

Exploring the Practical Application of the GenAI Intent and Orientation Model in Instructional Design

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The integration of Generative Artificial Intelligence (GenAI) into higher education is transforming the field of instructional design. It offers exciting opportunities to enhance teaching and learning, while also presenting unique challenges. Instructional designers (IDs) can play a pivotal role in navigating these changes, leveraging GenAI tools to streamline course development, foster personalized learning, and promote active engagement. Building on the recently-introduced GenAI Intent and Orientation Model, this article explores the implications of this foundational framework for IDs and instructors. Through illustrative scenarios, the article examines current and future practical applications of GenAI for instructors and IDs, such as creating course materials, enhancing learner support, and enabling reflective practices, according to the quadrants of this model. The discussion concludes with key implications for IDs, and strategies for overcoming challenges and fostering effective collaboration between IDs, instructors, and GenAI.

Introduction

The rise of Generative Artificial Intelligence (GenAI) is rapidly transforming the educational landscape, creating new opportunities while posing unique challenges for institutions, educators, instructional designers (IDs), and students. GenAI, powered by large language models (LLMs) and advanced algorithms, has redefined how content is created, enabling the generation of text, images, audio, and even code with remarkable precision. These technological advancements have begun reshaping higher education, compelling educators and IDs to rethink traditional teaching, learning, and assessment practices (Hodges & Kirschner, 2023).

Amid the shifting paradigm that GenAI has created, IDs stand at the forefront of this transformation (Kumar et al., 2024). Tasked with designing effective learning experiences, IDs have a critical role in integrating GenAI into educational environments. They must navigate the fine line between leveraging GenAI for efficiency and ensuring the preservation of academic integrity and pedagogical rigor.

To date, much of the discussion around GenAI in education has been tool-focused or conceptual, without fully diving into how these technologies integrate into the collaborative workflows between IDs and faculty. This article addresses that gap by introducing a model that aligns with real-world instructional design processes and decision-making. Utilizing the GenAI Intent and Orientation Model, we aim to provide a framework for understanding and harnessing the potential of GenAI to support and improve teaching and learning outcomes from the perspective of the ID.

Background

The emergence of Generative Artificial Intelligence (GenAI) marks one of the most transformative technological advancements in recent years, having profound implications for higher education. GenAI, a subset of artificial intelligence, refers to systems that can generate content in various formats such as text, images, code, and audio in response to user prompts (Peres et al., 2023). It operates on large language models (e.g. currently ChatGPT uses GPT 4o, Claude currently uses multiple versions of Claude3), which are advanced artificial intelligence systems trained on vast amounts of text data to produce outputs that mimic human responses. In barely two years since its public introduction in November 2022, GenAI technology has taken a huge leap forward thanks to advancements in the technology and availability of massive data sets.

However, the impact of GenAI has wide-ranging implications that are still being realized. It has already proven to be a transformative force, introducing both opportunities and challenges in higher education (Kumar et al., 2024).

The Educause Horizon Report (2023, 2024) identified GenAI as a technology that can have a significant impact on teaching and learning as it can open up opportunities for students to focus more on higher-order thinking such as analysis and evaluation of information. However, there are concerns related to overreliance on the technology which could stifle motivation for some students to develop their skills (Warschauer et al., 2023) and other concerns over algorithmic biases and inaccuracies (Lubowitz, 2023), academic integrity, and student data privacy (Ha et al., 2023). On the other hand, some believe that GenAI will usher in new ways of thinking and doing, thus requiring new skills to be developed (Eke, 2023).

The current state of university adoption of Generative AI (GenAI) shows a landscape of active engagement, experimentation, and strategic planning for future integration across various domains. In 2023, the Russell Group collaborated with educational experts to create a set of principles on the use of GenAI, which has been adopted by many institutions (Russell Group, 2024). The principles focus on building AI literacy, supporting students, ensuring academic rigor and integrity are preserved, adapting teaching and assessment, and working collaboratively to share best practices.

