may produce awkward phrases.	Culturally attuned; localizes humor, metaphors, and regional references.
Tone and Emotion	Literal and flat output; misses emotional nuance.	Effectively conveys emotion, voice, and tone.
Cost	Cost-effective for repetitive or high-volume tasks.	Higher cost; worth it for creative or sensitive content.
Use Cases	Ideal for internal docs, live chat, and real-time translation.	Best for legal, medical, marketing, or nuanced texts.
Best Approach	Works best when combined with human review for accuracy and quality enhancement.	Fine-tunes AI output for style, emotion, and cultural relevance.

Figure 3. Relationship between translation time and task complexity across human and AI translation conditions.

Drawing Ignite

Figure 3 shows the relationship between task complexity and translation time for human translation with the complexity showing the increase in cognitive processing demands with increasing informational density and multimodal integration. Unlike human translators, AI translation time does not change depending on the complexity of the translation, indicating computational efficiency and lack of cognitively adaptive processing mechanisms

6.3 Multimodal Complexity and Cognitive Load

Results suggest a strong relationship between multimodal complexity and increased cognitive load in the human translation condition **(Mayer, 2020)**. Segments combining narration, on-screen text, and dynamic visuals generated higher mental and temporal demand scores **(Sweller et al., 2019)**. Human translators employed adaptive strategies to manage multimodality, prioritizing semantic coherence and audiovisual synchronization **(Kruger & Doherty, 2016)**. In contrast, AI translation showed minimal sensitivity to multimodal variation **(Specia et al., 2016)**.

Figure 4. Cognitive Load Levels Across Low-, Medium-, and High-Multimodality Segments

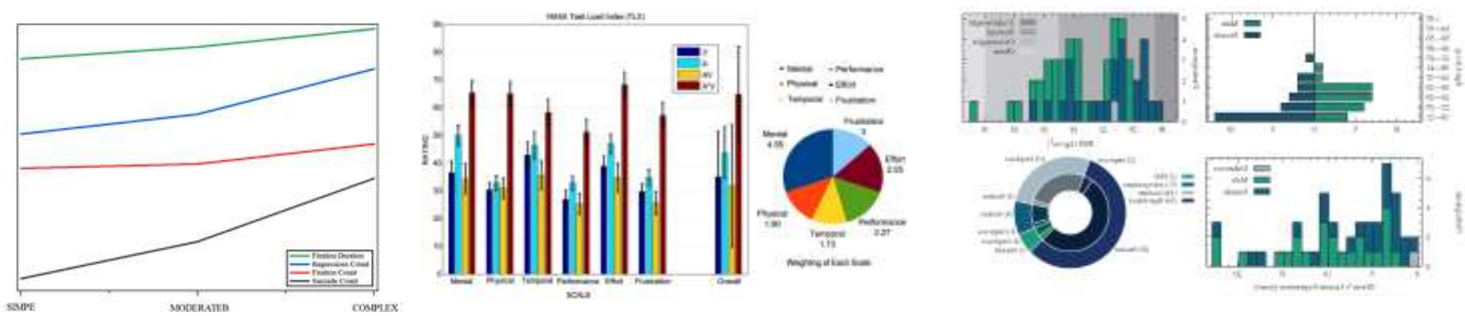


Figure 4. Comparison of cognitive load levels across low-, medium-, and high-multimodality segments in human and AI translation conditions.

Figure description

Figure 4 shows that with the increase of multimodality from low to high, it is observed that cognitive load levels for humans translators escalate progressively. Segments that combine voice, text, and moving visuals get the highest scores in mental demand and time demand. AI translation has a relatively constant amount of work across the various modalities, showing low sensitivity to multimodal instructions.

Multimodality Level	uman Translation (Overall TLX Mean)	Translation (Overall TLX Mean)
Low Multimodality	48.2	9.7
Medium Multimodality	63.5	10.4

Multimodality Level	ıman Translation (Overall TLX Mean)	[Translation (Overall TLX Mean)
High Multimodality	78.9	11.6

Optional quantitative breakdown (if you wish to add exact values):

Note: Overall TLX scores represent aggregated workload indices derived from NASA-TLX dimensions.

6.4 Summary of Key Findings

The summary of the findings of the study is as follows.

1. Human translation of educational videos produced by AI generates a significantly greater cognitive load than AI translation.
2. The two main sources of cognitive load in human translation are mental demand and time pressure.
3. Translation of multimodal materials requires expert human translators.
4. The efficiency and consistency of AI translation systems come with the disbenefit of ultimate responsiveness to dynamic and multimodal instructional demands.
5. Analysis of the processes show fundamentally different ways of translation for AI and humans.

