

**CHANCES AND CHALLENGES OF CHATGPT AND SIMILAR MODELS  
FOR EDUCATION IN M&S**

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**ABSTRACT**

This position paper summarizes the inputs of a group of experts from academia and industry presenting their view on chances and challenges of using ChatGPT within Modeling and Simulation education. The experts also address the need to evaluate continuous education as well as education of faculty members to address scholastic challenges and opportunities while meeting the expectation of industry. Generally, the use of ChatGPT is encouraged, but it needs to be embedded into an updated curriculum with more emphasis on validity constraints, systems thinking, and ethics.

**1 INTRODUCTION**

The release of ChatGPT by the Open Artificial Intelligence (OpenAI) consortium created significant discussions, not only in the academic community, but also in many other communities. GPT stands for generative, pre-trained transformer. This means that it can generate text, speech, and even computer code and images from the knowledge gained in its training, usually followed by a fine-tuning phase, which allows the generation of domain-specific texts. The underlying transformer architecture was introduced by Google in 2017, as described in (Luitse and Denkena 2021). While until recently the majority of AI applications have been designed for a special domain, and often focused on a special application within this domain, OpenAI's objective is to provide a general-purpose AI that can be accessed and integrated via open application programming interfaces (API). While in earlier versions the input and output were

limited to text, the user interfaces and APIs capabilities were significantly improved over the recent years, resulting in the broad possible support of tasks.

ChatGPT belongs to the family of large language models (LLM). An LLM comprises a multi-layered neural network that is trained via deep learning to process, analyze, and interpolate complex data. LLM utilizes several capabilities of neural networks and combine them in a powerful way, such as creating a semantic map of terms in which similar terms are close to each other, so that comparable concepts can be recognized when terms and sentences are transformed into numerical expressions usable by the computational AI methods. These concepts are used for word embedding, the mapping of terms to numerical values, as well as attention mechanisms that allow to recognize and reproduce sentiment-related constructs. This allows ChatGPT to produce coherently written texts and provide access to a large set of knowledge in user-interface based exchanges with humans.

However, the topic of this panel is not the technical background, but what this new technology means for education, in particular for Modeling and Simulation (M&S) education. Part of the audience may remember discussions about the use of calculators when they became broadly available in the seventies. Will students still learn the principles of mathematics, or will they only be able to solve math problems when they have a calculator at hand? Do the curricula have to adapt to the availability of this new tool, or shall it be banned from the classrooms? Should children learn to use this tool as early as possible, or should such education wait until higher grades? How shall students be educated to recognize when the result presented by the calculator is absurd?

With the advent of technologies like ChatGPT, we are facing similar questions today, and again there are good arguments on both sides. There are for sure dangers of cheating and asking ChatGPT to quickly provide some homework solution that may be good enough for a passing grade, or maybe even way better than just a passing grade. On the other hand, ChatGPT can become a very smart tool, or even a mentor that has access not only to the full body of knowledge for M&S, but that can give advice on software engineering as well, including providing examples. What does this mean for M&S curricula? Do we still have to emphasize software engineering principles and computational methods? Or shall we focus way more on the creative part of modeling? How do we prepare students to know how to best use ChatGPT, and how do they know when the provided GPT solutions are out of scope for the task that needs to be supported or the problem to be solved? What does this mean for teaching faculty? What continuing education programs are needed to educate the workforce? Will we need to emphasize the importance of ethics more in the classroom, as discussed in (Shults et al. 2018), and others. These are some of the questions that panelists were asked to have in mind when preparing for the panel and providing position statements for this accompanying paper. The following sections provide their input to this discussion.

A word of warning: As the development of AI accelerates into the unknown, the opinion of the authors may turn out to be completely wrong as we are mostly educators not futurists.

