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How Effective Embodied Learning for Robotics Instruction

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Abstract

Teaching robotics technology is known challenging due to the multidisciplinary nature of the subject. Leveraging rich robotics instruction videos available online is an effective instructional approach in assisting the learning process for desirable outcomes especially for the flipped classrooms. Teaching robotics with embodied learning instruction technique involves the use of physical embodiment in the learning process for the desirable outcomes. For this purpose, the selection of high quality videos and understanding of the effectiveness of the embodiment process is important. Until present, there is however very little research dedicated to the systematic understanding of the effectiveness of the physical embodiment focused videos and their potential user engagement in learning robotics. With this research, we have selected 100 Youtube videos with and without embodied learning components randomly, where the comments of the videos were also obtained. Overall, there are 22581 user comments for the 50 videos with embodied learning components. In contrast, there are only 5076 user comments for the videos without embodied learning components.

The sentiment of Youtube video comments were obtained. The sentiment analysis of the video comments showed that the use of embodied learning is effective in engaging learning of robotics, where embodied robotics learning videos receive more number of user comments. In terms of percentage of the sentiment of the user comments, the use of embodied robotics learning videos receive less negative user comments in comparison to the conventional robotics learning videos. In contrast, the use of conventional learning videos receive more positive user comments than the embodied learning centered videos. Experimental results have shown that the use of embodied learning centered videos is effective in facilitating the learning of robotics technology. In summary, our research showed that the use of embodied learning centered videos is effective in engaging user's learning. However, the use of the embodied learning centered videos may lack certain aspects of the learning experiences embedded in the conventional learning centered videos. This is likely attributed to the confusing instructional examples used in the videos and lack a clear explanation of the underlying knowledge, which is therefore able to compromise the learning experiences and the education of the robotics workforce.

Introduction

Learning robotics technology is challenging due to the multidisciplinary nature of the subject, which involves mathematics, electronics, software, mechanical engineering, and materials science. One effective way in enhancing the learning is through the use of videos. Studies show that having students watch rich types of robotics instructional videos is helpful to enhance the learning outcome in robotics technology related classes[1,2]. The use of videos is especially interesting and important for the flipped classroom teaching, where the use of videos plays critical roles in preparing students for the relevant lectures[3].

Throughout the use of videos to enhance learning effectiveness, active engagement and effective interaction with videos are important through the learning process to achieve the desired learning outcome. Educational theories such as Piaget's constructivism and Vygotsky's constructivism theories emphasize the importance of active engagement and interaction in the learning process. Piaget's theory suggests that learners construct knowledge through experiences and interactions. Vygotsky's theory, on the other hand, highlights the role of the interaction and adoption of tools to facilitate the interaction [4,5]. Regardless of the learning paradigms, through the learning process, we expect to better engage students to promote the active participation and interaction for maximized learning outcome. Such active participation of the learning process is able to help to engage the underlying learning activities of students for effective and enjoyable learning experiences.

Embodied learning is a learning approach where physical and virtual environment through physical engagement, sensory interaction, and kinesthetic learning are emphasized to demonstrate the underlying concepts which otherwise find hard to comprehend. This learning paradigm is particularly impactful for STEM education because it involves hands-on experiences and manipulation of the physical components throughout the learning process. By engaging learners physically with the use of posture, gesture, eye contact, facial expression, and real tangible objects, embodied learning helps learners to bridge the gap of theoretical knowledge instruction and learner's perception of the underlying knowledge, thus able to and aiding in better retention of knowledge[6,7]. The use of embodied learning can lead to better academic performance, increased engagement, and more positive attitudes towards learning. It is known that the the use of embodied learning has significantly improved student performance in STEM fields compared to traditional lecture-based instruction[8]. Similarly, embodied learning has significantly improved student performance in STEM learning [9,10].

Embodied learning is also known particularly beneficial for robotics education. The complexity of the robotics technology makes it challenging for teaching robotics. Robotics development requires strong hands-on skills. Such hands-on skills can be well satisfied through the embodied learning method. Embodied learning has potential to better engage motor skills and memory retention of the learning process[7]. Specifically, both motor skills and memory are crucial for learning of robotics. In robotics education, students do not only learn theoretical aspects of the robotics technology but also apply this knowledge through activities such as building, programming, and operating robots. All these processes require significant motor skills through the process[11]. Embodied learning has made the learning process motor skills driven, enjoyable, thereby improving student motivation and participation the learning of robotics [12,9]. Embodied learning is not only applied in physical environment but also in simulation environment. Studies have involved the creation of virtual lab environment to encourage students in learning programming and control of robots without the need for physical components. Hence the use of videos, especially the high fidelity 3D driven demonstration, is known helpful to engage learners in the environment thus better facilitate the learning [13,14].

Despite the evident benefits of the embodied learning, it is challenging to effectively execute embodied learning in practice. Embodied learning involves multiple elements including physical interaction, sensory engagement, kinesthetic learning, and mind-body connections [15,16,17]. The complexity of the multiple components makes it challenging for effective execution of the embodied learning. Specifically, there is no study dedicated to studying the effectiveness of embodied learning of the robotics technology. Furthermore, embodied learning also requires the strong execution capability of the instructors by engaging learners through hands-on skills, effective visualization, and sensory engagement with students [18,19]. The effectiveness of the learners responses to the embodied teaching strategy needs to be quantified to understand the impacts of the learning of robotics. Through a clear understanding of the learner's engagement with embodied learning, it will help us to design the most effective learning strategy to improve robotics technology workforce training.

