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A process model and evaluation for developing course materials for computing curriculum using AI

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Abstract

In this article, we present a process model for the creation of curricular artifacts by Subject Matter Experts (SME) in computing using Generative Pre-trained Transformers (GPT) based Artificial Intelligence (AI). We then test an SME-created artifact against one created by an SME with AI assistance within the process model's confines. A quantitative analysis of the two artifacts and their effectiveness at meeting Student Learning Outcomes showed that the artifact created by an SME with the help of AI was no better or worse than the more time-consuming method of the SME creating it alone. SMEs can make more customized, more appropriate, and effective curricular artifacts using AI that meet the needs of learners.

Keywords: artificial intelligence, course development models, IS education, IT education, computer-assisted education, learner-centered education

Introduction

Artificial intelligence (AI) has recently gained attention in business and general media. AI and machine learning algorithms and techniques have been available for many years; however, increased access to computational power, information, and resources has recently provided a platform for widespread generalized access to new interfaces. As new AI platforms are made available, developers can expose public interfaces that obfuscate the complexities of machine learning and allow for interaction from individuals without the requisite more profound knowledge required to execute machine learning algorithms. Generative Pre-trained Transformers (GPT) are one such platform that provides access to an AI platform that outputs text-based natural language for applications. With the GPT platform, OpenAI, a company dedicated to AI research, developed a chatbot application called ChatGPT that allows for natural language user interaction and generates text output from AI trained from general Internet data. Providing AI-augmented human language text responses to the public has generated some attention, and industry sectors are exploring new ways to use the previously unavailable technology without developing software or other advanced AI tools. Specifically, in higher education, some important questions have surfaced about how learners might use ChatGPT (Rudolph, 2023), and some educators are adjusting learner assessment strategies (Baidoo-Anu, 2023).

Among the attention of educators is a common concern from industries that AI applications like ChatGPT could become practical enough to replace workers who perform tasks that AI tools can also perform. Educators are experiencing similar concerns when learners can generate results for course assessment materials with readily available AI tools. As higher education teachers and subject matter experts (SMEs) in computing, we often ponder the philosophical question of the value of teaching skills like programming that today can be, at least in part, generated by an AI tool. Addressing such questions is beyond the scope of this article; however, the potential effectiveness of AI tools and their impact is relevant to how educators in higher learning approach the introduction of AI tools. ChatGPT is currently adequate at solving basic program writing in the computing discipline. However, asking ChatGPT to develop a customized Enterprise Resource Package (ERP) application for a business that could be compiled and deployed exceeds the purpose of the online tool. It highlights the continued need for human programmers. Recent research has found that these GPT platforms often produce inaccurate technical output (with high confidence in accuracy) when evaluated by a subject matter expert (Moehring, 2025). Thus, while domain experts can use the tool to refine and improve output, novice users cannot discern inaccurate output and would feel confident that the output is accurate. GPTs are conversational and refine output by providing natural language feedback, presumably correcting inaccuracies. In this regard, subject matter experts like higher education educators can play a valuable role in evaluating the accuracy of GPT outputs, refining inputs to feed back into AI tools, and producing more accurate future outputs.

In this article, we introduce a process model for using an AI tool to aid subject matter experts in generating course materials that support known curriculum taxonomies and frameworks. As of this paper's writing, we are unaware of an existing process model for utilizing AI in creating curricular artifacts. We acknowledge that the benefits of AI may only be relevant to some curricula and disciplines. To this end, we focused on creating content for a typical computing programming course. Programming courses use artifacts that help learners grasp programming in small discrete concepts. For example, in JavaScript, there is a particular way to create a for loop and how the loop works. An educator would look at existing materials and customize those or generate new artifacts from scratch to produce learning materials. We introduce a similar course content generation process that includes using an AI GPT tool to aid an educator and subject matter expert with some of the mundane and time-intensive tasks. This novel process takes advantage of the strengths of both roles; the educator provides oversight and refinement, ensuring the materials support curriculum produced with taxonomies and frameworks, while the AI contributes suggestions and content generation. We make the following contributions:

1. *Introduce a process model for developing course materials for computing courses using an AI tool to augment content creation for subject matter experts.*
2. *Provide results of a quantitative study supporting the hypothesis that generated material using the augmented AI process is as effective as traditional methods for achieving student learning outcomes in computing programming courses.*

Recent developments in AI tools like ChatGPT can help computing educators generate meaningful course content that supports student learning outcomes. A process that includes AI in course material generation may not always create more effective content; rather, by offloading work to AI, educators may have more capacity to improve, refine, or customize content through rapid iteration. Depending on the individual skills of the educator, it is also likely that using an AI tool could aid in the accuracy and speed of creating course artifacts that support the learning outcomes. An iterative process involving AI may generate some course material slower; however, educators avoid typing and proofing, enabling more time for revising and reviewing course materials. By offloading these tasks to AI in a collaborative process, subject matter experts and educators can focus on the customization and appropriateness of course materials that better meet the needs of the learners.