## **2 PREPARING STUDENTS FOR THE FUTURE (BARRY)**

The rapid advancement in LLM technology has paved the way for its integration into various domains, including M&S. As the industry will increasingly expect graduating students to possess LLM skills, it is crucial to examine the roles these models can play in M&S education and practice, address the challenges associated with their adoption, and propose the necessary changes in academic curricula to prepare future professionals.

LLMs have the potential to revolutionize the practice of employing M&S to inform decisions across the systems engineering lifecycle. This potential necessitates an overhaul of M&S education. Specifically, industry is beginning their use in the Writing Problem Statements and conceptual operations (ConOps), Building Initial Code Sets for Simulations, and Designing Experiments.

## 2.1 Problem Statements and ConOps, Initial Code, and Design of Experiments

LLMs can assist engineers in formulating precise problem statements by analyzing large volumes of text and extracting relevant information. This can lead to a more accurate understanding of the problem and enable the development of more effective solutions. Additionally, LLMs can aid in the creation of ConOps by providing suggestions for potential operational scenarios, strategies, and solutions based on their extensive knowledge base.

Suppose the assignment was to build a simulation that will inform a project aiming to optimize traffic flow in a smart city. The engineer could ask the LLM to generate a problem statement and ConOps. The LLM can significantly accelerate the problem definition as shown by the samples in figure 1.

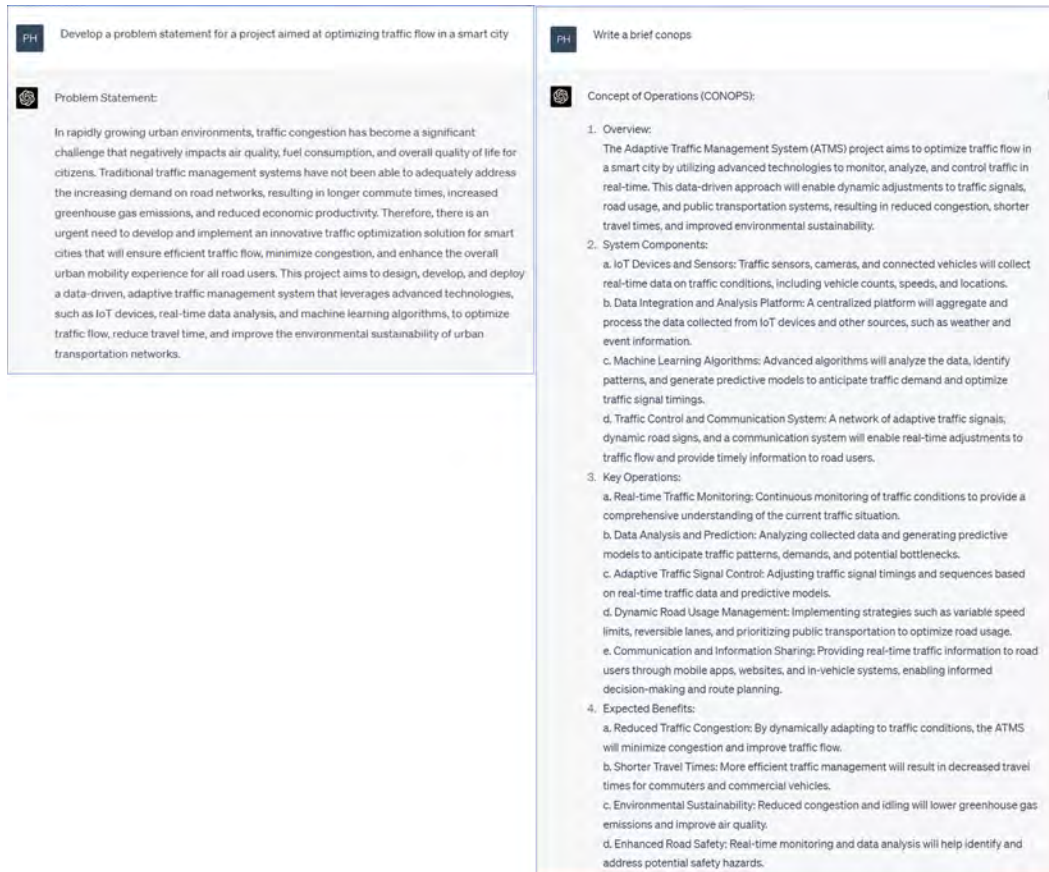


Figure 1: Problem Statement and ConOps Sample.

