Towards the Generation of Learning Objects with Generative Artificial Intelligence

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***Abstract*— This paper describes ongoing research on the use of Generative Artificial Intelligence (GenAI) in generating learning objects. Learning Objects are digital or non-digital artifacts, which can be used, re-used or referenced to augment or enhance the learning process. Examples of these are presentation slides, images, text, surveys, quizzes, and hands-on exercises. The unprecedented availability and capability of GenAI tools in recent years brings us to consider how their technical capacities and abilities can bring about effective and useful learning objects. We first explore the published literature to survey work that has been reported in the field of applied GenAI to generate learning objects. Next, we provide a review of their technical features and closely look at the distinctive features of the tools used in various GenAI models. The focus of this research is to develop a method of utilizing freely available GenAI tools to expedite the generation of learning objects and to evaluate their effectiveness. Specifically, we seek to optimize the utilization of these AI-generated learning objects for active-learning applications and learning best practices.**

Keywords—generative AI, learning objects, active learning

I. Introduction

In a very short duration of time, Generative Artificial Intelligence (GenAI) gained so much attention prompting a flurry of inquiries into how it can and should be utilized. The creative feats these software models are capable of achieving are in extremely high demand in the information age, and they will become highly valuable once they have been appropriately integrated into the information pipeline from creators to their media. This opportunity raises the question of where, when, and how to utilize these tools to optimize content creation.

Education is a domain which can greatly benefit from this optimization, as it can significantly aid instructors in enhancing courses and achieving learning goals. These goals are becoming more complex as students demand more accessibility and ease of use from their courses. Among these demands is access to an intuitive and informative course shell containing a rich collection of learning objects to support students' learning in both synchronous and asynchronous courses. As instructors offer new courses, they are called upon to perform the time-consuming curation of many of these repositories of learning objects. As a potential solution to this problem, we propose a methodology for using GenAI to create a subclass of learning objects which we term AI-generated learning objects (AIGLO). This methodology can greatly accelerate the generation of viable learning objects for the online, post-secondary learning environment.

II. Literature Background

A. Types of GenAI

Described herein are the different GenAI types and their distinct characteristics. Knowledge of these characteristics bolsters our understanding of the prompt-response patterns exhibited by various tools implementing these models, empowering an informed analysis of AI-generated content.

Bandi et al. classify GenAI models into variational autoencoders (VAEs), generative adversarial networks (GANs), diffusion models, transformers, language models, normalizing flow models, and hybrid models [1].

VAEs utilize two neural networks: an encoder and a decoder [2]. The encoder is trained to compress input data into a developer-specified number of dimensions, outputting a Gaussian probability distribution for each of these dimensions. The decoder then samples these distributions and attempts to reconstruct the initial data set [2]. VAEs' loss function is represented by a reconstruction loss function minus the KL divergence of the sampling [2].

Like VAEs, GANs include two neural networks known as the generator and the discriminator; as the generator trains to replicate features of its corpus in a probabilistic output, the discriminator trains to differentiate between samplings from the generator and samplings from the initial data set [3]. Thus, the generator's loss is calculated based on the discriminator's estimate of the probability that the generator's output was not part of the training corpus [3].

Diffusion models learn to remove artificial noise from images by learning "mean and covariance functions" within a Gaussian diffusion process for restoring the images [4].

The Transformer artificial neural network architecture encodes inputs and outputs, then performs a positional encoding of the embeddings by adding a position-specific value to each component of each token's embedding [5]. The value added to each component of each token's embedding is the output of a sinusoidal function whose parameters include the ordinal position of the token with respect to the other input tokens and the dimension of the embedding to which they will be added [5]. Next, the Transformer performs self-attention on the positionally encoded embeddings, establishing a relationship between each token and each token in its context in each parallel head of self-attention [5]. Each head stores different weights used to transform positionally encoded tokens into queries, keys,

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and values for self-attention [5]. The contextualized composite representing each token, generated by each head of attention contains an equal portion of the dimension of the latent space, so the output of all heads of attention are concatenated to create a contextualized representation of each token [5]. Before the contextualized input and output embeddings are utilized to teach the model the relationship between them, the input embedding is refined through a two-layer position-wise feed-forward neural network [5]. Then, the refined input embedding provides input vectors for keys and values while the contextualized output embedding provides queries to another instance of the multi-head attention algorithm [5]. Finally, the input-contextualized output embedding feeds another feed-forward network for refinement and then into a softmax function to generate the final output [5]. The Transformer's decoding is autoregressive [5]. In natural-language-processing applications, Transformer-based machine learning models learn input tokens' meaning in a global context as well as in specific prompts.