The scope of output that AI is capable of generating is limitless. However, evaluations of these models reveal potential issues within specific domains. In this article, we connect the output of AI to curriculum development models to limit the scope of evaluation and understand the capabilities it provides, particularly since, over time, we have come to understand the efficacy of artifacts created using curriculum development models. There is a difference between creating artifacts with AI using ad-hoc querying versus a structured process with AI feedback. A structured process provides the framework to ensure alignment with learning outcomes and enhances the consistency of output. Thus, in this article, we provide both a process model by which to approach the use of AI in the generation of these artifacts as well as an evaluation of its effectiveness.

Background

AI is rapidly gaining traction as new adoptees gravitate to the leading edge of the technology, employing its widespread capabilities in several areas. The diffusion of AI technology has converged Machine Learning (ML), Natural Language Processing (NLP), Computer Vision, Robotics, and Expert Systems in the hierarchy where the notion of its potential to advance humankind is plausible through continuous amelioration in this phase of its lifecycle (Rogers, 2005). In addition, AI's use in our future culture will likely extend its reach as a tool that will foster technological advancements, improve life experience, and create a more productive and fruitful existence. The following section will discuss the history of AI as it has progressed to the next stage of the industrial revolution in our civilization, where it may become a viable technology across information systems throughout our globe.

AI Use in Modern Technology and Systems

It is important to explore the role of artificial intelligence in education and, more specifically, in curriculum development. How the general population and industry use AI may highlight how it can impact productivity and satisfaction. Educators experience many different dimensions of influence from AI, but this paper explores AI as a viable platform for designing and developing curricula. AI was part of an initiative in the 1950s where developers wrote code to model human logic. The initial purpose was to attain funding and show the potential to advance computing platforms further. Throughout the decades, AI development has met many setbacks and unachieved goals, but as technology has advanced, AI has improved, and big data and performance have helped establish mainstream use for artificial intelligence (Anyoha, R., 2020).

As AI progressed over the years solving problems and incorporating a semblance of human intelligence, Sarker (2002) highlighted five categories of processing: Analytical AI used in patterns, In Functional AI which executes tasks, Interactive AI that communicates with another object, Textual AI which uses natural language processing, and Visual AI which recognizes and organizes images and other media. Sarker (2022) described three layers or processes of an AI platform contributing to AI systems. This processing includes Deep Learning (DL), Machine Learning (ML), and the overarching Artificial Intelligence (AI) integration into the human client.

Novel implementations of AI for task-based communications simulate human cognitive behaviors that demonstrate elements of the five categories of AI processing, as described by Sarker (2022). These implementations primarily use ML and DL processes. Each technology has unique characteristics and interleaves or is exchangeable as to the necessity of the AI objective. Machine Learning, typically used in predictive analytics and pattern analysis, is constructed from rules, procedures, and complex algorithms. Its robust learning techniques include supervised, which is task-driven, unsupervised data-driven, semi-supervised labeled and unlabeled, and reinforcement environment-driven approach. DL utilizes a neural network approach that builds on layered abstracts and learns much like its partner ML. In addition, Sarker mentioned the notion of "Smarter AI," which has adopted data-driven learning as an intelligent system. These advancements are now seen in business and industry, and we will explore some of them later. Novel

AI techniques substantiate AI as a viable tool for people to use in different domains, and its role in education and course development has been growing recently.

In protecting information and technology, Artificial Intelligence is used in various cyber security scenarios, where cyber predators forage crafty attacks using AI in conjunction with machine learning (ML) to penetrate the attack surface of their targets; however, the cyber defense positions also implement countermeasures anchored in AI to resist cyber predators (Sayegh, 2023). A common concern is that Generative AI will significantly assist the work of Cyber Security Analysts, where AI performs tedious investigations of large data sets, and the analyst would focus on other forms of cyber defensive work (Weigand, 2024). Strategic competitors, including China and Russia, are investing in AI technology to improve national security. Countries use autonomous machines, facial recognition, and intelligent systems in many applications. The United States Department of Defense has used similar technology since 2018, when the government established the Joint Artificial Intelligence Center (JAIC), and research and development budgets were over 130 billion dollars (U.S. GAO, 2023).

A report by Matheny et al. (2022) highlighted AI scientific advances in the healthcare field in several areas. From the perspective of saving and improving the quality of life, many health information systems use AI for patients' preventative, just-in-time, and assisted intervention (JITAI) and aiding family support. Preventative systems for diseases like diabetes use AI to monitor and make predictions from indicator data in glucose management systems. JITAI provides real-time results and intervenes based on analysis of event history. In addition, AI aids in communication using natural language processing (NLP) to bridge the communication gap for patients with communication complications, including cognitive disabilities. Clinicians use AI systems that combine information about patients' electronic health records (EHR), devices, and personalized social media to help deliver a more comprehensive data perspective (Matheny et al., 2022).