The use of videos through the robotics class instruction is able to address the challenges faced with embodied learning of the robotics technology in robotics classes. While it is difficult for an instructor to acquire the necessary hardware, software, lab environment, and related skills to enable students to learn robotics with embodied learning technique, it is feasible for the instructors to leverage rich robotics lecture videos featured with embodied learning techniques readily available on the internet to enable such embodied learning with videos experiences. Such learning experiences would be strongly beneficial to have students to become ready for the robotics technology learning. It would be also especially beneficial to the flipped robotics classes, where students need to watch videos beforehand to make themselves ready for the classes or laboratories of robotics.

The ability to select high-quality robotics instructional videos is beneficial for enabling effective learning experiences. The selection of such videos is however challenging, which is time consuming and tedious. Until present, it is unclear whether the videos featured with embodied learning or conventional learning technique is significantly different in terms of user engagement, emotional reaction to the videos, and the learning outcomes from the videos. Manually examining the video content and video comments by users would take significant amount of time for robotics course instructors. As such, it is desirable to propose an effective approach to identify such high quality videos of robotics instruction.

The recent arising of Large Language Model (LLM) is known successful in answering learner's questions successfully. More particularly, the use of the LLM for summarizing videos is known successful[20]. LLM is able to capture not only the high level summary but also the low level details of the videos[21,22,23]. The LLM is able to summarize the video using guidance of learners to specifically focus on the particular elements of the videos to obtain the desired summary[21]. With LLM, it is possible to summarize the video content known associated with the embodied learning such as physical interaction and sensory engagement therefore to discover the effectiveness of the embodied learning strategy. Additionally, it is known that LLM is also able to offer unique strength in understanding the sentiment of learner's comments on the videos[24]. The use of LLM is known able to achieve over 90% of accuracy for sentiment analysis[24]. LLM has also exhibited strong strength in sentiment analysis showing a strong generalization capabilities of the sentiment for the underlying of the tasks[25]. As such, the use of LLM for both video summary and video comments sentiment analysis is able to understand learner's response to embodied robotics learning.

The project aims to understand the user engagement of videos featured with embodied and conventional learning methods for robotics technology instruction. By systematically analyzing user engagement and sentiment toward the video content with the LLM methods, this study is able to provide a comprehensive understanding of how the videos featured with embodied learning method impact the learning effectiveness of the robotics technology. For this purpose, through the utilization of the LLM based data extraction, transcription, sentiment analysis, and statistical techniques, our research is able to ensure accurate and reliable video analysis for the desirable research outcomes. We seek to assess whether videos featured with embodied learning technique is able to better engage with learners in comparison to conventional learning videos. For this, the quantity and quality of video comments on each type of video were analyzed to gauge student interaction and participation. Subsequently, sentiment analysis was also performed to understand the emotional and cognitive responses of both embodied learning and conventional learning to understand the differences toward the videos. The comparison of sentiment distribution (positive, negative, neutral) for embodied learning videos versus conventional learning videos has been performed. We have also performed user study for understanding of the differences of the embodied centered learning videos versus the conventional learning centered videos. We have concluded the effectiveness and reception of these two different types of videos, thus helping instructors to identify high quality videos for their robotics classes.

Methods

0.1 Embodied Video Data Preparation

Comprehensive but random selection process was employed to identify 100 YouTube videos relevant to robotics education. These videos were categorized into two distinct groups respectively embodied learning and conventional learning. Through the selection process, we have paid close attention to reduce the biases for neither selecting biased videos from embodied learning nor conventional learning. The biases criteria are defined by the length of the videos and the number of comments for the video. We have not included the videos dedicated for entertainment purposes. Instead, we have carefully selected the videos that are dedicated for formal robotics engineering education purposes.

Among the 100 videos, 50 videos featuring embodied learning methods. These videos are characterized by activities centered by physical interaction, sensory interaction, and kinesthetic learning. In order to obtain these videos, we use keywords including robotics learning with physical interaction, robotics learning with sensory interaction, and robotics learning with kinesthetic learning to search the videos on Youtube. Each video is subjected to manual inspection to ensure that the instruction method used in the videos is embodied learning. Similarly, other 50 videos featuring conventional learning methods primarily focusing on theoretical instruction and visual demonstrations using power point slides and blackboard/white board were also obtained. Similarly, each conventional video is manually screened to ensure the correctness of the videos for this category. The selection criteria ensured a balanced representation of both learning approaches to facilitate a robust comparative analysis.