Language models tend to use recurrent neural networks, which permit neurons to send outputs to previous layers and to receive inputs from future layers, in order to improve their comprehension of input data and the relevance of their output [1].

B. *GenAI Tools*

ChatGPT is an online AI chatbot that allows users to interact with GPT-3.5 [6]. GPT-3.5 is a post-third-generation version of GPT [7], [8], [9], an autoregressive language model, meaning that it generates each output token with respect to each antecedent output token, reflecting on its new context after generating each token [10]. GPT employs the transformer machine learning architecture for unsupervised language learning and then utilizes its knowledge of language in supervised learning of specific linguistic tasks [11]. GPT's task learning is guided by human-labelled datasets of prompts, desired outputs, and effectiveness comparisons among responses [12]. This task learning utilizes Proximal Policy Optimization (PPO) [12], which balances learning with the maintenance of existing knowledge to cause GPT to deviate from its past policies without compromising its trust region, or the body of its knowledge that it has strongly validated [13].

DALL-E 3 builds on DALL-E 2, containing performance improvements and an expansion of the training corpus to include highly descriptive captions [14]. DALL-E's first release consisted of a discrete VAE that compressed images and then a transformer for image reconstruction from the compressed format [15]. DALL-E 2 reconstructs images from CLIP embeddings using a diffusion model [16]. CLIP is an encoder model that creates text embeddings of images [17].

Gemini is a family of pre-trained, transformer-based models that receives inputs and generates responses via digital audio, video, and text tokens within a multi-modal context [18]. Gemini's task-specific post-training is very similar to GPT's task training methodology: a corpus of prompts form the basis for supervised fine-tuning (SFT), reward-model (RM) training, and reinforcement learning from human feedback (RHLF) [18]. Gemini's SFT teaches the model features that ought to be included in its responses by providing it with examples of satisfactory responses for each prompt, and RM training informs Gemini's evaluation of different features with qualitative feedback from human graders on multiple responses to each prompt [18].

To make optimal use of GenAI tools, we look to the knowledge gleaned from a cutting-edge field of study known as prompt engineering, "the means by which LLMs are programmed via prompts" [19]. White et al. assert that prompt patterns, or templates for prompts, are useful and essential tools for meeting pattern-specific response goals [19]. They outline how prompts of each of these patterns can affect the responses delivered in their context and provide template phrases for each pattern.

AIPRM is a web browser plugin that offers users of ChatGPT access to a large repository of prompt templates that make use of the prompt engineering principles put forward by White et al., so we evaluate the efficacy of specific templates within their repository for meeting the needs of each phase of our LO-generation methodology.

C. *Active Learning*

Active learning is a strategy for engaging students in the content of educational courses by encouraging them to apply their knowledge to social and creative activities. Experimentation has shown that in lessons about biology and health, problem-based learning, an active learning approach, improves the learning outcomes observed by students and instructors [20], [21], [22]. These outcomes were explained by these factors, which we extrapolate to include learning environments under these conditions. As such, we consider the potential value of implementing this policy in an online post-secondary learning environment.

Assuming the validity of the popular pedagogical approach to post-secondary learning, students can effectively engage with online course materials when these materials are easy to integrate with their motivations, experience, need to know, readiness, and self-directedness [23].

D. *Learning Objects*

Learning objects are "any entity, digital or non-digital, which can be used, re-used or referenced during technology supported learning" [24]. In an online course shell, they facilitate instruction by scaffolding students' independent exploration and review of the course content and providing credible information about the course subject on demand.

Learning objects in the online learning environment must achieve specific educational goals. Haughey and Muirhead enumerate specifications that learning objects must meet to be considered viable [25]. Among these requirements, they note controversy on "whether a specific learning design should be used in designing the object" and how much reusability should weigh in learning object evaluation [25]. For the purpose of this study, we will consider that a specific learning design should be followed in the creation of learning objects to constrain the requirements of the objects and that reusability is unimportant. Given a review of learning-object evaluation frameworks, Haughey and Muirhead propose their own Learning Object Evaluation Instrument (LOEI) [25].

The contribution of this research work is three-fold. Firstly, we derive a structured workflow for learning object development through GenAI. Secondly, we develop the methodology for utilizing ChatGPT, a GenAI tool, for gathering and generating knowledge artifacts. Thirdly, we provide an evaluation of the results of the process and formulate constructive courses of action for future improvement.

III. Generative AI and Learning Objects

The objectives for this research are as follows:

- Formalize a process for utilizing GenAI to generate a suite of learning objects to teach post-secondary students about a broad and emerging topic through active learning.
- Perform an initial evaluation of the process of generating learning objects through GenAI.