There are some early challenges with the increasing use of AI in improving bias, discrimination, and uncertain outcomes (The Princeton Review, 2024). The expected growth in this field is projected to be over $110 billion, and AI technology is expected to disrupt many areas, including decision-making roles. Therefore, it is important to consider future ethical concerns (Parsons, 2024). Countries like the United States, Europe, and China recognized the need to develop more regulations, policies, and governance in the growing AI industry (Ryan-Mosley, 2024).

AI is integrally involved in the functionality of products in industry domains like robotics and manufacturing. An example of AI integrated into products is the automobile industry. New vehicles showcase the latest and futuristic technology, and these advancements validate our progress in engineering practices. AI has significantly improved automobiles with engineering advancements in accident prevention systems and driver monitoring technology (Gonzalez, 2023). According to Gonzalez, AI infuses technology in integrating the driving characteristics of the vehicle and driver, in addition to NLP and ML communication between both entities, thereby integrating them from a cybernetic perspective (Wiener, 1969).

In retrospect, exploring the foundation of Artificial Intelligence, along with its core technology attributes of DL and ML, shaped the adoption of this technology into many segments throughout the industry. With this perspective, the future notion of importance is how integral AI becomes in industries as viable and functional components in each segment. As AI use increases in industry, so does its role in education and the processes necessary to assess learning outcomes. The following section will investigate instructional design methods incorporating an AI platform with the appropriate process modeling to achieve grounded results.

Educational Methods of Course and Instructional Design

With the convergence of AI into our modern world, academia has used AI for many purposes and tasks, including adaptive learning, assistive technology, data analytics, and professional development (University of San Diego, 2023). In the course design process, lesson plans and other content are commonly used to attempt successful student outcomes. Prior education research provides various tools and models for structured course design. A further dive into some models may broaden the construct of using these established and effective methods of course development coupled with AI capabilities with the hope of improving the learning experience for the students.

Based on the discipline, there may be different measures of how students learn particular subjects, where some subjects assess learning through experiences such as music instruction compared to a subject like reading education. Approaches in course development and lesson plans may be different and include considerations such as how people learn. From this perspective, various characteristics of learning theories also affect the overarching approach to course design. Hinchliffe (2020) identified several areas with complex elements of Behaviorism, Humanism, Cognitivism, Constructivism, and Social Constructivism as one dimension that adds complexity to designing courses. In addition, the author(s) cited works involving developmental stages that include andragogy, motivation, and growth mindset as factors that influence the context for course design. Another consideration in developing courses is creating course outcomes. Existing research explores six levels (Remembering, Understanding, Applying, Analyzing, Evaluating, and Creating) used to improve deriving course outcomes known as Bloom's Taxonomy (Bloom, 1956). Bloom's approach towards a structured learning process combined with lesson plans and course assessments is recognized by the Teaching Innovation and Pedagogical Support report (Teaching Innovation and Pedagogical Support, 2022).

There are other course and instructional design models that are used as well. The ADDIE model is a framework that uses a structure based on analysis, design, development, implementation, and evaluation (Kurt, 2018). The authors reference this work, developed in the 1950s by the Center of Educational Technology at Florida State University and built for United States Armed Forces learners. Another similar model used in designing courses for students is the Successive Approximation Model (SAM). This model is an alternative to ADDIE and covers three phases of design, including the preparation phase, iterative phase, and evaluation phase (Allen et al., 2012). A more strategic-based design model is Merrill's Principles of Instructions, based on five strategies to influence student learning outcomes (Merrill, 2002). Kurt extrapolated Merrill's work by describing the model as task-oriented and covering concepts and principles of the real world. Activation, the first strategy in Merrill's Principles of Instruction, engages previous knowledge relevant to what is being learned and then uses Demonstration by observing skills and concepts of what is taught. Following these strategies, Kurt highlights Merrill's next steps in the model Application and Integration. These strategies help learners apply their knowledge, integrate the learned skills, and embed them in their lives (Kurt, 2022). Another more traditional model for instructional design is the Dick and Carey Model of Systematic Design of Instructions (Dick, 1990). This 10-step model starts with analysis, establishing instructional goals, and identifying behaviors and learner characteristics. The following design phase of the model involves implementing the creation of performance objectives, developing the assessment instruments, and constructing the instructional strategy. The final phase is selecting instructional materials, designing the methodology, and conducting a summative evaluation (Dick, 1990).