Other efforts by Institutions seek to incorporate GenAI tools safely and securely. For example, Arizona State collaborated with OpenAI to bring the ChatGPT Enterprise platform to the school while addressing issues of privacy and security (Davis, 2024). Other institutions such as Michigan State (Lessnau, 2023) and the University of California, San Diego (Baytas, 2023), developed their own GenAI tools hosted in their IT infrastructure. In these instances, institutions proactively sought innovative solutions for student access to GenAI by integrating safer and more private GenAI, emphasizing equity, accessibility, privacy, and in-house support. While institutions think through administrative policy on GenAI, it is not too early to explore the pedagogical implications as many higher education institutions already have.

Generative AI in Instructional Design

GenAI promises to reshape the workplace and the nature of work in general (Melina, et al., 2024), and the role of the Instructional Designer (ID) is not exempt. There is a significant overlap between the strengths of GenAI and the tasks an ID may perform in their typical day's work (Choi et al., 2024). Examples of this include, but are not limited to: creating a topical outline of a course; creating and aligning the foundational elements of a course such as learning objectives, assessments, and learning materials; and creating scripts for multimedia materials. Given typical market considerations and ever-increasing demand for productivity, IDs have a practical and professional obligation to engage with GenAI to support and improve their own practice, lest they be left well behind the curve of progress.

IDs in higher education often collaborate with faculty subject matter experts (SMEs) in designing or redesigning courses, developing instructional materials, aligning instructional strategies with learning outcomes, integrating technology tools, and ensuring accessibility and quality standards (Kenny et al., 2005; Kumar & Ritzhaupt, 2017). This requires not only a solid understanding of learning theory and pedagogy across different modalities, but also an understanding of the technologies that can support various teaching strategies. Studies including Richardson et al. (2019) and Olesova & Campbell (2019) have emphasized the critical role IDs play in fostering productive partnerships with faculty and promoting good teaching and learning outcomes across a variety of delivery modalities.

Across the various pedagogical approaches, while there is not always agreement as to what constitutes active learning, there is clear evidence that promoting active learning opportunities wherever possible is desirable (Prince, 2004). At the root of this is learner interaction - with the instructor, with each other, and with the content (Xiao, 2017).

The GenAI Intent and Orientation Model originated from this desire to promote all of these types of effective interaction, with the GenAI agent serving in multiple contexts. GenAI can serve a variety of purposes in an instructional situation - it can factor in as a learner's informed peer, a stand-in for their instructor, an assignment delivery vessel, or even a part of the learner's submitted product for an assignment. This model aims to classify these use cases and hopefully serve as a foundation for the development of entirely new uses which may not even be possible yet.

No pre-existing model fully overlaps with the GenAI Intent and Orientation Model. Design frameworks such as ADDIE (Branson et al., 1975) and Backward Design (Wiggins & McTighe, 2005) do not specifically address technology integration. Frameworks such as TPACK (Mishra & Koehler, 2006) and SAMR (Puentedura, 2006) focus on technology integration and pedagogical transformation without explicitly addressing the dynamics of interacting participants' intent.

New technological innovations have a strong history of disrupting the accepted and comfortable flow of teaching particular subjects. In the 1970s, the introduction of the handheld calculator seemed to portend the death of traditional mathematics education. Yet it did not (Demana & Waits, 2000). Beginning in the 1990s, the internet democratized access to information, transforming education by making vast amounts of knowledge readily available to anyone with an internet connection. GenAI, on the other hand, builds upon internet technology by enabling interactive and personalized learning experiences. It can generate content, tutor students, and create personalized learning experiences that were once thought impossible to achieve