The following set of instructions outlines how to create a slideshow and multiple-choice quiz questions to derive a set of learning objectives that are accessible, simple, and commonly used. Further, these instructions contain an outline for iterative expansion and improvement of learning objects. This would provide instructors an expedient map on the implementation of additional learning objects to address shortcomings of previously generated AIGLO.

To evaluate the quality of the study's AIGLO, we employ Haughey and Muirhead's LOEI, which specifies the following preferable characteristics of learning objects:

- Accurate and reflective of the knowledge concept.
- Provide clear instructions for their use.
- Easily usable.
- Student learning outcomes are explicitly known to the instructor and the learner.
- Clearly indicate the target learners.
- Provide a clear set of pre-requisite knowledge/skills.
- Use technology effectively to engage learners with the concept/skill/ideas.
- Provide structured information content in order to scaffold student learning.
- Provide an opportunity for learners to obtain feedback either within or outside the learning object.
- Able to stand-alone and reflect an awareness of the varying educational environments in which learning sequences and objects may be used by the learner.
- Designed to be appropriate for community and cultural affiliations, including language, dialect, reading and writing.
- Provide adequate documentation and user manuals for students and instructors.
- Facilitate the use of visual and auditory information to enhance learning and mental processes.
- Enable access to diverse learners and needs.
- Designed for very minimal instructor intervention. [25]

Specifically, the AIGLO for this study are evaluated by their achievement of the lesson objectives detailed in the "Lesson 1: Renewable Vancouver" section of [26], which are described below.

The workflow outlined here is highly procedural to ensure that the resulting AIGLO are highly reproducible. We strove to produce results that were meaningful according to the criteria.

A. The Workflow

Our workflow (Fig. 1) begins with the development of learning objectives that our learning environment seeks to fulfill. For this study, we use these student learning targets defined by Kluttz for a renewable energy lesson for students in Vancouver:

- Distinguish between renewable and non-renewable energy resources
- Identify energy sources used locally and the role they play within the local energy system
- Explain how local renewable energy sources might substitute for fossil fuel energy to meet community needs
- Describe local strategies to (1) decrease energy use, (2) increase the use of renewable energy, and (3) increase the supply of renewable energy [26]

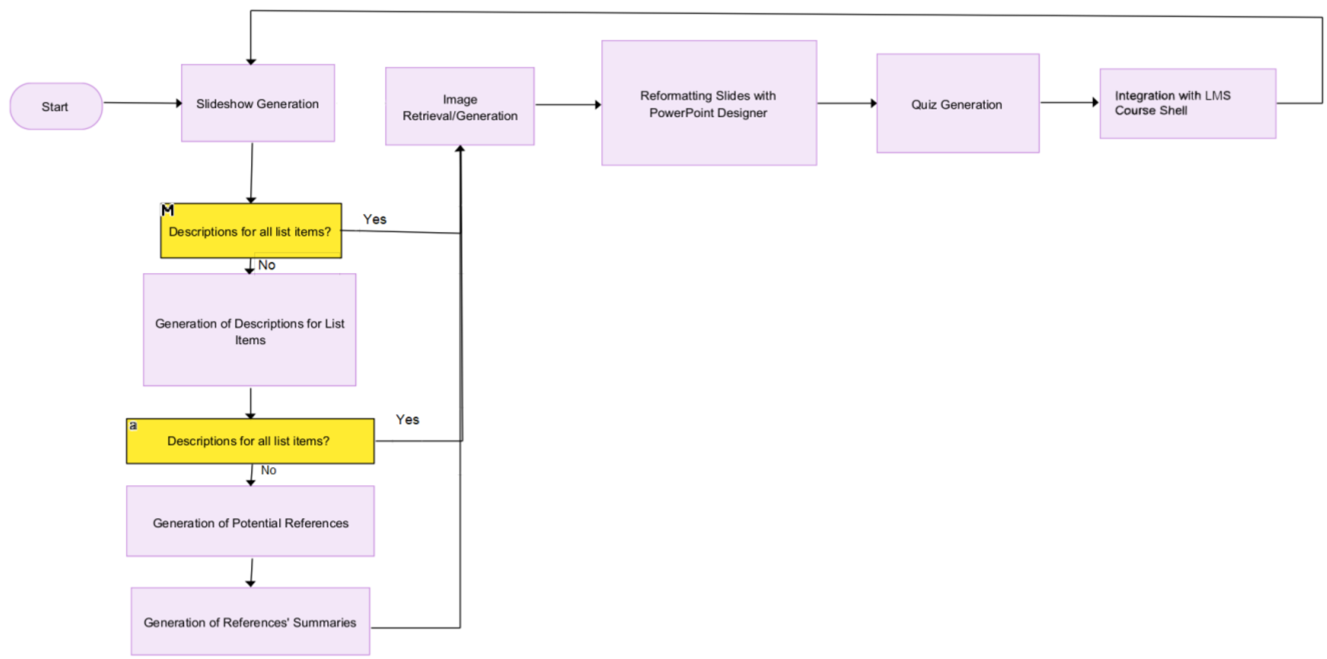

Fig. 1. Diagram of learning-object generation workflow.