Iterating with an LLM such as ChatGTP, which produced the samples above, can more quickly develop more detailed foundational documents upon which to guide the development and use of a model or simulation. While the output of the LLM will likely not be perfect, the quick start and the ability to easily iterate can dramatically accelerate the initial systems engineering for developing models.

Supporting to build initial code sets for simulation, LLMs can generate code snippets, templates, or entire programs based on natural language descriptions, thereby accelerating the development of initial code sets for simulations (Jiang et al. 2023). Engineers can provide a description of their requirements, and the LLM will generate a code snippet or template that can be modified and expanded as needed. This can greatly reduce the time spent on coding and allow engineers to focus on refining the simulation.

Continuing the example of the development of a smart city traffic management system, our engineer could request: "Develop a Python program to implement a machine learning model for predicting traffic

congestion based on historical data and real-time sensor inputs." The LLM might generate a code snippet which provides essential components for the smart city traffic management system, such as data pre-processing, model selection, and performance evaluation that the engineer can modify and expand the code as needed to address specific requirements and objectives.

To help with the design of experiments, LLMs can provide suggestions for appropriate experimental setups, data collection methods, and analysis techniques, streamlining the experiment design process. They can help identify relevant factors, guide the choice of experimental design, and suggest suitable statistical methods for analyzing the results. This can lead to more robust and efficient experiments, ultimately resulting in better decision-making and improved outcomes. For the smart city traffic management system, the engineer might ask the LLM for guidance on designing an experiment to evaluate the effectiveness of the proposed solution. The following experimental design approach was generated by ChatGPT:

1. Use historical traffic data to create a variety of traffic scenarios that reflect typical and extreme conditions.
2. Implement the proposed machine learning-based traffic management algorithms in a simulation environment.
3. Conduct a series of simulations using the created traffic scenarios to test the effectiveness of the proposed algorithms.
4. Compare the performance of the proposed algorithms with alternative traffic management approaches, such as fixed-time signal control and actuated signal control.
5. Evaluate the results using metrics such as average travel time, delay reduction, and energy efficiency.
6. Use statistical tests like the Wilcoxon signed-rank test or paired t-test to assess the significance of the observed differences in performance between the proposed solution and alternative approaches.

As before, additional detail can be requested as well as specific parameters for a design of experiments by iterative interaction with the LLM.

## **2.2 Curriculum Changes for M&S Professionals at Bachelors and Masters Levels**

To prepare M&S professionals for a future where LLMs will be integral to their work, academic curricula must evolve to incorporate relevant knowledge and skills. In addition to traditional courses in modeling and simulation, the advent indicates a specialization that would include specific courses such as:

- Introduction to Natural Language Processing (NLP): Understanding of the core concepts and techniques in NLP, including tokenization, part-of-speech tagging, parsing, and sentiment analysis.
- Machine Learning for NLP: Introduction to various machine learning techniques used in NLP, such as supervised, unsupervised, and reinforcement learning.
- Large Language Models and Few-Shot Learning: Principles and techniques behind LLMs, such as GPT-3 and its successors.
- Human-AI Teaming in M&S: Techniques for the development of effective collaborative workflows between human engineers and LLMs, optimize the integration of LLM capabilities into M&S processes, and assess the performance of human-AI teams in M&S settings.
- Ethics and Responsible AI: Examination of ethical considerations associated with the use of LLMs and other AI technologies in M&S.
- LLMs in M&S Applications: Hands-on experience in applying LLMs to various M&S tasks, such as writing problem statements, generating initial code sets, and designing experiments.