The Kemp Design Model was designed for flexibility and adaptiveness to accommodate a broad spectrum of learners with varying needs for instructional methods. This model has a nine-step approach, which consists of: 1. Identifying the instructional problems. 2. Identifying the learners and mapping their characteristics. 3. Define the learning content and tasks. 4. Specify the SMART (Specific, Measurable, Attainable, Relevant, Time-bound) objectives for instruction. 5. Construct the logical association of the content to the learning outcomes. 6. Identify the strategies and method process. 7. Define the delivery and messaging. 8. Create the delivery mechanism. 9. Establish a summative evaluation and assessment (Morrison et al., 2013). Another design technique used in educational course construction is Scaffolding, where the guidance from the teacher dissipates as the student progresses to competency, allowing for a more self-regulated learner (University at Buffalo, 2025). As outlined by the University at Buffalo, the Scaffolding design strategies of the course design process include four categories: Unit and Lesson Planning, Instructional Practices, Monitoring Learning, and Learning Activities.

In contrast to many models, another technique used in course design is "Flipping the classroom," where the traditional lecture becomes secondary to assignment-based learning (Brame, 2013). Brame highlights similar course design disruptors, including the Inverted Classroom and Peer Instruction. Berrett (2012) observed how this method or course design improves the traditional design methodology by reaching students with different learning characteristics. Other models involve embracing a psychological perspective. The Backward Design/Understanding by Design (UbD) model provides a three-phase approach to identifying desired results, determining assessment evidence, and planning learning experiences and instruction (Burnham, 2021).

We base this research on the two-prong converging paths of AI and course design. Combining these domains by utilizing AI to select the best design attributes and creating customized design course structures for the student learners could advance the course design practice. Furthermore, this research presents a dynamic design process that uses a systematic course design method explicitly tailored to the student's needs and course material for the computing sciences. With this perspective, the following section examines the composition of structured processes to assist in the course design process, incorporating Artificial Intelligence as its core. This additional process would be another tool used to improve and further transform our existence through the embracement of "machines" (Weizenbaum, 1976).

AI Use in Education

Recently, the educational community has garnered interest in how AI disrupts education. In a survey article, Lo (2023) illustrates the depth of research published about AI's impact on education, such as answering questions, generating course materials/assessments, providing advice, facilitating collaboration, providing feedback, and preventing plagiarism. Most related to this research is background related to using AI to develop and generate course materials. Researchers found that within many fields, including science, AI can potentially help improve student performance by generating practice materials, summaries, and explanations and providing instructors with the ability to provide personalized learning materials (Kasneci, 2023). In their work, Topsakal used AI to generate dialogue and teach children a foreign language (Topsakal, 2022). Their framework provided an integration of ChatGPT to produce dialogs for instruction in the educational subdomain of foreign language learning. In hospitality and tourism, research suggests that AI could aid students in learning customer service skills by generating artificial simulations in a controlled environment (Ali, 2023). AI was also successfully used in reading comprehension to generate end-to-end quizzes for assessment (Dijkstra, 2022). Computing research has evaluated AI as being "outstanding" at accurately answering questions related to programming and yet unable to pass a software engineering course (Lo, 2023).

Many researchers are exploring the idea of generating curricular materials using AI within the literature. Current exploration is ad hoc, and the role and existence of a subject matter expert (SME) needs to be clarified. Similarly, the process of generating material using AI is unclear. This research aims to add to the current body of knowledge by introducing a process model that clarifies the SMEs' role and their relation to AI. Additionally, we seek to evaluate if such a process model can generate effective materials that address course SLOs faster and more flexibly.

A Process Model

Currently, we are not aware of a process model for using AI to augment the creation of course materials to deliver computing curriculum. In this section, we propose a process that uses AI for course development that supports existing curriculum development frameworks and taxonomies. Curricula developed within these existing frameworks and taxonomies serve as input for this process. While the natural feedback from experience using course materials fits in some frameworks or taxonomies, this process focuses only on the essential component of course material generation. Future work may explore other ways to use AI for curriculum development. However, this article does not address the curriculum improvement process.

Proper curriculum development is usually guided by frameworks like Understanding by Design and/or taxonomies such as Bloom's Taxonomy (Bloom, 1956). These techniques are widely accepted as guides to creating or improving curriculum and allow designers to implement courses that deliver the curriculum to learners. Course materials such as assignments and rubrics provide feedback on if and to what extent the course achieves learning goal(s). This standard iterative curriculum development process depends on good instruments and competent educators who continuously improve and refine course instruments. Pedagogical research provides a mechanism to share best practices and highlight curriculum successes and practical course material. The purpose of the process we present in no way intends to change the value of existing components that improve the learning process in computing education but incorporates a valuable tool within the existing ecosystem with the hypothesis that SMEs can generate effective course materials using an improved process with some added benefit.