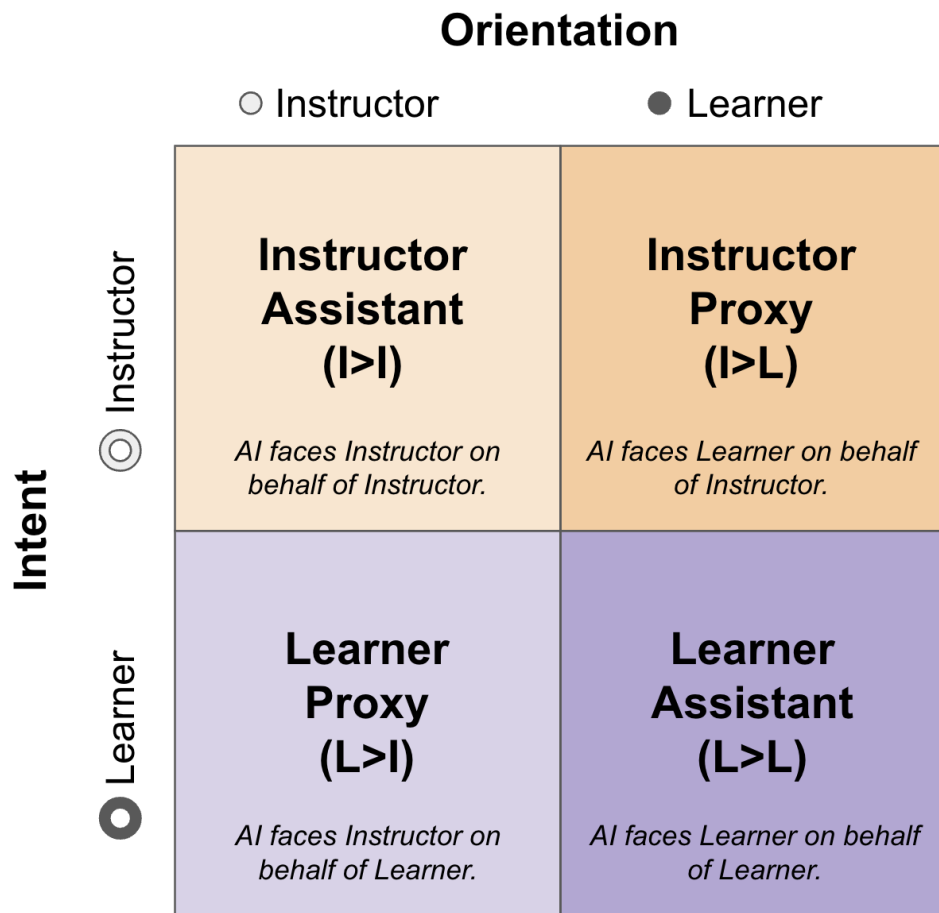
at scale. These uses can be better understood, classified, and conceived by considering the GenAI Intent and Orientation Model.

The GenAI Intent and Orientation Model

Introduced in mid-2024, the GenAI Intent and Orientation Model (Pike et al., 2024) explores GenAI's potential uses within the instructor-student relationship. It endeavors to accomplish this by considering the purpose ("intent") of the originating actor in using GenAI, as well as the person on the receiving end of the GenAI product to whom it is oriented. In doing so, this model provides a conceptual scaffold that accounts for both the originator's purpose and the audience's need, which was previously missing.

Figure 1

GenAI Intent and Orientation Model



Perhaps what could be considered the most "typical" uses of GenAI are those in which the tool serves the intent of the original actor, and its output is also oriented toward that person. Two quadrants in the Intent and Orientation Model describe this - the I>I "Instructor Assistant" quadrant, and the L>L "Learner Assistant" quadrant. The majority of use cases will fall into these categories. The instructor using GenAI to create measurable learning objectives or lesson plans, or the learner using GenAI to

formulate an outline of an essay or generate basic code to perform an operation - all of these circumstances have GenAI serving the needs of the original actor.

But what about the potential for a GenAI product to originate with one actor, but serve the purposes of another? This is where the other two quadrants of the Intent and Orientation Model enter the conversation. As time progresses and these technologies evolve, these types of interactions present what may be even more exciting and innovative opportunities.