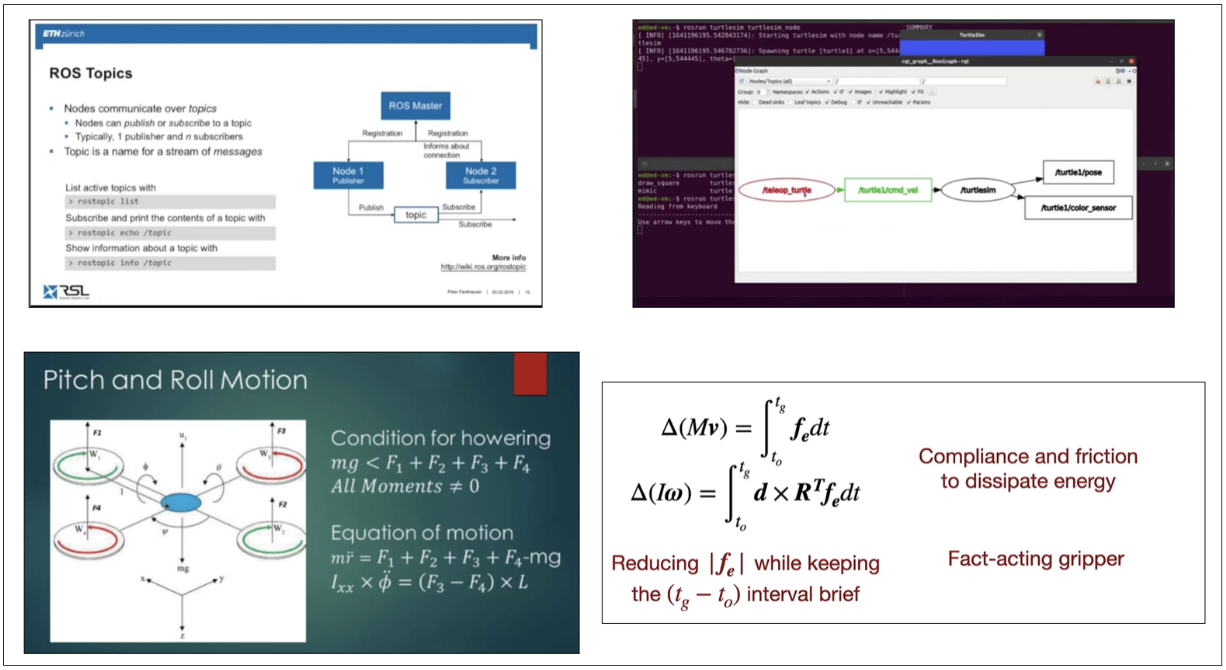

Figure 1: The examples of videos using the conventional teaching method. It shows the use of text, image, and diagram centered instruction approach for the teaching of robotics.

It should be noted that the videos emphasizing embodied learning can also involve power point slides through the entire instruction process. For this condition, the videos focusing on the use of hardware and gesture through the entire instructional process will be classified as embodied learning centered robotics teaching. On the other hand, if the videos are more focused on the use of conventional power point slides instruction with little presence of hardware and gesture based learning, the videos will be classified as conventional type robotics learning.

The example of videos of embodied learning and conventional learning are shown in Figure 1 and Figure 2. Evidently, through the use of embodied learning videos, it shows that the embodied learning has been emphasized through the use of physical interaction, sensory interaction, and kinesthetic learning. The videos in Figure 1 show the use of videos mostly leveraging image, text, and diagrams to instruct robots. Through the conventional instructional method, as shown in Figure 1, it shows that the instructor presents detailed explanations about electronics used for building the robots primarily relying on PowerPoint slides. Through the conventional centered learning videos, it doesn't involve the use of physical construction of robots to assist the teaching. Mostly, the conventional videos focus on illustrating the concepts and mechanisms of the robotics technology to audiences.

In contrast, embodied learning videos in Figure 2 show that robotics hardware along with text,

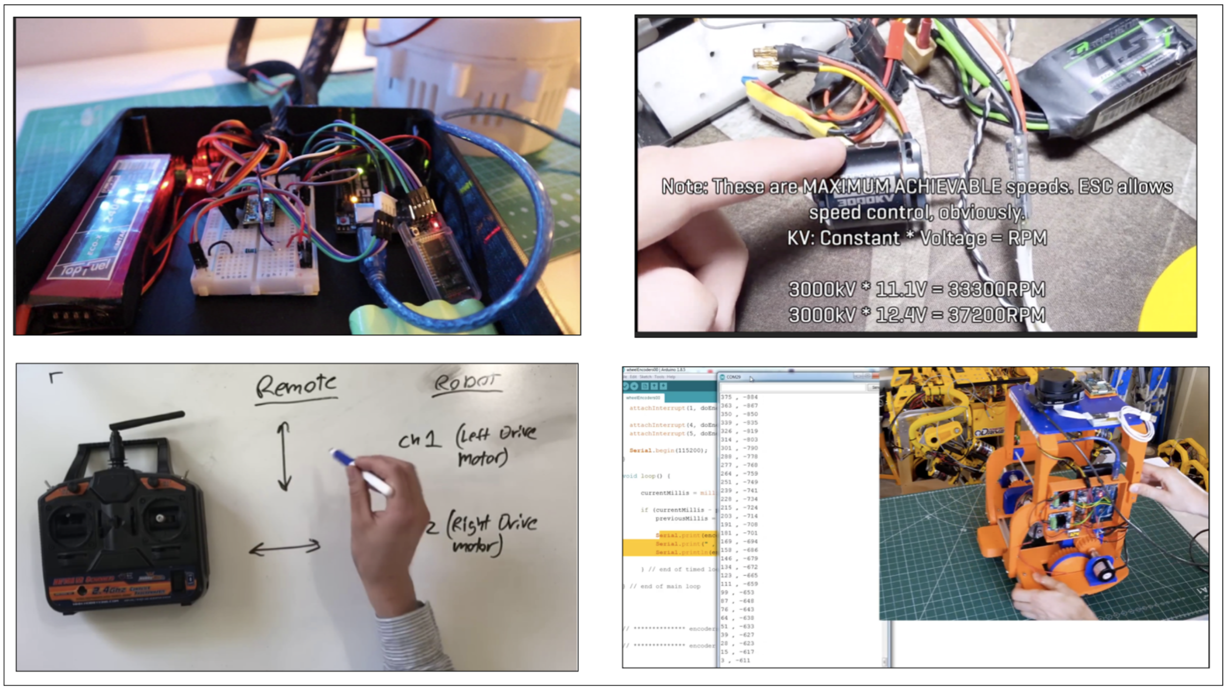

Figure 2: The examples of videos using embodied teaching method. It shows the use of actual robotics hardware along with others such as text, handwriting, and programming through the instructional process.