In general, output from curriculum development takes shape in various forms. Educators commonly use student learning outcomes (SLOs) derived from program development to describe curriculum goals. SMEs use the curriculum development process to provide information on various course materials. When using AI, an SLO can be used to guide the creation of different forms of materials needed for a course. For example, to accomplish an SLO related to learners being able to write a programming "for" loop, the SME may generate a video describing and showing a debugger iterating through the loop. Course materials related to the topic might include an assignment where learners create a simple program for submission, a rubric to evaluate that assignment, and a quiz or exam question to assess if the learner remembered the programming concept. This section provides a detailed description of a process that describes how an SME can use an AI tool to speed up or better refine creating course materials that support the chosen SLOs.

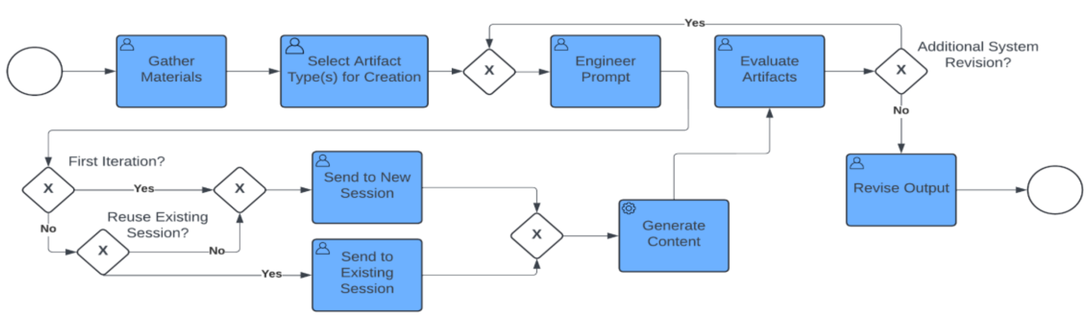

Figure 1. The process model for Subject Matter Experts to utilize AI in the development of curricular artifacts.

Figure 1 illustrates the process model we created for developing curricular artifacts by SMEs utilizing AI. In constructing our process model, we used 7PMG to validate against guidelines to ensure our process model was both understandable and reduced the probability of errors. While 7PMG uses event-driven process chains, it is still adaptable to other modeling notations. When considering 7PMG, our model addresses all relevant suggested guidelines:

- **G1.** Our model uses as few elements as possible, which increases its understandability and reduces the chances of errors.
- **G2.** We have minimized the routing paths per element to the minimum possible while maintaining the behavior of the stated process.
- **G3.** Our process model contains a single start and end event.
- **G4.** Our model is well structured.
- **G5.** We avoided using OR routing altogether. XOR gateway routing is the only routing we use.
- **G6.** All activity labels are verb-object, making the process model less ambiguous.
- **G7.** The model has less than 50 elements and so needs no further decomposition.

Our process model contains several *User [U]* and *System [S]* tasks that are necessary to support the creation of the curricular artifacts:

- *Gather Materials [U]* - The SME must gather materials relevant to creating artifacts. A commonly expected activity related to the SLO is the SME looking to create artifacts from a curriculum development process. Whether SMEs use existing course materials or materials previously used by others, the same process can provide either more verbose or improved variations of those artifacts.
- *Select Artifact Type(s) for Creation [U]* - The SME creates specific artifacts as part of the process. They derive the artifacts using goals, modality, and taxonomies.
- *Engineer Prompt [U]* - The SME must engineer a prompt to provide the Generate Content system process in the future. The prompt must include the desired materials and artifact types that have not been previously provided or now need additional revision.
- *Send to New Session [U]* - The SME directs the prompt to a new session. The engineered prompt provides the only context for the GPT. This prompt is useful if approaching the process for the first iteration or if prior iterations were unsuccessful in capturing the SME's new context.
- *Send to Existing Session [U]* - The SME directs the engineered prompt to an existing session considering the previous contexts in addition to the engineered prompt.
- *Generate Content [S]* - The GPT system task generates content. This process saves the SME the mundane and sometimes arduous work of manually generating course material from scratch.
- *Evaluate Artifacts [U]* - The SME must validate the artifacts, checking them against the input provided and the SME's goals. The SME's evaluation is necessary to ensure the AI output is accurate and appropriate for supporting the SLO. In cases where the output needs refinement, the SME either manually refines and includes the material or asks the AI tool to refine or modify aspects of the previously generated output. SMEs judge the effectiveness and usefulness of the tool's output.
- *Revise Output [U]* - The SME must make any final manual alterations to the generated artifact. Depending on the state of the generated content and satisfaction of the SMEs' desired outcome, this task may result in no changes or extensive changes.