We will begin by identifying each of the four quadrants and will shift to mapping typical ID tasks to the model itself. However, it is appropriate to first mention the obvious: designing and developing a course is inherently an Instructor/ID-oriented activity, at least in terms of the intent being served by GenAI. Therefore, we will primarily focus our mapping exercise on the two quadrants of the model that originate with the Instructor. But since we are giving short shrift to the Learner Intent quadrants in this way, we will revisit them in the Implications and Conclusions sections below.

Instructor Intent, Instructor Orientation (I>I)

This quadrant, for the ID or instructor, could come into play across any of the steps of any instructional design model. In this realm, the instructor and/or ID building the course engages a GenAI platform to accomplish some of the typical work involved in building a high quality course. It is as simple as this: the user has a need, and for whatever reason decides to engage with a GenAI tool to aid in accomplishing a particular task on their own behalf.

The ID, in this circumstance, is entrusted with a certain level of knowledge and capability. Though they are not tasked with teaching the course, they are assumed to be familiar with the opportunities and constraints associated with teaching the course. However, given their likely lack of nuanced knowledge in a particular SME's discipline, an ID will still need to closely engage with an instructor in order to create course content that satisfies all needs, including level-appropriate learning objectives, level-appropriate language and terminology, and content that matches the stringent requirements of a particular academic or professional program. So for the purposes of this work, the ID is considered an extension of the Instructor.

Learner Intent, Learner Orientation (L>L)

This quadrant includes some of the most fruitful potential interactions between human and machine, but also the most disruptive and concerning use cases as well. In this circumstance, the learner has a need that they have determined to be crucial enough to engage with a GenAI tool and, regardless of the constraints set by the instructor, the learner uses a tool that may move them forward on their learning journey, or may serve as an "easy way out" that keeps them from learning key foundational concepts.

However, the appropriateness of the use cases in this quadrant may depend upon the activity and the instructor. After all, if certain learning activities are foundational and may require learners to constructively struggle with particular concepts, then there is likely to be a dividing line between foundational learning activities and the potentially GenAI-enhanced activities that may follow and build upon them. Put more simply: the instructors need to help learners understand the "why" behind critical concepts before they allow them to engage with GenAI to further expand their own capabilities. This underscores the importance of clear communication of expectations, perhaps even at the assignment level (Bowen & Watson, 2024), around GenAI between instructor and learner, but that is a topic for another article!

Instructor Intent, Learner Orientation (I>L)

Now we shift to a new realm, in which the person who initially engages with GenAI is seeking to serve someone else's needs rather than their own. In this quadrant, the instructor creates materials, including but not limited to sophisticated prompts and custom GPTs, that are intended to serve the learner's needs in a given situation. The GenAI tool serves as an "Instructor Proxy" at the learner's moment of need. This brings exciting potential for addressing vexing instructional problems.

Beyond serving both the instructor's and the students' teaching and learning purposes, integrating GenAI-based activities into coursework moves us toward the topic of promoting students' GenAI literacy. As research increasingly highlights the importance of preparing students for a workforce where they will work alongside GenAI, building students' GenAI literacy has become a crucial component of course design (Chiu, 2024). So this I>L quadrant describes an important step not only toward promoting students' content knowledge toward their degree, but toward the necessary skills they will need to succeed after graduation.

Learner Intent, Instructor Orientation (L>I)

The final quadrant provides fertile ground for thinking about the implications of tools and pedagogies yet to come. In this quadrant, the learner is the one engaging initially with the GenAI tool, but the artifact they create is oriented toward the instructor. The GenAI Intent and Orientation Model labels this quadrant "Learner Proxy," so it is most fruitful to consider the question "how might a student engage with GenAI in order to inform or improve their instructor's teaching?" In other words, in L>I scenarios, the student uses GenAI to produce something - data, a report, or perhaps an individualized learning plan - that the instructor then uses to improve teaching decisions or provide tailored feedback. This quadrant positions the learner as an indirect but intentional contributor to instructional insight.