## **2.3 Moving Forward**

By integrating LLMs into M&S education and practice, we can better prepare professionals for a future where human-machine teaming is an essential component of the development and use of M&S (McDermott et al. 2018). The partnership between humans and LLMs has the potential to enhance the speed, efficiency, and effectiveness of M&S in industry, ultimately resulting in better decision-making and improved outcomes. Academic institutions must adapt their curricula to ensure that future M&S professionals are equipped

with the knowledge and skills necessary to leverage the strengths of LLMs and address their limitations as students leave their institutions and begin their professional careers.

The successful integration of LLMs into M&S practice depends on overcoming unique challenges and charting future directions. Specifically, additional research is necessary to ensure ethical and responsible use, development of collaborative workflows, continuous learning and adaptation, and evaluating and improving LLM performance as students transition to the professional world.

- **Ensuring Ethical and Responsible Use of LLMs:** Addressing potential biases in the training data, providing transparency in the decision-making process, and ensuring data privacy are key ethical considerations when using LLMs (Sallam 2023). Educators must be trained in ethical AI practices to ensure future use by students of LLMs is appropriate and responsible.
- **Developing Collaborative Workflows:** Optimizing the partnership between humans and LLMs requires the development of collaborative workflows that enable seamless integration of LLM capabilities into the M&S process (Gao et al. 2023). This may involve creating platforms that facilitate easy interaction between engineers and LLMs and adapting existing M&S tools and frameworks to accommodate LLM inputs and outputs. Industry will expect students be able to use these platforms in the same fashion that there are expectations for basic programming skills.
- **Continuous Learning and Adaptation:** As LLMs continue to evolve, it is essential for educators to stay informed about the latest developments and be prepared to adapt the curriculum accordingly. The technology for LLMs is maturing at an extremely rapid rate requiring frequent updates into the curriculum to prepare students for future jobs in industry.
- **Evaluating and Improving LLM Performance:** While LLMs have demonstrated impressive capabilities, there is still room for improvement in their performance and reliability (Raj et al. 2022). Researchers, educators, and practitioners must work together to evaluate LLM outputs, identify areas for improvement, and develop strategies for enhancing LLM performance in M&S applications.

### **3 OPPORTUNITIES FOR LLMS IN SIMULATION EDUCATION (LOPER)**

In the coming years, AI-driven software may deliver on the promise of revolutionizing the way people teach and learn. AI will learn your interests and your learning style, so it can customize content to keep you engaged. It will measure your understanding and give you immediate feedback. The emergence of LLMs and chatbots are part of this revolution. While they are interactive, smart, creative, and fun, they are also “charming little liars”. The data sets they are trained on are filled with biases, and despite their seeming authority, some of their answers are nonsensical, offensive, and just plain wrong (Goode 2023). That caution aside, this technology is moving fast, and provides a new way of envisioning a human/AI instructor team.

Applied correctly, AI can be a force multiplier for instructors, automating some aspects of their work and allowing them to dedicate more time to tasks where humans are uniquely capable. Applied incorrectly, AI can impede the connection between student and instructor that makes one-on-one interaction so effective (van Lent and Schmorow 2022). The key phases of an instructor’s job are preparation, teaching, demonstration, and facilitating practice. Weaved across these phases are the additional jobs of curriculum planning, motivating, adapting the experience to the student, assessing, and providing feedback (van Lent and Schmorow 2022). Described below are three opportunities for LLMs to be integrated into simulation education which address these additional jobs.