In the following methodology, ChatGPT discussions are not deleted except where explicitly stated. "Unfamiliar topics" refers to topics that are perceived to be unclear to intended students. These topics would include the unfamiliar concepts related to the general topic on hand. Since this workflow is iterative, the process will repeat from the first step after the completion of the final step. We utilize GenAI tools to build learning objects for an online post-secondary learning environment with the following process:

1. In a new Chat (context) of ChatGPT, prompt GPT with the sample wording of the fact check list prompt pattern detailed by White et al., substituting "renewable energy" for "cybersecurity" [19].

2. In the same Chat, on the first iteration of the workflow, prompt GPT by inputting Kluttz's learning objectives to AIPRM's "Generate PPT Template with One Click" prompt template. To preserve the information implied by their original context, two of the learning objectives are modified; the modified learning objectives are:

    - Identify energy sources used in Vancouver and the role they play within the Vancouver energy system

    - Explain how Vancouver renewable energy sources might substitute for fossil fuel energy to meet community needs

    For subsequent iterations, ask about the most abstract unfamiliar concept from the previous iteration.

3. Create a PowerPoint slideshow containing the content suggested by ChatGPT's response.

4. In the same Chat, ask ChatGPT for more information about topics for which it provides no description in the slideshow template it generates. If ChatGPT provides no helpful information in its response that has not been integrated into the slideshow suite, ask it to provide peer-reviewed, open-access scholarly resources for the information.

    a. Copy the contents of each resource ChatGPT suggests into a Microsoft Word Document.

    b. Divide each article into four sections: introduction, methods, findings, and discussion. Prompt ChatGPT to summarize each of these key structural components of each article provided, copying them from the Word document into ChatGPT's text input box.

        i. Select clarifying phrases from its descriptions to include as sections under the most closely related topic in the slideshow.

5. In the Chat containing the slideshow, prompt ChatGPT to visualize the slideshow topics using one of the following methods:

    a. In the Chat where ChatGPT generated this slideshow, query ChatGPT with, "Suggest queries for Google Images to locate images to include for each slide of the slideshow that you generated." Use ChatGPT's queries in Google Images, excluding quotation marks, and insert the first image result for each query next to its corresponding section. Use the Creative

Commons Licenses search filter and use only the images retrieved that are stored in PNG, JPEG, GIF, TIFF, or Bitmap formats.

  b. Copy and paste the section headers for lists into the input box for the online preview of Microsoft Designer's Image Creator and click the Generate button. Select the image in the top left corner of the output section and copy the image. Paste the image into the corresponding slide of the PowerPoint slideshow.

The former procedure for finding visual aids for the slideshow may be more effective for embedding technical diagrams since DALL-E's designs primarily provide visual appeal and topical relevance.

6. Use PowerPoint's Designer feature to automatically format the slideshow.

7. Evaluate slideshow quality against criteria outlined under Haughey and Muirhead's "Development of an Evaluation Instrument" [25].

8. Prompt ChatGPT to generate a multiple-choice quiz question for each sentence of the list slides in the slideshow using Tamas Dukai's "Multiple Choice Quiz Generator " prompt on AIPRM. Create a new Chat for these promptings but perform them all in the same Chat.

9. Copy ChatGPT's responses and paste them into a new text document associated with the slideshow.

10. Upload the PowerPoint slideshow to the online course shell. Create a multiple-choice quiz in the online course shell containing the questions contained in the quiz document.

B. Preliminary Results

According to steps 1-4, a text-based slideshow template was generated. According to Steps 5a and 6, a slideshow containing images collected from Google image searches was generated and formatted (Fig. 2). According to Steps 5b and 6, a slideshow containing images collected from Microsoft Designer's Image Creator feature was generated and formatted (Fig. 3). According to Step 8, a multiple-choice quiz testing comprehension of the slideshow's shared textual content was generated. A quiz artifact can be found in [27].