Though this may require broadening the definition of "intent" on the learner's side, the simplest way to view this quadrant, for now, is the known and familiar concept of learning analytics. When a student engages with course content in a digital environment, such as a Learning Management System (LMS), the LMS typically collects a considerable amount of data. Page views, clicks, time spent viewing a specific page, and other data combine with assessment performance data to paint a detailed portrait of a learner's experience with and progression through a course (Macfadyen & Dawson, 2010). These learning analytics data can be crucial tools for evaluating and improving courses, but this trove of data is not always contained or expressed in a way that can easily be applied by the instructor.

Plug learning analytic data into a GenAI system trained to sift through data and provide specific actionable insights, though, and an instructor can quickly recognize and remediate areas of concern, whether at the individual student level or the broader course level. Data experts may exist that can provide this service already, and some IDs may even be trained in this way, but none of them can likely offer the expediency that a GenAI platform can. In this way, a GenAI platform can provide guidance that faces the instructor, on behalf of the learner, and result in an improved teaching and learning experience for all.

GenAI-enhanced learning analytics may be the best way to conceptualize this quadrant for now, because it is based on a concept with which we are already familiar. Let us consider a potential use case as the GenAI tools, and our comfort and familiarity with them, continue to evolve.

As instructors' capabilities expand by virtue of their partnership with GenAI, a particularly self-regulated learner, as described by Zimmerman (1990), may find themselves wanting to articulate their particular learning needs to the instructor. The learner could then engage with GenAI by inputting their needs, preferences, and learning goals into a prompt, and the GenAI platform responds with a formal individualized learning plan that could be shared with the instructor. This may result in more effectively personalized learning, which recognizes and potentially reshapes existing content in the course to better suit the needs of the individual learner. With GenAI, this could eventually be scalable even in large courses.

Applying the Intent & Orientation Model to Instructional Design

In order to apply this model to instructional design tasks, we need to first identify typical ID tasks. This is a tall order, given that ID roles and tasks vary greatly throughout education and industry, but there are some commonalities we can explore and later

classify.

IDs are often going to be involved in a course design process in order to ensure proper structural alignment of all important course elements, such as learning objectives, assessments, activities, and selected learning materials. This may include creating these things from scratch or massaging existing materials to fit the need. But the range of engagements may go well beyond that, from program-level curriculum mapping, to identifying and targeting industry standards related to a course or discipline, to redesigning a face-to-face course for online or other flexible delivery modality, or creating sophisticated interactive multimedia learning objects. Within higher education alone, the tasks will vary greatly depending on the employer and the need.

Application Scenarios

Instructor>Instructor

As mentioned previously, these are predominantly straightforward use cases that we have already seen emerging in ID practice. Examples include, but are not limited to: creating course components (learning objectives, assessments, etc.) that are appropriate for the level and type of student likely to enroll in a given course, suggesting lesson plans that combine these design elements with teaching strategies and practices in the classroom, and creating scripts and storyboards for multimedia content to be integrated into a course.

GenAI typically performs well in these scenarios, provided a quality prompt or series of prompts that guides the tool to consider critical concepts such as alignment between course components or perhaps course delivery modality. However, backing up a little, GenAI's relative strengths as a collaborative "brainstorm" partner can also be leveraged during the design process to ensure that the ID or instructor is considering all angles. Though arguments over whether GenAI should be considered "creative" will probably rage on for some time, its ability to quickly create hypothetical responses or scenarios can help its user by reminding the user or sparking ideas that they may not have considered or remembered in a given moment (Schwanke, 2024). So while the platform itself is not necessarily creative, it can absolutely enhance the user's creativity.

Example 1: I>I Scenario

A Biology instructor has been handed a sparse syllabus by their department head and told in no uncertain terms that they will be teaching this course starting the following week. The syllabus contains only the governance-approved learning objectives for the course and a brief narrative description of the course. The instructor reaches out to the institution's instructional design group for help in developing the course.