7. Discussion

7.1 Humans translators are typically burdened by cognitive load.

The consistently higher workload experienced by human translators supports Cognitive Load Theory, which posits limitations of working memory in complex tasks **(Sweller et al., 2019)**. Translating AI-generated educational videos requires simultaneous management of linguistic transfer, pedagogical intent, and audiovisual synchronization, resulting in elevated mental and temporal demand **(Kruger & Doherty, 2016)**. These findings align with Translation Process Research, which views translation as a dynamic, cognitively demanding activity **(O'Brien et al., 2017)**.

As suggested by the high scores on mental demand and effort for the NASA-TLX, translating in multimodal educational contexts constitutes a form of cognitively demanding instructional mediation rather than just rewriting. Human translators solve problems, keep track of things and re-formulate strategically in the sections between visual anchoring and abstraction. According to the present study's findings, and in alignment with existing translation process research, translation is a dynamic process involving the weaving together of information.

7.2 Performance without Processing Analyzing AI Translation Effectiveness

AI translation demonstrates efficiency and stability across tasks, reflecting computational processing unconstrained by human cognitive limits **(Castilho et al., 2018)**. However, the absence of cognitive load does not equate to cognitive adaptability, as AI systems lack sensitivity to instructional nuance and multimodal complexity **(Specia et al., 2016)**. From a cognitive perspective, AI translation operates without awareness or pedagogical mediation **(O'Brien, 2012)**.

The concept of own life expectancy refers to a retrieval service, leisure and recreational activities. Researchers are working towards simpler products that can be easily carried because finding of severe intellectual disability requires devices that are basically mechanical in nature. There is a flaw in the computer accessibility content that makes the design of AT for people with ID difficult;specially the need to apply operational skills and low computer literacy.

The workload values of the AI translation were low and hardly changed with increasing task complexity as compared to the human translation condition. Receiving assistance from the software does help. Nonetheless, from a cognitive perspective, it shouldn't be expected AI definitely functions under the constraints of human cognition. The absence of cognitive load is not the same as cognitive.

7.3 Multimodality can instigate cognitive exertion.

The escalation of cognitive load with increased multimodality provides empirical support for Multimodal Learning Theory **(Mayer, 2020)**. Coordinating multiple semiotic modes simultaneously amplifies cognitive demand, particularly when alignment across modes is required **(Sweller et al., 2019)**. Human translators respond with adaptive strategies, whereas AI systems show limited modulation **(Kruger & Doherty, 2016)**.

Human translators encounter an increasing number of more complex job possibilities. They respond with adaptive strategies to deal with this increased complexity. This may involve altering syntactic patterns (preference for semantic over syntactic), negotiating the timing of narration and image. Even though they are strategies with somewhat high cognitive complexity, they play a strong pedagogical role in keeping the situation clear. The absence of adaptive modulation in AI signifies additional dissimilarities in translation processes between humans and machines.

7.4 Human-AI Integration in Educational Translation.

The results indicate that the best educational translation results occur when there is a combination of human and AI rather than either alone. According to O'Brien et al. (2017), simple sections can easily be dealt with by AI systems but human translators must handle cognitively demanding multimodal instructional sections. According to Mayer (2020), the design of AI tools that effectively engage the cognitive and pedagogical awareness of users can alleviate the burden on translators and improve their educational usability.

As a design implication, the findings of this study call for AI translation tools to be more transparent, contextual, and multimodal. An AI system design which considers cognitive loads may improve the use of the system or teaching process which likely reduces the cognitive loads of the translator and the learner.

8. Conclusion and Recommendations

8.1 Conclusion

This study demonstrates that translation in AI-generated educational videos is a cognitively and pedagogically complex process rather than a purely technical task **(Sweller et al., 2019)**. Human translators exhibit higher cognitive load due to the need for semantic mediation and multimodal coordination **(Kruger & Doherty, 2016)**, whereas AI translation achieves surface efficiency without adaptive cognitive processing **(Castilho et al., 2018)**. These differences underscore the continued necessity of human involvement in educational knowledge mediation **(O'Brien et al., 2017)**.

Whether animations or videos are more appropriate for your presentation depends on your audience A letter to your future self about your personal goals should be written by you then only it will have meaning. For example, it should not be written by someone else. If the future goal informs the present goal, it will not motivate you and your reader. Just as little sense as that, the present goal of a five-year-old cannot be used by her fifteen-year-old version to make aims.