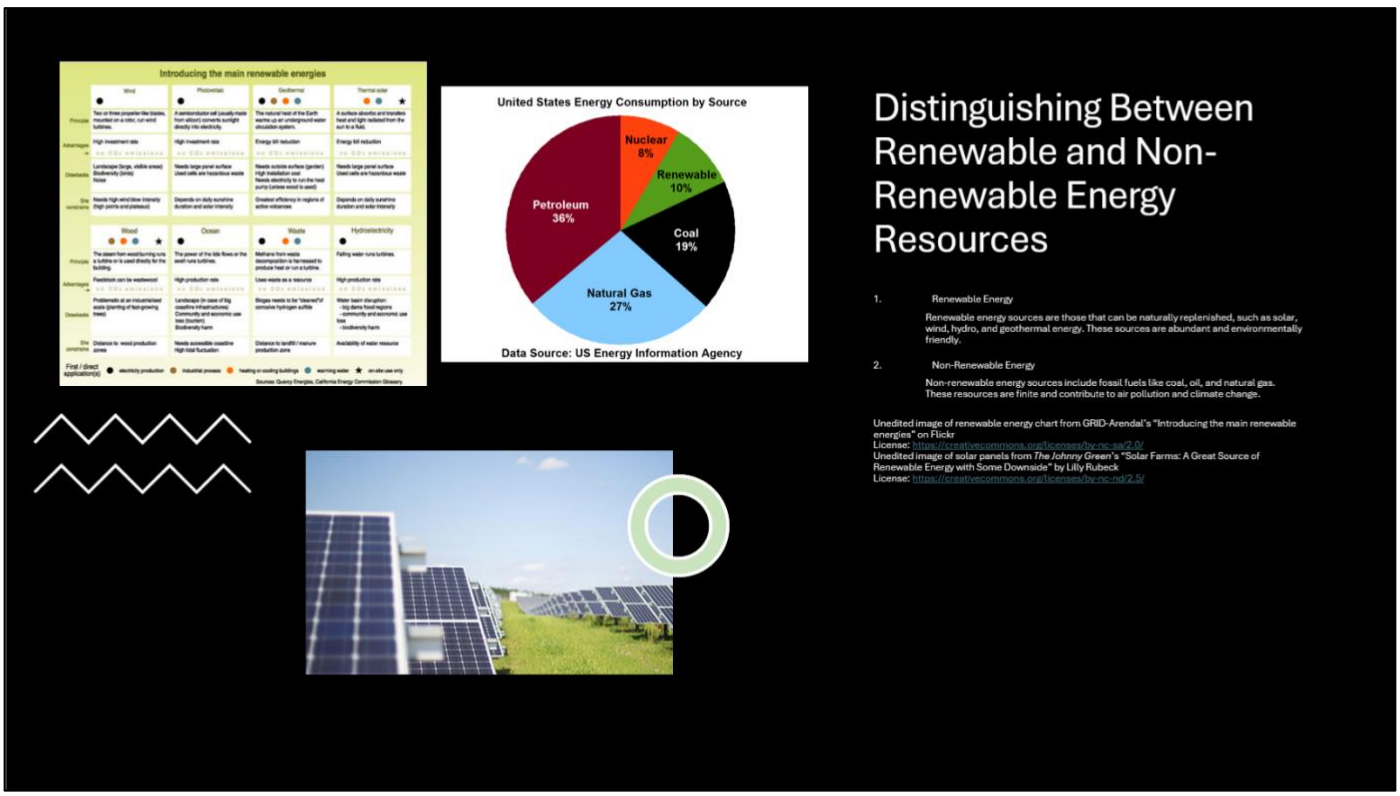

Fig. 2. Slide generated by outlined workflow using Option A of Step 5.