handwriting, and programming have been used to illustrate the instruction of robotics technology. Specifically, the involvement of robotics hardware through the instruction frequently involves gestures shown in Figure 2. Clearly, the gestures are helpful to better illustrate the instructional process. It is able to augment the learning of the robots making it easily for learners to orient their attention through the process. The videos included in the embodied learning instruction include the use of various electronics such as voltage regulator, breadboard, wiring, batteries, LCD panels to illustrate the DIY process of the robotics hardware. Other components crucial for learning robotics including remote controller and mechanical frames of the robot are also important for the inclusion of embodied learning centered videos. It is important to note that the software to control robot is also included in the embodied learning. As shown at the bottom right of Figure 2, the learning of robotics Arduino programming involves putting the robot in the scene to facilitate the learning process of the Arduino robotics programming.

0.2 The Extraction of Video Comments

Our research utilized ”youtube-comment-downloader,” a Python-based tool, to systematically extract user comments from YouTube videos. The extraction process began with the installation of the tool using the command: pip install youtube-comment-downloader. Upon successful installation, the tool efficiently retrieves comments by specifying the target video URLs and the desired output format. The extraction process was initiated through a command-line instruction: youtube-comment-downloader –url ”https://www.youtube.com/watch?v=M6yqhDTL3k” –output comments.json, which fetched comments from the specified video and saved them in a JSON file. This command-line utility parsed the provided video URL to access the comment section and iteratively retrieved detailed information about each comment.

The retrieved JSON file contained video comments and the related meta data including the comment ID, text, timestamp, author, channel ID, votes, and replies of the comments. Such comprehensive and well structured data facilitate a rigorous analysis of user engagement, sentiment, and community interactions within the comment sections for the 100 videos.

The research utilized a Python script to process the data in the JSON file. For this purpose, it extracts text comments from the JSON file. To maintain the integrity of the comments as paragraphs, internal newlines within the text were removed. The cleaned text was then written to the output file, with each comment followed by two newlines to ensure proper spacing. It thus enabled an efficient extraction and storage of the comments in a format suitable for the subsequent analysis.

For analysis of the comments in the comments JSON file, each comment was analyzed using OpenAI GPT-3.5-turbo model. Through the use of the GPT LLM model, video comments were pre-processed to prepare the video comment data for the sentiment analysis. The comment data pre-processing includes the cleaning of the data. The data pre-processing removed the duplicates and empty entries. The data pre-processing also removed the non relevant comments to the learning process such as the advertisement centered or adversary centered comments. This analysis helped the understanding of viewer engagement by distinguishing between detailed feedback and general comments of the videos. It thus provides an understanding for the levels of the user engagement of the videos.

0.3 Sentiment Analysis

Sentiment analysis is a technique used to determine the overall sentiment expressed in a piece of text, such as customer reviews, social media posts, or emails. This analysis categorizes text into positive, negative, and neutral sentiments. Sentiment analysis evaluates the comments and assesses the level of learner's engagement to learn the robotics instructional videos. Sentiment analysis helps to understand the attitude of learners towards the content. For instance, the positive comments indicate the satisfaction of the learning process. In contrast, the negative comments reflect the dissatisfaction or criticism of the learning process of the videos, and neutral comments suggest neither satisfaction nor dissatisfaction of the videos.

The comments used for sentiment analysis were pre-collected embodied learning videos and conventional learning videos. Overall, the dataset comprised 22,581 comments from 50 embodied learning videos and 5,076 comments from 50 conventional learning videos. This extensive collection facilitated a robust analysis of viewer sentiments across different educational content formats, ensuring that the findings were representative and reliable.

The implementation of sentiment analysis was carried out using Python and relevant libraries. The analysis began with the creation of a sentiment analyzer tailored for English text using the pysentimiento library. The comments extracted from YouTube videos were then analyzed using the sentiment analyzer, which predicted the sentiment of the text.

The analysis workflow included initializing counters to record the number of positive, negative, and neutral comments. As each paragraph was analyzed, the script calculates the probabilities of each sentiment category, which were then normalized to determine the overall sentiment distribution. The results were outputted as overall sentiment probabilities and counts, providing a comprehensive view of the sentiments.

0.4 Experimental Data Analysis

We have also performed a preliminary study with participants for learning robotics technology with videos. In total, participants have watched 135 videos including 75 embodied videos and 60 conventional videos, where some participants have chosen for watching the same videos due to their interests of these videos. Comments from the participants were captured following watching and learning with the videos to express their leaning experiences from the videos, where we have given the participants instruction to express the most useful achievements and learning outcome associated with videos and the related confusion attributed to the videos.

The gathered data responses for individual videos underwent aggregation and data cleaning before combining the different student inputs from each video into one unified set so that we can analyze the responses effectively by the integration of the duplicated responses of the same video together. The sentiment analysis of the videos was subsequently performed with a fine-tuned LLaMA language model for processing the responses, which were shown effective and accurate for the analysis of the sentiment of the natural language text[26,27,28,29].

0.5 Statistical Analysis

The statistical analysis of the sentiment data involved several key steps to ensure the validity of the results.Initially, the comment data underwent a Box-Cox transformation to normalize the distribution of sentiment scores which is shown in Figure 3 and Figure 4.