The instructional designer may use what little information is available in the syllabus, combined with a conversation with the instructor, to develop a detailed prompt. Something like:

You are an experienced university-level Biology instructor. You need to create a Cell Biology course for third-year Biology majors. Pre-requisite courses include Introduction to Biology, Genetics, and General Chemistry. Given the following learning objectives and brief course narrative [which are either attached as a file or copy/pasted below the user's prompt, depending upon the capabilities of the tool], create a topical outline for this course, which will be delivered during a 16-week semester.

In this example, the ID and instructor are providing all relevant information that they have available, and asking GenAI essentially for a starting point. But given the information at hand, they have provided the GenAI tool with a sufficient amount of information for it to be able to generate a useful response. The user, defined here as the combination of ID and instructor, has the subject matter expertise to identify shortcomings or issues in the artifact, and is able to continue "conversing" with GenAI

to mold it into a refined and useful document. Moreover, this entire engagement has created this useful document in a few minutes, whereas experienced IDs will recognize that it may have taken multiple meetings over multiple days/weeks to reach this point prior to GenAI.

Once the course outline has been created to the liking of the ID/instructor duo, they can continue on with more tasks with the help of GenAI. Since they know what topics will be covered at what point in the course, they can begin fleshing that out further via lesson objectives, lesson plans, and assessment plans, all of which are well within the capabilities of a properly prompted GenAI tool. Beyond that, GenAI can also help tremendously with the identification, curation, and/or creation of learning materials such as journal articles, instructional videos, and the like.

Instructor>Learner

Now we carefully approach the less-trodden path in which the instructor or ID creates an artifact with GenAI, but the learner uses that artifact. This is less about the design and development of the course and more about the delivery, but in the preparation of learning materials referenced above, it is still reasonable to expect an ID to be centrally involved in creating this type of content.

Given the current limitations of GenAI, this is where practitioners should start getting a little nervous, because designing and creating a custom GPT or prompt and then handing it over to another user means losing control of the GenAI artifact when that handoff occurs. A knowledgeable user should always verify the quality of a GenAI output, but that is not fully possible in this case.

An informed user should always create and test their own prompts and GPTs (Bowen & Watson, 2024), but each GenAI response is uniquely generated in a moment in time rather than responding in a pre-programmed fashion. This means that even an informed user's thorough testing does not guarantee that each and every learner will experience the same quality of response or guidance from the tool as a result of a common prompt. For this reason, some level of reflection or metacognitive evaluation by the learner after using the artifact is still a critical piece of the puzzle, because that is what may allow an instructor to recognize shortcomings in the learner's interaction with the GenAI artifact and correct course for that learner.

Some potential examples of I>L include adaptive practice generators, in which custom GPTs or prompts create practice problems matched to individual student skill levels; scaffolded project guides, in which GPTs or prompts break down complex assignments into manageable steps; and formative assessment tools that provide low-stakes practice opportunities with immediate constructive feedback. While the instructor and/or ID will have to think through each of these prompts thoroughly to ensure a high quality engagement with learners, all of these can enable learners to continue constructively on their learning journey outside of the classroom.

Example 2: I>L Scenario

The same Biology instructor returns, this time after having engaged with the ID and GenAI to continue planning and creating critical course elements. The semester has started, and now the instructor wants to create some intelligent tutoring systems to help the students at their moment of need, should they get "stuck" while studying complex course concepts outside of class time.

The instructor and ID sit down once more and determine a course of action. The students in this case do not have paid licenses to specific GenAI tools, so they are not able to reap the benefits of shared custom-created GPTs. This means that a sophisticated prompt is necessary, which the instructor distributes to the students, and the students can copy and paste the prompt into the GenAI platform of their choosing and then interact with it in the resulting conversation thread. The multi-stage prompt, in this case inspired by Mollick and Mollick (2023), reads something like this:

You are a knowledgeable and engaged Biology tutor at a university. Your job is to explain Cell Biology concepts to the user, a junior-level Biology student. Your explanation should be phrased in clear and concise language while still including relevant details, should include an example or analogy to guide the learner's understanding, and should then check to confirm their comprehension. First, you will introduce yourself and ask the student what topic or concept they would like explained, and you will wait for their response. Secondly, you will ask the user what they already know about this topic, and you will wait for their response. Third, considering the user's inputs to the first two questions to customize the response, you will provide an explanation of the topic or concept in no more than 3 paragraphs, along with relevant examples and/or analogies. At the end of this response, you will ask the user whether they understand the information provided. If their answer is yes, you will provide 2 or 3 open-ended questions for the learner to answer. Based upon those answers, you will determine whether the student's understanding is appropriately accurate and, if it is, you will offer an encouraging closing message and invite the user to revisit this prompt in the future if they need to. If their answer is no, you will ask what part of the concept or topic they don't understand, and wait for their response. Once they provide that response, you will rephrase your previous response to better address their area of concern, and finish by asking them if this response has helped them understand the topic or concept better. If yes, then you will provide 2 or 3 open-ended guiding questions as above. If no, you will repeat the remediation steps above.

This type of prompt can be made broader, as in Mollick and Mollick's original example (2023), or it can be tailored to fit a specific assignment or topic in the course. Either way, the ID and instructor craft the prompt, the instructor shares it with learners at the appropriate time, and learners can then interact with the prompt if/when it suits them. Ideally some sort of follow-up occurs between instructor and learner for quality control purposes, but either way, the learner has an agent readily available at their moment of need in order to maintain progress in a course.

Implications for Instructional Design

Opportunities and Evolving ID Roles

The emergence of GenAI is incredibly impactful for IDs. Within the past 10 years, it was common to see formal ID/instructor engagements programmed for an entire semester, and just establishing the basics, such as writing measurable learning objectives, creating well-aligned assessments, and creating thoughtful lesson plans, may take up at least half of that time. Sometimes, just achieving the goal of having well-aligned objectives and assessments may have taken nearly a whole semester, when an ID without autonomy or control was paired with an over-exerted pre-tenure professor.

Even with GenAI outputs requiring supervision from a well-trained eye, it is still plain to see how significant an impact even a standard GenAI platform can have under the tutelage of an AI-literate ID teamed up with a trained expert in a discipline. What once took weeks may now take minutes. What once required significant effort to mind-map and storyboard just to ensure a shared vision between two people can now be accomplished in seconds, given at least one knowledgeable user.

From a practical standpoint, IDs can supercharge their practice by becoming prompt masters. As seen in the Biology tutor prompt example above, good prompts may take up considerable space and time to plan, create, and test. Combine this with the fact that some GenAI platforms may enable uploads of significantly-sized reference materials as part of the prompting process to achieve a product of the proper depth and detail, and one can easily see how relevant this type of fluency is. A key tip, again with a hat tip to Mollick and Mollick (2023), is not just to learn to prompt well, but to document and store those prompts in a way that can be revisited, like books in a library.

Perhaps the best news, at least for now, is that the worries about "the machines replacing us," on both the ID and instructor sides, seem overblown. Outstanding and game-changing as they are, common GenAI platforms can, and do, still make mistakes...sometimes elementary ones. Even GPT-4's impressive and widely-touted 90% score on the Uniform Bar Exam has

been called into question for several methodological reasons (Martinez, 2024). So for now, the best directional guidance for IDs seems to be less about “find a new AI-proof job” and more about “figure out how to collaborate with AI most effectively.”

Threats and Challenges

That being said, there are some pitfalls to consider with GenAI use as an ID. First and foremost, the well-known shortcomings of GenAI as a whole have to be considered. The general-purpose platforms offered by the major players in the GenAI space, such as OpenAI’s ChatGPT, Anthropic’s Claude, and Google’s Gemini, all were trained on massive amounts of data, but that data came from the open internet, and thus the platforms are subject to the same inaccuracies and biases that anyone may find on the internet.