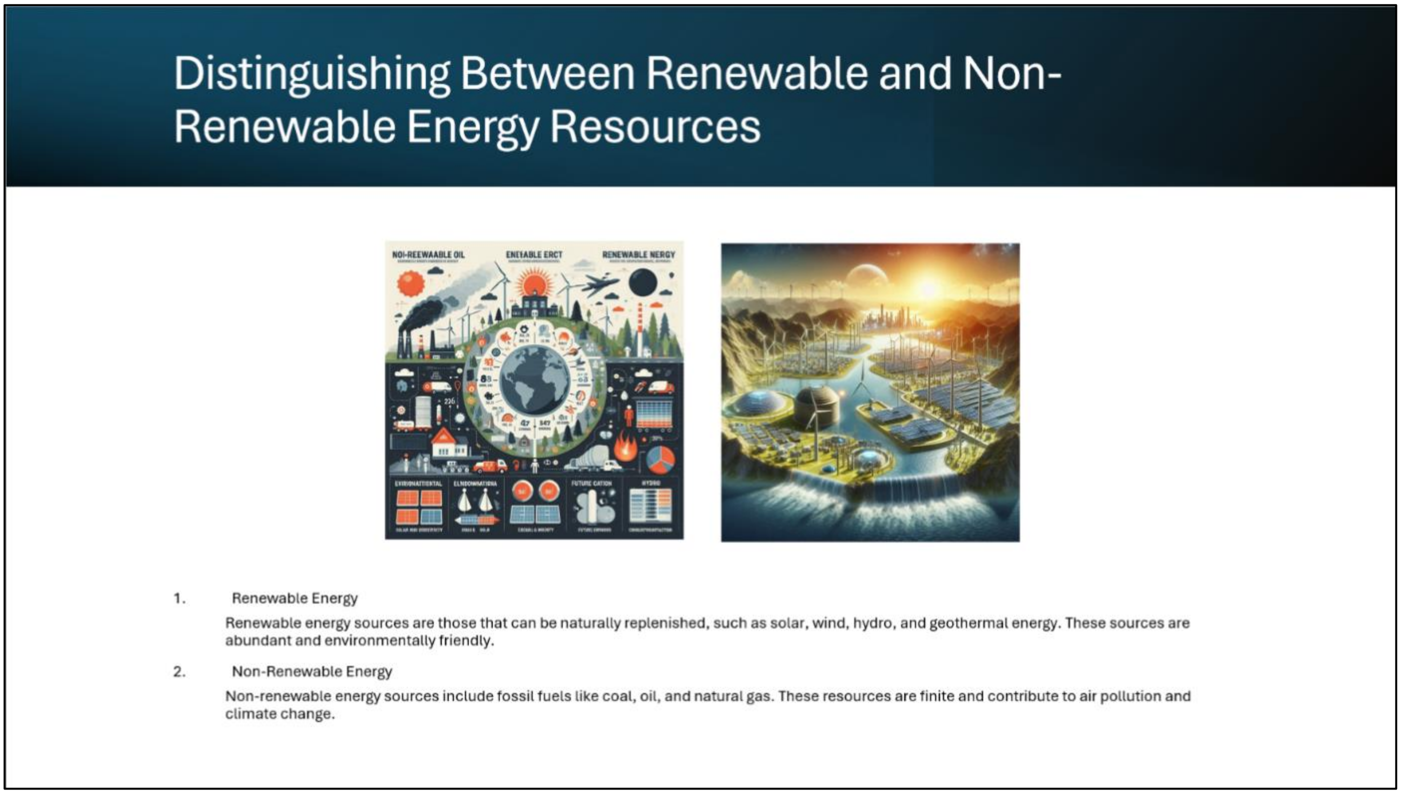

Fig. 3. Slide generated by outlined workflow using Option B of Step 5.

By the LOEI detailed by Haughey and Muirhead, the generated slideshows are effective in promoting students learning insofar as they:

- have learning objectives that are explicitly known to the instructor and the learner
- have a clearly identified group of target learners
- provide an opportunity for learners to obtain feedback, either within or outside the learning object
- do not require instructor intervention to be used effectively in a mixture of learning environments and learning sequences

However, the slideshows also fail to meet the requirements:

- be accompanied by clear instructions for using the learning object
- have a clear set of pre-requisite knowledge/skills with connections to prior and future learning
- have associated help and documentation files for students and teachers including contextual assistance
- be accessible to learners with diverse needs

Additionally, the achievement of many learning objectives listed by Haughey and Muirhead could not be reliably evaluated without subject-matter expertise, knowledge of instructors' expertise with GenAI tools and educational computer hardware and software, pedagogical expertise, or familiarity with students' culture. The learning objectives associated with each of these evaluative bodies of knowledge are listed below.

Subject-matter expertise:

- be accurate and reflect the ways in which knowledge is conceptualized within the domain

Knowledge of instructors' technical expertise:

- be accompanied by clear instructions for using the learning object
- be easy to use

Pedagogical expertise:

- use technology that helps learners to engage effectively with the concept/skill/ideas
- structure information content in order to scaffold student learning
- stand-alone and reflect an awareness of the varying educational environments in which learning sequences and objects may be used by the learner
- use visual and auditory information whose design enhances learning and mental processes

Familiarity with student culture:

- be appropriate for community and cultural affiliations, including language, dialect, reading, and writing

While GPT was prompted to generate a fact-check list for the slideshow template it generated, it failed to produce this response, instead generating only the slideshow template.

The images retrieved using the Google images prompts suggested by ChatGPT were usually relevant, but some images had only topical relevance to the slideshow's textual content without fitting the description provided in the image search query. For instance, some of the images of statistical charts collected from Google Images described data collected about U.S. energy consumption despite the inclusion of the keyword "Vancouver" in the search query.