The Box-Cox transformation is a method for stabilizing variance and making the data more closely approximate a normal distribution, which is essential for subsequent statistical testing. This transformation was applied separately to the counts of positive, negative, and neutral comments for both embodied and conventional robotics learning videos. The transformation parameters λ for each sentiment category were determined, and the results were plotted to visualize the effect of normalization. Based on the value of λ, the results show that overall, before the normalization, there is some skewed behavior, especially for negative and neural comments for the embodied learning centered videos, which has smaller λ values. But after normalization, the distribution are all approximate to the normal distribution.

Following data transformation, a two-way Analysis of Variance (ANOVA) test was conducted to compare the sentiment distributions for the different learning methods and comment types. The ANOVA test was used to determine whether there were any significant differences in comment counts based on the learning method, the type of sentiment, and the interaction between these two factors. Specifically, the analysis sought to identify how these factors independently and interactively influenced the sentiment distributions to evaluate the impacts of learning method (embodied vs. conventional) and the sentiment of comment (positive, negative, neutral) on the

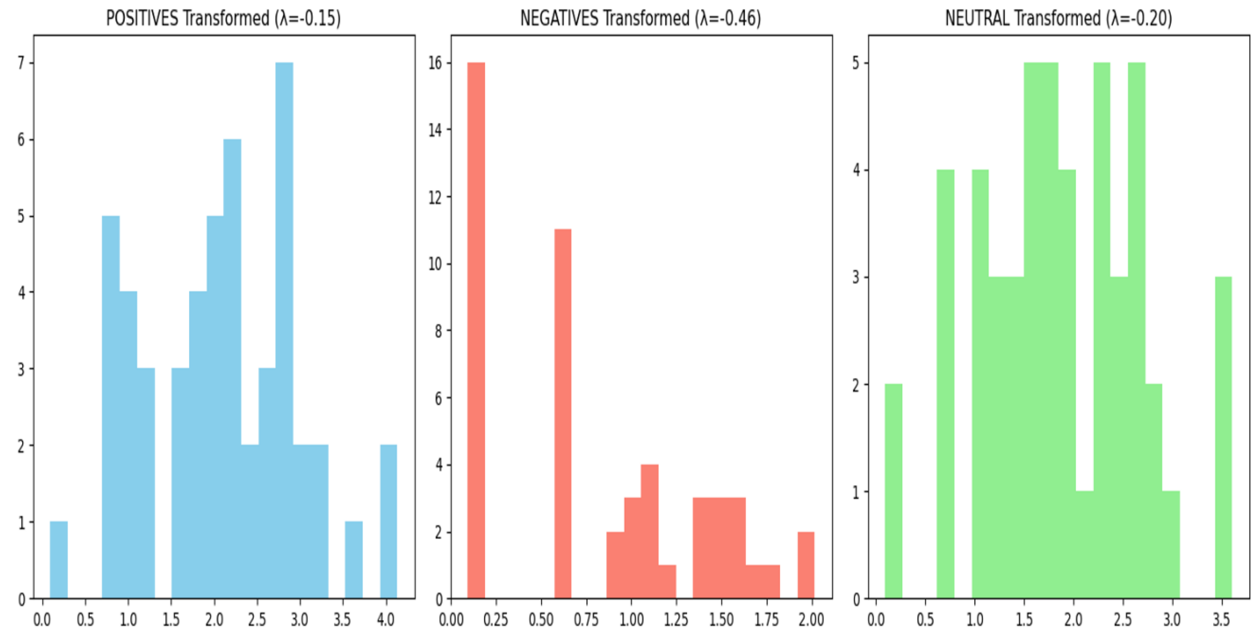

Figure 3: Normalization of the positive, negative, and neutral comments using Box-Cox transformation for conventional robotics learning videos.

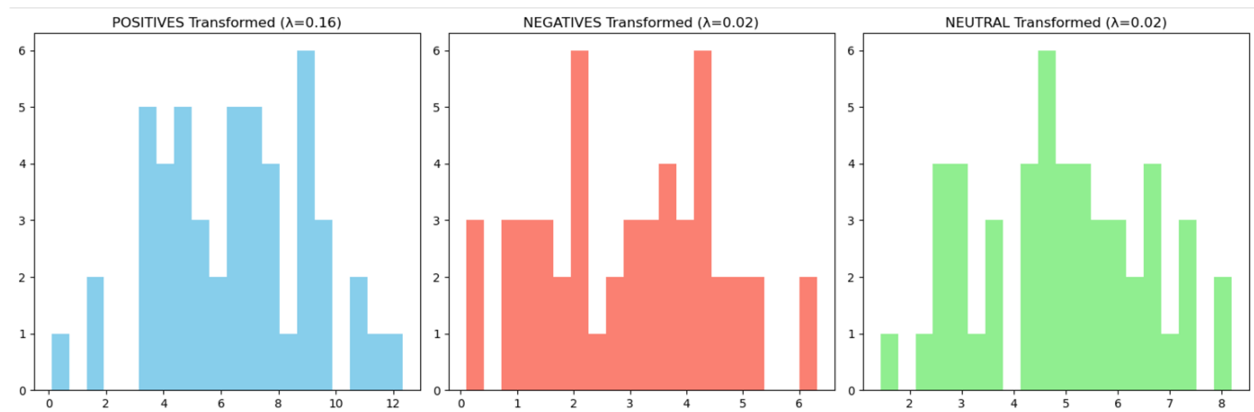

Figure 4: Normalization of the positive, negative, and neutral comments using Box-Cox transformation for embodied robotics learning videos.

number of comments for the videos.