Several possible routes are available in our process model, but all use XOR gateways. As a result, a single flow is possible at any time, and flow through the process model is unambiguous from one of two possible tasks. Alternatively, it flows from one task to two possible tasks depending on the notated logic in the process. One of the critical gateways asks SMEs to determine whether "Additional System Revision?" is necessary. The following sections highlight typical but non-exhaustive reasons SMEs would refine AI-generated output:

Inaccurate Output

AI tools can generate incorrect materials. The AI can only be as good as the training data combined with the "learned" feedback from interaction. Even with the recent developments, AI tools are trained from open data found on the Internet, which has no formal mechanism for accuracy validation. In addition, the interaction feedback used in the AI "learning" process has no suitable mechanism for judging validity. The benefit of the recent development in AI tools is the abstraction of complex machine learning from the end user. However, the best place to determine content validity is when the AI tool generates the output because the user was not involved in the training process, feature set design, and predictive validation.

In most cases with novel interfaces, the AI does not report prediction confidence metrics, leaving the end user to accept the output provided by the AI. Without additional expertise, the user of these novel AI tools has no background to validate the tool's output. In many cases, SMEs can quickly validate the output, and when the AI tool receives corrective feedback from SMEs, the underlying predictive power of the AI is presumably improved. The process model has SMEs Evaluate Artifacts and provides a gateway where the SME can continue this corrective action cycle until accurate output is obtained or accepted for manual refinement with Revise Output. The process provides a gateway to reuse an existing session in all but the initial cycle.

Mismatched Output

Stakeholders gather, record, review, and approve system requirements in software development. Similarly, the process model requires SMEs to Gather Materials. However, traditional problems occur when these documented requirements are sent to developers and returned with software that meets the requirements but does not match the expected result. This scenario has contributed to software development models like Agile to help reduce the frequency of unexpected results. AI tools may produce a similar result that may technically be accurate but does not match the expectation of the SME. In this case, the SME would attempt to use the AI tool to revise output until it matches expectations or it becomes necessary to adjust manually.

Incomplete Output

Incomplete output is a possible result of AI output. The result may be accurate in the content provided and even match the SME's expectations, but it may still not be complete. For pedagogical course materials, this can happen when a request has layers of functional dependencies. However, the AI can only provide a single layer because its trained purpose is more general. For example, with simple multiplication, a knowledge dependency would be understanding addition. Addition requires knowledge of number systems, and the dependencies may continue for many layers. SLOs often contain these knowledge prerequisite graphs, and it is necessary to generate course materials that support the end objective and provide background on some necessary prerequisite content. SMEs would need to precisely direct AI tools to include supporting knowledge content in the output through the Engineer Prompt step. The possibility also exists where an AI tool may not be able to accommodate this problem, and the SME would need to refine the output in the Revise Output step manually.

Failure to Produce Output

Novel generalized AI tools like ChatGPT highlight the ability to process natural language input flexibly. Language processing seems adequate and should improve, but it may still need to be able to process poorly articulated user input. If an SME observes that the AI tool cannot produce output or it appears irrelevant, the input may need to be updated or changed. Again, some queries for content generation may be beyond the capability of the AI, and the SME would need to refine or generate the material manually. This situation would reduce any benefits associated with using an AI tool.

Customization of Output

The AI tool output may be correct and complete but must be customized to the SMEs individual goals or the learning environment. For example, an SME wants to include a custom dimension on a rubric or create an assignment in a specific programming language or multiple languages for demonstration. Another reason for customizing assignments is to include locally relevant domain content. If the learning location is close to banking, the assignment could be customized to include a part associated with computing problems specific to that industry. The SME can instruct the AI tool to customize prior output for another iteration and provide new output for review.

The decision to stop the AI tool from refining output is a multifactored decision by the SME. The process recommendation allows the tool to create the best output possible, but the SME decides based on their preferences and design constraints. At some point, the iterations of AI-generated output may only include small or insignificant improvements. The number of iterations needed for individual SMEs will naturally balance with experience. First-time content may include unnecessary iterations for an SME. However, with time and use, the same cooperative work can be created with a more comfortable number of iterations, and the utility of the AI tool will be maximized.

Using AI tools to aid in course content generation does not imply that the output materials or individual artifacts are more effective at supporting SLOs. The AI tool only provides output as suggestions, and the output's quality may or may not be helpful to the SME. However, using AI tools requires little or no prerequisite learning for the SME, and the content is generated almost immediately in most cases. If the SME incorporates only some content using the process, AI can help. The SME is an essential decision-maker in the process we describe, and the effectiveness of the output is at the discretion of the SME. Regardless of whether the SME uses AI to help create course material, the effectiveness of materials and how they support the learning outcomes remains part of a more extensive process left to educators and explicitly not offloaded to AI.