The images generated by DALL-E from section headings were topically relevant and consistent with descriptions provided in the prompts and in the body of their respective slides. However, one of the generated images contained distorted alphabetic characters and incomplete words, which may cause some students and instructors confusion and negatively affect learning goals (Fig. 4).

Fig. 4. Image generated by DALL-E with the prompt "Non-Renewable Energy".

Slideshow generation took 118 minutes for the slideshow containing images collected from a web search. Much of this time (47 minutes) was spent collecting attribution information to ensure legal use of the images included. In contrast, slideshow generation for the slideshow containing AI-generated images took 71 minutes. Multiple-quiz question generation was a 24-minute process.

IV. Conclusions and Future Works

To better address the unmet pedagogical objectives of AI-generated learning objects, it would be helpful to better elucidate the specific learning environment(s) in which they will be deployed, including the learners who will utilize them. A model of the interplay between AIGLO and their operational learning environment could be approximated by consultations with various experts about the subject of the AIGLO and post-secondary instructors. It could also be extrapolated from surveys of students and instructors both before and after deploying the AIGLO to gather data about the educational context and evaluations of instruction implementing AIGLO, respectively. The same types of data collection may be helpful in editing the AI-powered LO-generation framework to improve its pedagogical efficacy and reduce its cost.

For a greater degree of automation, GenAI users will need a more effective epistemic framework for identifying, authenticating, and validating the sources of the claims included and implied by AIGLO. Independent learners may greatly benefit from an LO generation process that requires minimal prior knowledge. A highly expedient and self-validating LO-generation procedure may also be helpful to instructors for enriching their responses to students' inquiries in real time.

Further research should also address the need for a more sophisticated prompt engineering framework, as the qualities necessary for highly effective AIGLO and fast LO-generation processes will vary widely due to variations in instructional contexts and domains. A more generalizable prompting methodology would be helpful for instructors whose course content is very different from the content presented here. The images generated by DALL-E may be improved by a more sophisticated methodology as well.

While the images generated for this slideshow were helpful, for other topics that are more technically involved and abstract, a higher degree of complexity and knowledge of the subject area may be necessary for visualizations included in a slideshow presentation containing this content. Prompting techniques that take these objectives into account may advance the adoption of AIGLO across a broader range of academic disciplines.

Although ChatGPT does not currently support the creation of active-learning instructional designs, it is an excellent tool for generating engaging multimedia materials for the classroom and learning assessment tools that can supplement formal education. Future research directions may include the development of a more structured and parameterized framework for AIGLO and evaluation of the framework for different instructional contexts. This will help facilitate and expand use of AIGLO for diverse learner needs, instructional styles, and domains.

References

[1] A. Bandi, P. V. S. R. Adapa and Y. E. V. P. K. Kuchi, "The power of generative AI: A review of requirements, models, input–output formats, evaluation metrics, and challenges," *Future Internet*, vol. 15, no. 8, Jul. 2023. Accessed: Oct. 19, 2023, doi: 10.3390/fi15080260. [Online]. Available: https://www.mdpi.com/1999-5903/15/8/260

[2] X. Tong et al., "Generative models for de novo drug design," Journal of Medicinal Chemistry, vol. 64, no. 19, pp. 14011-14027, Sep. 17, 2021. Accessed: Nov. 16, 2023, doi: 10.1021/acs.jmedchem.1c00927. [Online]. Available: https://pubs.acs.org/doi/10.1021/acs.jmedchem.1c00927

[3] I. J. Goodfellow et al. (Dec. 2014). Generative adversarial nets. Presented at the 28th Advances in NeurIPS. [Online]. Available: https://proceedings.neurips.cc/paper_files/paper/2014/file/5ca3e9b122f61f8f06494c97b1afccf3-Paper.pdf

[4] J. Sohl-Dickstein, E. A. Weiss, N. Maheswaranathan and S. Ganguli, "Deep unsupervised learning using nonequilibrium thermodynamics," 2015, *arXiv:1503.03585*.

[5] A. Vaswani et al. (Dec. 2017). Attention is all you need. Presented at the 31st Advances in NeurIPS. [Online]. Available: https://proceedings.neurips.cc/paper_files/paper/2017/file/3f5ee243547dee91fbd053c1c4a845aa-Paper.pdf

[6] OpenAI. "ChatGPT." OpenAI. Accessed: Dec. 8, 2023. [Online.] Available: https://openai.com/chatgpt

[7] OpenAI. "Models - OpenAI API." OpenAI. Accessed: Dec. 8, 2023. [Online.] Available: https://platform.openai.com/docs/models

[8] T. B. Brown et al., "Language models are few-shot learners," 2020, *arXiv:2005.14165*.