Results

The analysis of the total number of comments revealed a significant difference between embodied learning and conventional learning videos. One hundred embodied learning videos received 81.65% of comments, while the conventional videos received 18.35% comments shown in Figure 5.

The difference between the number of comments of embodied versus conventional types of videos

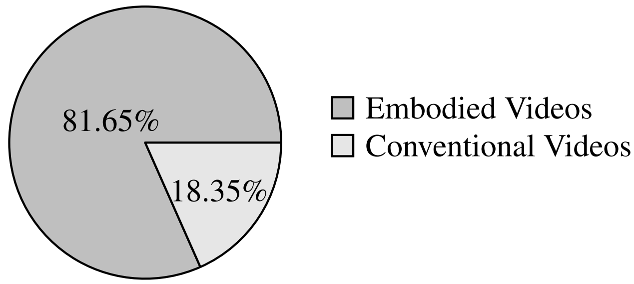

Figure 5: Proportion of Comments Across Video Types: Embodied learning videos generated the majority of comments (81.65%) compared to conventional videos (18.35%), indicating higher user engagement for the videos chosen for the experiment.

is evident. This substantial difference between the embodied and conventional robotics learning indicates that embodied videos are able to engage a significantly higher number of learners for producing comments compared to the conventional videos, suggesting greater viewer engagement and interaction with embodied robotics learning videos. It is also observed through the videos that in contrast to the use of conventional type demonstration videos, the use of the embodied learning centered robotics demonstration videos has been able to better engage more user discussion and comments across different instructional types of videos including electronics, machine learning, robotics mechanical design, robotics kinematics, and human-robot interaction.

The sentiment distribution analysis between embodied and conventional videos reveals significant differences across various sentiment categories. In this research, we have used three different categories including positive, negative, and neutral comments. Specifically, we have used the ratio of the specific type comments versus all the comments for the fair comparison between the different types of sentiment of the users reaction toward the videos.

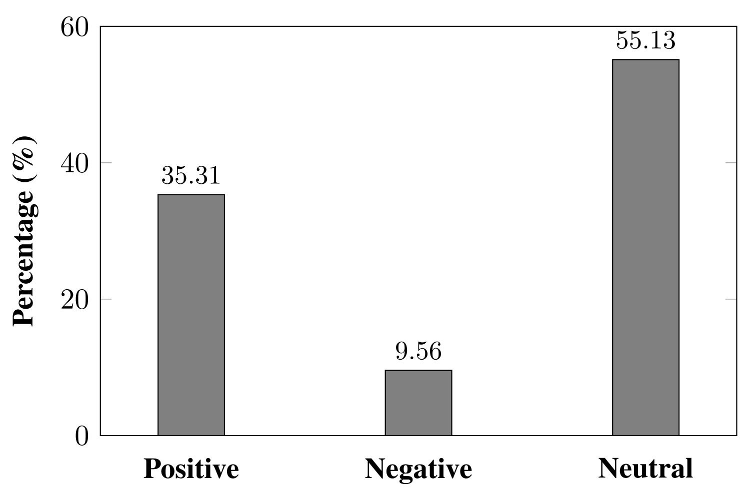

Figure 6: Distribution of YouTube video comment sentiments for embodied learning content. The majority of the comments were neutral (55.13%), followed by positive (35.31%) and a smaller portion of negative sentiments (9.56%).

The results show that for the embodied learning centered videos, among the total number of

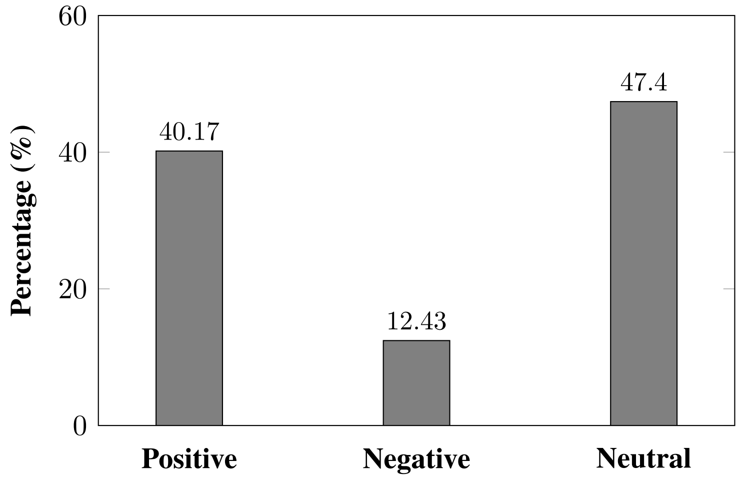

Figure 7: Distribution of YouTube video comment sentiments for conventional learning content. The majority of the comments were neutral (55.13%), followed by positive (35.31%) and a smaller portion of negative sentiments (9.56%).

comments, there are 35.21% positive comments, 9.56% negative comments, and 55.13% neutral comments shown in Figure 6. It shows that the neutral comments account for the majority of the comments followed by positive comments and negative comments for the embodied learning centered videos. In contrast, for the conventional learning centered videos, it includes, 40.17% positive comments, 12.43% negative comments, and 47.40% neutral comments shown in Figure 7. Similarly, the result showed that neutral comments account for the majority of the comments followed by the positive and negative comments for the conventional learning centered videos.

The ANOVA analysis results are shown in Table 1.