As the SME determines that the AI output is adequate, the process includes a final step of manual refinement. The expectation is that the effort needed for the manual adjustments can be minimal, allowing the SME to spend more time evaluating suitable materials and significantly less time on composition. A peripheral interaction of generating course material using an AI tool encouraged the authors to believe that the process could save considerable time and energy on tasks like composition and proofing, leaving more time to improve materials. With the tools only recently being made readily available and easy to use, the extent of any benefit - time or otherwise - is part of future evaluation. The following section provides an example evaluation of using the process to generate course material for an intermediate computer programming course.

Methodology

We designed a survey as an instrument to compare the course materials developed using the process model with the original course material that was known to support the course's SLOs. The survey was designed to be given to SMEs in the computing discipline who would understand programming course objectives and have the experience to evaluate the effectiveness of course materials.

The survey started by displaying an SLO and then showing a group of course artifacts from the original course material. The respondent would evaluate the effectiveness of the artifact in supporting the SLO on a Likert scale of one to seven, with one being "Not at all effective" and seven being "Very effective." Next, the respondent evaluated similar course artifacts associated with the same SLO created using the process model. For each respondent, we randomized the order of the original course material and the process model course materials preventing order biasing. The hypothesis for the method was:

> **H0:** There is no difference in the effectiveness of supporting the SLO in the traditionally generated materials vs the material generated when assisted by an AI tool.
> **H1:** There is a difference in the effectiveness of supporting the SLO for the traditionally generated material vs the material generated when assisted by an AI tool.

We randomized the condition order of the question sets to the respondents to avoid any ordering or learning effects. The study was a within-subjects design, and the survey was distributed to computing faculty at multiple universities in the United States via unsolicited email approved by our home universities IRB. Response rates on surveys are traditionally very low. Given the small number of computing faculty, our sample size is expectedly on the smaller end. A total of 12 computing faculty members fully completed the survey.

Results/Discussion

We tested the effectiveness of three different pieces of material: the assignment, rubric, and discussion question. The non-parametric ranked data was analyzed using a series of three Wilcoxon Signed-Rank Tests with the significance criteria set at p=.01667. We chose this p-value using a standard Bonferroni adjustment that accounts for the fact that we ran three Wilcoxon Signed-Rank Tests and desired our overall test to have a p=.05. We found that the effectiveness of the assignment created with a traditional process (m=3.33, sd=1.15) and the effectiveness of the assignment created with the assistance of an AI tool (m=3.66, sd=.88) was not significantly different (Z=0.726273, p=.467671). Similarly, we found that the effectiveness of the rubric created with a traditional process (m=3.16, sd=.93) and the effectiveness of the rubric created with the assistance of an AI tool (m=3.5, sd=1) was not significantly different (Z=.973329, p=.330390). Furthermore, we found that the effectiveness of the discussion question created with a traditional process (m=3.08, sd=.90) and the effectiveness of the discussion question created with the assistance of an AI tool (m=3.91, sd=.51) was also not significantly different (Z=2.341197, p=.019222). Overall, all results indicated we failed to reject H0, indicating no significant difference between the traditionally generated course materials and course materials created with an AI tool.

We take a neutral stance in scientific studies to see where the data leads us. One of four possibilities were likely to have emerged from our evaluation of the process model: 1) The AI-assisted materials were more effective than the SME materials at addressing student learning outcomes. This finding might have provided evidence that we need to adopt AI or are doing our learners a disservice without using AI. 2) AI-assisted materials were less effective than SME materials in addressing SLOs. This finding might have cast doubt on the ability to use AI for curricular material generation, at least when using our process model/current technology. This result could indicate that using AI for curriculum development may not address SLOs. 3) The evaluation results were mixed. This finding provides a basis for careful future inquiry into understanding the facets of mixed effectiveness and perhaps adds to the debate around the usefulness of AI in curriculum design. Finally, 4) AI-assisted and SME materials were no more or less effective in addressing the SLOs. We consider this a positive finding from the survey results in this paper, which indicates that SMEs remain effective in addressing SLOs for learners. The benefit of AI use and our process model for curriculum design may not be more effective teaching materials. However, it may improve the speed of creating compelling and customized course materials. We find that SME input and oversight in the process model strengthens the SME role in generating effective curriculum materials to address SLOs.

Artificial intelligence, or machine learning in this case, is a tool anyone can use to help accomplish a task or problem. A woodworker uses a random orbital sander that randomly oscillates to create beautiful pieces of woodwork. The sander can only create smooth contouring surfaces if operated by a skilled person. A novice using the same sander can operate the tool and remove rough surfaces from wood, but the skilled operator can create a more accurate and better outcome expertly. Similarly, higher learning educators can use AI tools to help create high-quality course materials. SMEs in higher education have skills sufficient to evaluate AI output for course materials. We consider the potential benefits of using AI tools to perform tasks like material composition and proofing, allowing SMEs to focus on quality and appropriateness.