[9] A. Radford, J. Wu, R. Child, D. Luan, D. Amodei and I. Sutskever, "Language models are unsupervised multitask learners," unpublished.

[10] L. Floridi and M. Chiriatti, "GPT-3: Its nature, scope, limits, and consequences," *Minds and Machines,* vol. 30, no. 4, pp. 681-694, Dec. 2020. Accessed: Dec. 8, 2023, doi: 10.1007/s11023-020-09548-1. [Online]. Available: https://link.springer.com/article/10.1007/s11023-020-09548-1

[11] A. Radford, K. Narasimhan, T. Salimans and I. Sutskever, "Improving language understanding by generative pre-training," unpublished.

[12] OpenAI. "Introducing ChatGPT." OpenAI. Accessed: Mar. 31, 2024. [Online]. Available: https://openai.com/blog/chatgpt

[13] J. Schulman, F. Wolski, P. Dhariwal, A. Radford and O. Klimov, "Proximal policy optimization algorithms," 2017, *arXiv:1707.06347*.

[14] J. Betker et al., "Improving image generation with better captions," unpublished.

[15] A. Ramesh et al., "Zero-shot text-to-image generation," 2021, *arXiv:2102.12092*.

[16] A. Ramesh, P. Dhariwal, A. Nichol, C. Chu and M. Chen, "Hierarchical text-conditional image generation with CLIP latents," 2022, *arXiv:2204.06125*.

[17] A. Radford et al., "Learning transferable visual models from natural language supervision," 2021, *arXiv:2103.00020*.

[18] R. Anil et al., "Gemini: A family of highly capable multimodal Models," 2024, *arXiv:2312.11805*.

[19] J. White et al., "A prompt pattern catalog to enhance prompt engineering with ChatGPT," 2023, *arXiv:2302.11382*.

[20] F. Laili and L. Lufri, "The effect of active learning in the form of scientific approach with the use of students worksheet based on problem based learning (PBL) on students' biological knowledge," *J. of Phys.: Conf. Ser.,* vol. 1387, no. 1, Nov. 2019. Accessed: Nov. 17, 2023, doi: 10.1088/1742-6596/1387/1/012047. [Online]. Available: https://iopscience.iop.org/article/10.1088/1742-6596/1387/1/012047

[21] S. Mumtaz and R. Latif, "Learning through debate during problem-based learning: an active learning strategy," *Adv. in Physiol. Educ.,* vol. 41, no. 3, pp. 390-394, May 2017. Accessed: Nov. 17, 2023, doi: 10.1152/advan.00157.2016. [Online]. Available: https://pubmed.ncbi.nlm.nih.gov/28679577/

[22] Y. Al-Thomali, "The effect of active learning with block and problem based learning on motivation, and academic performance of dental students - a prospective study," *Int. J. of Current Res. and Rev.*, vol. 13, no. 5, pp. 110-118, Mar. 2021. Accessed: Nov. 17, 2023, doi: 10.31782/IJCRR.2021.SP145. [Online]. Available: https://ijcrr.com/uploads/3485_pdf.pdf

[23] E. F. Holton, L. S. Wilson and R. A. Bates, "Toward development of a generalized instrument to measure andragogy," *Human Resour. Develop. Quart.,* vol. 20, no. 2, pp. 169-193, Mar. 2009, doi: 10.1002/hrdq.20014

[24] *IEEE Standard for Learning Object Metadata*, IEEE Standard 1484.12.1-2002, Sep. 6, 2002.

[25] M. Haughey and B. Muirhead, "Evaluating learning objects for schools," *e-J. of Instructional Sci. and Technol.,* vol. 8, no. 1, 2005. Accessed: Mar. 31, 2024. [Online]. Available: https://files.eric.ed.gov/fulltext/EJ850358.pdf

[26] J. Kluttz. "Teacher's Guide: Renewable Energy Module." The University of British Columbia. Accessed: Mar. 31, 2024. [Online]. Available: https://calp2016.sites.olt.ubc.ca/files/2019/01/Lesson-Plan-Renewable-Energy-RCS_CALP-UBC-1.pdf

[27] A. Black. "awb25-uwf/Towards-the-Generation-of-Learning-Objects-Using-Generative-Artificial-Intelligence." GitHub. Accessed: May 6, 2024. [Online]. Available: https://github.com/awb25-uwf/Towards-the-Generation-of-Learning-Objects-Using-Generative-Artificial-Intelligence