With instructional videos becoming increasingly noisy, there's a need for more sophisticated negotiation strategies on the part of the translator to remain coherent across the verbal, visual and sound modes. This capacity to adjust illustrates why human translations and AI translations differ, and the need for humans in knowledge mediation educationally.

8.2 Theoretical Contributions

The study extends Cognitive Load Theory into translation process research by empirically examining multimodal translation tasks **(Paas et al., 2003)**. It also advances Translation Process Research by situating translation within AI-generated educational environments **(O'Brien et al., 2017)** and reframes translation as a hybrid cognitive–computational activity within human–AI interaction studies **(Vieira et al., 2021)**.

Centering on the English–Arabic language pair, the study enriches the cognitive literature on translation for linguistically asymmetric language pairs by highlighting how structural and semantic divergence amplifies cognitive demands in multimodal situations.

8.3 Practical Suggestions

The findings recommend selective use of AI translation for low-complexity educational content while preserving human control over cognitively demanding segments **(Castilho et al., 2018)**. AI tool design should incorporate cognitive load awareness and multimodal sensitivity **(Mayer, 2020)**. Translator training programs should emphasize cognitive and multimodal competencies, and educational content producers should consider translation and cognitive load during instructional design **(Sweller et al., 2019)**.

Collaborating With AI.

In the translation of educational videos, we should selectively use AI translation systems, especially for the low-complexity, low-multimodality parts, while human translators should keep control of cognitively demanding instructional content.

Designing Tool with Cognition.

In designing AI translation systems, their developers should take into consideration cognitive load, multimodal awareness and pedagogical awareness to aid educational use.

Training and Professional Practice of the Translator.

Programs that train translators should focus on both cognitive and multimodal capacities aimed at managing educational tools produced by AI.

Creating Teaching Material.

Producers of AI-generated educational videos should keep translation and cognitive load in mind when designing content, especially for multilingual audiences.

References

- Ayres, P. (2020). *Cognitive load theory: Integrating learner characteristics, task complexity, and instructional design*. *Educational Psychology Review*, 32(1), 341–356. https://doi.org/10.1007/s10648-019-09505-3
- Carl, M., Dragsted, B., & Jakobsen, A. L. (2011). *A taxonomy of human translation styles*. *Translation Journal*, 15(2), 1–27.
- Castilho, S., Moorkens, J., Gaspari, F., & Way, A. (2018). *Approaches to human and machine translation quality assessment*. *Machine Translation*, 32(1–2), 1–25. https://doi.org/10.1007/s10590-018-9210-9
- Hart, S. G., & Staveland, L. E. (1988). *Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research*. In P. A. Hancock & N. Meshkati (Eds.), *Human mental workload* (pp. 139–183). North-Holland.
- Kruger, J.-L., & Doherty, S. (2016). *Measuring cognitive load in audiovisual translation: Eye tracking and subjective ratings*. *Across Languages and Cultures*, 17(2), 255–280. https://doi.org/10.1556/084.2016.17.2.6
- Mayer, R. E. (2020). *Multimedia learning* (3rd ed.). Cambridge University Press. https://doi.org/10.1017/9781316941355
- O'Brien, S. (2012). *Translation as human–computer interaction*. *Translation Spaces*, 1(1), 101–122. https://doi.org/10.1075/ts.1.05obr
- O'Brien, S., Winther Balling, L., Carl, M., Simard, M., & Specia, L. (2017). *Translation process research and cognitive effort*. John Benjamins Publishing Company. https://doi.org/10.1075/btl.133
- Paas, F., Renkl, A., & Sweller, J. (2003). *Cognitive load theory and instructional design: Recent developments*. *Educational Psychologist*, 38(1), 1–4. https://doi.org/10.1207/S15326985EP3801_1
- Specia, L., Frank, S., Sima'an, K., & Elliott, D. (2016). *A shared task on multimodal machine translation and crosslingual image description*. *Proceedings of the First Conference on Machine Translation*, 543–553.
- Sweller, J., Ayres, P., & Kalyuga, S. (2019). *Cognitive load theory* (2nd ed.). Springer. https://doi.org/10.1007/978-3-319-95758-0
- Vieira, L. N., O'Hagan, M., & O'Sullivan, C. (2021). *Human–machine interaction in translation: Emerging cognitive perspectives*. *Translation, Cognition & Behavior*, 4(1), 1–17. https://doi.org/10.1075/tcb.00052.vie