Table 1: Sentiment ANOVA analysis of embodied versus conventional learning approaches

Source	Sum of Squares	df	F	PR(¿F)
Learning Method	766.276867	1	325.116150	1.83021e-49
Comment Type	292.123585	2	61.971136	3.491095e-23
Interaction Effect	63.280895	2	13.424417	2.635658e-06
Residual	692.938197	294	nan	nan

The key findings from the ANOVA analysis are as follows:

- **Learning Method - Embodied versus Conventional** : The learning method has had a highly significant impact on the number of comments received by the videos. The statistical evidence showed an F-statistic of 325.116150 with a p-value of 1.830210e-49, indicating that the type of learning method used in the videos significantly affected the number of comments received.
- **Comment Type**: The type of comment also significantly affected the number of comments.

The F-statistic for comment type was 61.971136 with a p-value of 3.491095e-23, demonstrating that positive, negative, and neutral comments varied significantly in their frequency.

- **Interaction Effect**: There was a significant interaction between the learning method and the type of comment. This interaction effect had an F-statistic of 13.424417 and a p-value of 2.635658e-06, indicating that the influence of the learning method on comment counts was dependent on the type of comments.

These results suggest that both the learning method and the type of comment affected the number of comments received for the videos. Additionally, the impact of the learning method on comment counts varies depending on the type of comment, indicating different engagement levels based on the learning methods used.

The experimental data analysis shows that participants have expressed strong positive learning experiences with learning robotics with videos. Most of participants have expressed that learning robotics with videos is a useful learning strategy, which is both convenient and effective. The sentiment analysis shows differences of the embodied learning centered videos versus the conventional learning centered videos, where over 22% of participants expressed that the use of embodied learning centered videos have facilitated their learning of robotics technology. In contrast, over 18% of participants have expressed that the use of conventional learning centered videos is also effective.

Discussion

The project aims to understand the user engagement of videos featured with embodied and conventional learning methods for robotics technology instruction. Specifically, we have examined the differences of the embodied learning centered videos compared to the conventional learning centered videos for their engagement with users. This comparative analysis was achieved by systematically examining user comments and the sentiments of the user engagement. The study utilized advanced data extraction, transcription, sentiment analysis, and statistical techniques to ensure accurate and reliable results, providing valuable insights into the effectiveness of these educational methodologies.

The analysis of the user comments revealed a significant difference in terms of engagement between embodied and conventional videos. Overall, embodied learning centered videos received higher number of user engagement in terms of the number of comments received. The higher number of comments indicate that viewers are more involved and responsive to the video content that involves physical activities and hands-on experiences. This aligns with the principles of the embodied learning, which emphasize active participation and physical interaction as the key factors in enhancing the learning outcomes.

The sentiment distribution analysis further highlighted the differences between embodied and conventional videos. Embodied videos received less percentage of the negative comments in comparison to the conventional learning centered videos. This disparity suggests that embodied learning centered videos generated less negative comments on the videos. However, the conventional learning center videos generated higher percentage of the positive comments than the embodied learning centered videos. These findings suggest that embodied videos may not be able to generate significant number of positive user comments for the videos, but it may be able to reduce the potential negative comments toward the learning process.

The two-way ANOVA test revealed that both the learning method (embodied vs. conventional) and the type of comment (positive, negative, neutral) significantly affected the number of comments received. The interaction effect between the learning methods and the type of comments indicate that the impacts of the learning method on comment counts varied depending on the sentiment of the comments. These results underscore the importance of the learning method in influencing viewer engagement and interaction.

The findings from this study have important implications for the field of robotics education. The higher user engagement and stronger emotional responses elicited by the embodied videos suggest that incorporating embodied learning principles can significantly enhance educational outcomes. By actively involving students in the learning process, it will better facilitate the learning and prepare students for difficult robotics learning process. It thus aligns with educational theories such as Piaget's constructivism and Vygotsky's social constructivism, which emphasize the importance of active engagement and social interaction in the learning process.

It is also expected that the future research will explore the investigation of videos which have implemented the use of advanced embodied learning technologies such as virtual reality (VR) and augmented reality (AR) known able to enhance the effectiveness of embodied learning process for robotics. Through examining these videos, it becomes possible to understand whether these videos can better engage students in learning the underlying content. It is known that these technologies can create immersive learning environments where students can interact with virtual objects and practice assembling and programming robots without the need of physical components. It is therefore expected that theses videos will better engage students in the learning process for the enhanced learning outcomes.

While the study provides valuable insights into the benefits of embodied learning, several challenges involving the use of embodied learning need to be addressed for effective implementation in practice. It includes the need for specialized equipment, teacher training, and curriculum design. Future research should focus on exploring the long-term impacts of embodied learning centered curriculum, identifying best practices for its implementation, and leveraging emerging technologies to enhance its effectiveness and reduce potential adversary impacts. Additionally, studies should investigate the potential embodied learning in other educational fields beyond robotics to determine the potential benefits to facilitate the underlying learning process.

In conclusion, the research demonstrates that embodied robotics learning approach, characterized by hands-on activities and physical interaction, enhances student engagement and educational outcomes in robotics education. By fostering active participation and engagement with learning, embodied learning methods can transform educational practices and improve the learning experiences. This study contributes to the identification of valuable videos to enhance learning of robotics. This is especially useful to help the remote learning or online learning classes where use of videos has been proven beneficial for robotics education.

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Conflict of Interest

We do not declare the conflict of interests through the research.

References

[1] Amy Eguchi. Robotics as a learning tool for educational transformation. In *Proceeding of 4th international workshop teaching robotics, teaching with robotics & 5th international conference robotics in education Padova (Italy)*, volume 1, pages 1–6, 2014.