Beyond that, the operating model of these tools, in which prompts are used to further train the LLMs, means that IDs and instructors alike must take great care to prevent introducing personal or private data into these systems (Duffourc et al., 2023). There may be some protections offered at some institutions, via licensing agreements or locally-hosted GenAI platforms, but it is still a best practice to keep this type of information out of the GenAI realm. This is particularly relevant as we start to mix GenAI with the learning analytics and “data lakes” resulting from broad LMS usage at institutions - we must ensure that protecting student data privacy remains at the forefront of our institutional priority list.

There are other structural worries relating to GenAI, including the environmental impact of the massive servers necessary to power these tools (Leffer, 2024), and intellectual property concerns related to individuals’ proprietary works being included in the training data (Appel et al., 2023). So it is important for IDs and GenAI users in general to recognize and control for the potentially problematic extensions of GenAI use.

There are also practical considerations more specific to the educational realm. One is that different tools seem to perform with different quality in different types of tasks. One platform may generate more useful Python code than another, for example, while yet another platform may provide better “creative writing”-style content. Much of this type of evaluation is in the eye of the beholder, but it is still beneficial for an ID to familiarize themselves with multiple platforms in order to determine which ones better meet their preferences in a given situation.

Another consideration is one that runs parallel to a well-known pedagogical element of ID: chunking (Caskurlu et al., 2021). Just as IDs help instructors break up their content into manageable “chunks,” so that students don’t experience cognitive overload, GenAI platforms sometimes struggle when asked to do too much in one interaction. Some of this may be due to a limited context window, in which the platform “forgets” something that happened early in a string of prompts (Bergmann, 2021). But even in less-lengthy interactions, an ID should be mindful to break up tasks into more manageable pieces. For example, once a satisfactory topical outline exists, platforms seem to provide better lesson plans based upon that outline when asked to generate a small number of them at a time, as opposed to an entire course’s worth.

Finally, a particularly onerous challenge related to GenAI, and one that often sits top of mind among teaching faculty, is that of academic integrity. As learners gain access to AI assistants, instructional designers must collaborate to create appropriate assessments, help faculty clarify the boundaries of AI use for their students, and cultivate a culture of academic honesty. Establishing clear policies and expectations, providing AI literacy training, and designing assessments and activities that are more resistant to AI misuse are essential steps for IDs and faculty alike.

Conclusion and Future Directions

The GenAI Intent and Orientation Model was intended to serve as a foundation upon which to build our developing understanding and practice of incorporating GenAI into the teaching and learning process. For IDs in particular, it can offer a framework to guide GenAI incorporation into their daily practice as well as into the modules and courses they build.

The I>I and L>L quadrants are conceptually simple, as the user is engaging with GenAI to serve their own purposes. But both still require oversight - a knowledgeable and trained practitioner on the I>I side who can prompt well enough to maximize the value of the interaction, and clear policies and communication on the L>L side to guide learners toward proper and informed use of GenAI tools.

The I>L quadrant considers the value of tried and tested prompts and custom GPTs, which are exchanged from instructor to learner, in order to promote improved teaching and learning outcomes for all parties. It may enable instructors to better meet the individual needs of students, and maintain instructional momentum outside of the classroom - a time previously out of reach for an instructor who is unwilling or unable to be “on call” at all times during the administration of a course. Though these interactions will require knowledgeable human oversight and evaluation for the foreseeable future, they can still bring great value to the teaching and learning process on both sides.

The L>I quadrant is, as of this writing, mostly speculative, if we take the idea of learner “intent” at its most literal. But as the tools develop, this quadrant offers exciting prospects in terms of giving learners more input and control over their instructional experience. It is widely recognized that reflective and engaged learners, combined with timely guiding feedback from instructors, experience better learning outcomes (Guo, 2022), and this quadrant may help provide a foundation to guide the development of next-generation learning environments and tools that empower learners to create and conquer their own learning paths.

As GenAI tools continue to evolve and expand, and as new discipline-specific tools emerge, the specifics of how GenAI interacts with the teaching and learning process will also evolve. This is why it is important to consider central grounding principles and frameworks, and we believe that the GenAI Intent and Orientation Model can provide this solid foundation as we continue speeding headlong into this new frontier of learning.

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