In this article, we focus on an intermediate programming course in the computer science curriculum. It is unlikely that AI tools would be suitable for every course across the computing curriculum. The course materials we generated with the process model in our evaluation were as effective as those generated without the assistance of AI. We did not evaluate the process's capabilities in any other domain. Future work would be needed to determine if the process would be effective or beneficial in other domains or areas that generate learning materials.

The process model presented in this article was compatible with existing education taxonomies and frameworks. Curriculum designers can use development guides like Bloom's Taxonomy, Integrated Course Design, or Backward Course Design. SMEs who engage with learners can use the proposed process model to help with learning materials if the designer determines the process is helpful for their context. We consider the process model to help SMEs focus on improving course materials. AI tools are well situated to help create materials in a short amount of time, and SMEs are capable of quickly evaluating and refining the output. For example, the process can produce specific types of material and quickly modify content parameters like tone, theme, verbosity, content, difficulty, goal, and evaluation. AI tools can adjust programming assignment components like starter code or example invocations and remove unnecessary or superficial elements.

If the process model improves efficiency in creating course material, designers could create customized materials for individual learners and improve the education process. For example, a learner completes an assignment but still needs clarification on the assignment's concepts. The learner could ask for similar assignments to better learn the concepts. This pattern of individual attention can stretch the instructor's time and focus. The instructor can use an AI tool to quickly create alternate assignments, assess the assignment's accuracy and appropriateness, and deliver it to the student. High-achieving learners may ask for examples with increasing complexity. Incorporating an AI tool in the process of creating course material has the potential to quickly create course materials that adapt to a wide variety of situations and provide individualized instruction.

Ethical Considerations

Recently, we have observed some concern and controversy about the role of AI tools like ChatGPT in higher education. We approached novel AI tools from a different perspective, exploring ways they could help educators create content for higher education. This perspective is not meant to ignore the other valid concerns about the power of AI to disrupt the learning process. Additionally, we have not directly addressed how current and future AI tools may affect the job of educators in higher learning institutes.

Currently, the output of these tools is impressive, but they still need to gain the capability of self-refinement needed to judge artifact quality. However, if AI tools can help create adequate learning materials, those same tools are likely capable of creating solutions for the course materials. We are aware of the ethical consideration of the example inherent in using an AI tool to create a learning artifact and then restricting the learner from using an AI tool to help with the solution. This ethical conundrum and other ethical considerations are multifaceted and acknowledged as genuine concerns. We present the process model and continue to encourage the education community to debate ethical considerations of AI's influence.

Conclusion

Novel AI tools like ChatGPT have recently generated widespread media attention, leading to concern about the role of AI in higher learning. In this article, we looked at using AI as a tool to help with creating course materials. We created an iterative process model, using an AI tool for content composition and collaboration with an SME to refine and validate output. We evaluated the process model using an intermediate computer science programming course to generate new/alternative learning materials that supported one of the course SLOs. We surveyed computing faculty at several universities in the US to provide evidence of some effectiveness of learning artifacts created with this process compared with original course material to support the SLO. Results indicated no difference in the effectiveness of the traditionally generated material and the material generated with the assistance of an AI tool. This work provides the following stated contributions:

1. *A process model for including AI tools to aid subject matter experts in creating course material.*
2. *An evaluation comparing the effectiveness of output materials from the process with AI and the original course materials in supporting a course learning outcome.*

The future role of AI tools is uncertain, and the full impact of AI on higher education is still in progress. The discussion of AI impact will likely continue until the effects are known and we have experienced mitigating challenges. Our process model embraces AI tools to help in doing what AI is good at - composing and proofing information compiled and analyzing from large data sets. We demonstrate the current need for domain experts to evaluate and validate the output from AI tools and expect that need to exist for some time. We consider the role of experts in higher education as complementary to AI tools and necessary for effective course instruction.

Future Work

This research motivates future directions for using AI in the education space. We need to explore how AI tools might affect the larger area of education curriculum development frameworks and taxonomies. Through readily available and simplistic interfaces, AI will improve and grow. There are several additional research questions around using AI tools to improve SLOs or analysis of applications to current education taxonomies and frameworks. Can an AI tool be given a framework with knowledge goals and produce learning outcomes and course objectives? Would it be possible for AI to combine multiple frameworks to suggest others and perhaps be involved in the extensive scope of curriculum development? Future work can observe how this interaction could work and if the results are helpful. We also focused on using AI only in the computing domain. It is unclear how effective AI tools would be in creating materials for other disciplines. Future work in other disciplines can provide insight and evidence on the effectiveness of using AI as a tool to help in the education process. We encourage those in the computing and other education disciplines to explore these questions to build on existing research.

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