[2] Carlotta A Berry. Robotics education online flipping a traditional mobile robotics classroom. In *2017 IEEE Frontiers in Education Conference (FIE)*, pages 1–6. IEEE, 2017.

[3] J Berrío Perez. A "flipped classroom" for mobile robotics teaching. In *INTED2014 Proceedings*, pages 3076–3085. IATED, 2014.

[4] Jean Piaget, Margaret Cook, et al. *The origins of intelligence in children*, volume 8. International Universities Press New York, 1952.

[5] Lev Semenovich Vygotsky and Michael Cole. *Mind in society: Development of higher psychological processes*. Harvard university press, 1978.

[6] Mina C Johnson-Glenberg, David A Birchfield, Lisa Tolentino, and Tatyana Koziupa. Collaborative embodied learning in mixed reality motion-capture environments: Two science studies. *Journal of educational psychology*, 106(1):86, 2014.

[7] Steven A Stolz. Embodied learning. *Educational philosophy and theory*, 47(5):474–487, 2015.

[8] Cassandra Durkee. Different methods of embodied cognition in pedagogy and its effectiveness in student learning. Master's thesis, San Jose State University, 2018.

[9] Scott Freeman, Sarah L Eddy, Miles McDonough, Michelle K Smith, Nnadozie Okoroafor, Hannah Jordt, and Mary Pat Wenderoth. Active learning increases student performance in science, engineering, and mathematics. *Proceedings of the national academy of sciences*, 111(23):8410–8415, 2014.

[10] Carly Kontra, Susan Goldin-Meadow, and Sian L Beilock. Embodied learning across the life span. *Topics in cognitive science*, 4(4):731–739, 2012.

[11] Jan Peters, Katharina Mülling, Jens Kober, Duy Nguyen-Tuong, and Oliver Krömer. Towards motor skill learning for robotics. In *Robotics Research: The 14th International Symposium ISRR*, pages 469–482. Springer, 2011.

[12] Michelene TH Chi and Ruth Wylie. The icap framework: Linking cognitive engagement to active learning outcomes. *Educational psychologist*, 49(4):219–243, 2014.

[13] Christopher J Dede, Jeffrey Jacobson, and John Richards. *Introduction: Virtual, augmented, and mixed realities in education*. Springer, 2017.

[14] Mina C Johnson-Glenberg and Colleen Megowan-Romanowicz. Embodied science and mixed reality: How gesture and motion capture affect physics education. *Cognitive research: principles and implications*, 2:1–28, 2017.

[15] Michael L Anderson. Embodied cognition: A field guide. *Artificial intelligence*, 149(1): 91–130, 2003.

[16] Lawrence W Barsalou. Grounded cognition. *Annu. Rev. Psychol.*, 59(1):617–645, 2008.

[17] Alexander Skulmowski and Günter Daniel Rey. Embodied learning: introducing a taxonomy based on bodily engagement and task integration. *Cognitive research: principles and implications*, 3:1–10, 2018.

[18] Chris Dede. The role of digital technologies in deeper learning. students at the center: Deeper learning research series. *Jobs for the Future*, 2014.

[19] Soujanya Poria, Erik Cambria, Rajiv Bajpai, and Amir Hussain. A review of affective computing: From unimodal analysis to multimodal fusion. *Information fusion*, 37:98–125, 2017.

[20] Bin Huang, Xin Wang, Hong Chen, Zihan Song, and Wenwu Zhu. Vtimellm: Empower llm to grasp video moments. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 14271–14280, 2024.

[21] Jia-Hong Huang. Multi-modal video summarization. In *Proceedings of the 2024 International Conference on Multimedia Retrieval*, pages 1214–1218, 2024.

[22] Hang Hua, Yunlong Tang, Chenliang Xu, and Jiebo Luo. V2xum-llm: Cross-modal video summarization with temporal prompt instruction tuning. *arXiv preprint arXiv:2404.12353*, 2024.

[23] Dawit Mureja Argaw, Seunghyun Yoon, Fabian Caba Heilbron, Hanieh Deilamsalehy, Trung Bui, Zhaowen Wang, Franck Dernoncourt, and Joon Son Chung. Scaling up video summarization pretraining with large language models. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 8332–8341, 2024.

[24] Frank Xing. Designing heterogeneous llm agents for financial sentiment analysis. *ACM Transactions on Management Information Systems*, 2024.

[25] Wenxuan Zhang, Yue Deng, Bing Liu, Sinno Jialin Pan, and Lidong Bing. Sentiment analysis in the era of large language models: A reality check. *arXiv preprint arXiv:2305.15005*, 2023.

[26] Xiaofei Sun, Xiaoya Li, Shengyu Zhang, Shuhe Wang, Fei Wu, Jiwei Li, Tianwei Zhang, and Guoyin Wang. Sentiment analysis through llm negotiations. *arXiv preprint arXiv:2311.01876*, 2023.

[27] Zeyu Wang, Yue Zhu, Shuyao He, Hao Yan, and Ziyi Zhu. Llm for sentiment analysis in e-commerce: A deep dive into customer feedback. *Applied Science and Engineering Journal for Advanced Research*, 3(4):8–13, 2024.

[28] Tong Zhan, Chenxi Shi, Yadong Shi, Huixiang Li, and Yiyu Lin. Optimization techniques for sentiment analysis based on llm (gpt-3). *arXiv preprint arXiv:2405.09770*, 2024.

[29] Frank Xing. ‘designing heterogeneous llm agents for financial sentiment analysis. *arXiv preprint arXiv:2401.05799*, 2025.