#### **3.1 Personalized Learning**

Everybody has different learning preferences, which means all students can benefit from personalized teaching materials. LLMs enable a unique way to address this. For example, ChatGPT can explain Newton’s laws of motion to a student who learns better with images rather than words, by generating an explanation that features balls rolling on a table (Heaven 2023). Teachers could use LLMs to prepare

different versions of their materials to cover a range of students' learning needs, personalizing material for students and making customized tutors the norm. The [Teachable AI Lab](#) at Georgia Tech is using LLMs for intelligent tutoring systems, by making it easier for educators to create them. They use GPT to transform teacher instructions into rich, symbolic, hierarchical representations of task knowledge that can be used in a tutoring system to provide personalized hints, feedback, and instructional recommendations to students (AI-ALOE 2023). By translating language instruction into symbolic structures and using tutoring system methods to provide students with accurate and explainable instruction, they avoid the data bias issue mentioned earlier.

The future of textbooks could be bundled with chatbots trained on their contents. After reading the course text, students can have a conversation with the bot about the book's contents. The chatbot could also generate personalized quizzes to tutor students on topics they understand less well. This work is happening now - the [Quizlet app](#) uses ChatGPT to customize material and adjust the difficulty of questions based on how well students know the material they're studying (Heaven 2023). The [LEAR Lab](#) at Vanderbilt University is using LLMs in their iTell framework to provide personalized feedback to users of intelligent textbooks. At the end of chapter sections, users summarize the material, and LLMs assess the accuracy of the content, as well as the wording used. LLMs can also generate questions specific to paragraphs that users skimmed or skipped (AI-ALOE 2023).

### 3.2 Critical Thinking

Teaching methods that get students to be creative and think critically lead to a deeper kind of learning than rote memorization. LLMs can lower the barrier to students who are getting started in a new area of study. For example, some students get stifled by "staring at a blank page". LLMs can generate a first draft of an assignment, to help the student focus on the critical aspects of the task. In other words, it can help students move beyond particular pain points when they aren't necessarily part of the learning goals (Heaven 2023). LLMs can also generate counterarguments to a student's positions. By exposing students to an endless supply of opposing viewpoints, chatbots can help them look for weak points in their own thinking, e.g., one instructor asked her students to use ChatGPT to generate an argument and then had them annotate it according to how effective they thought the argument was for a specific audience (Heaven 2023).

While LLMs can help take a student's ideas into implementation, it's not a free pass - students need to understand the underlying principles of what they want to accomplish in order to get good results (remember the adage... garbage in garbage out). This fundamental understanding is essential to know how to generate the prompt. In other words, a student needs to understand how to write a simulation program before they can generate a prompt to produce good code. Note that instructors may also need to change the way they think about grading assignments, by including the prompt as well as the results. Here is an example to illustrate the importance of precision in generating a prompt to simulate N-body dynamics (Kerce 2023).

Generate a stubbed out python program using numpy. Include function definitions, but not the internal code that implements the functions. Instead just return 0. The program should include a full main call using the "if \_\_name\_\_ == \_\_main\_\_" construction, and the main program should be complete.

The purpose of this program is to simulate N-body dynamics using the following pairwise force laws for pairwise spring, transverse velocity dampening, and velocity dampening:

```
fpw(x, y) = epsilonx_y * b * (norm(x-y) - D) * (y-x)/norm(x-y)
ftv(x, y, vx) = - gammat * (vx - dot(vx, (y-x)/norm(y-x)) * (y-x)/norm(y-x))
fvd(vx) = - gamma * vx
```

The variables  $x$ ,  $y$ , and  $vx$  are vectors. The variables  $\gamma$ ,  $\gamma_t$ ,  $b$  and  $D$  are scalars that are the same for all pairs of particles. The variable  $\epsilon_{x_y}$  is a scalar variable that masks whether or not  $x$  should be influenced through a force from  $y$ . The

variables  $x$  and  $y$  represent the positions of particles, and the variable  $v_x$  represents the velocity of the particle with position  $x$ .

For coding conventions, make sure to use function definitions where it makes reading the code most efficient. Also make sure to include a main function. Document the code clearly and thoroughly.

### **3.3 Online Learning**

Teaching is often structured as a single instructor teaching many students in a classroom setting, but today much of that instruction is offered online. While learners learn from digital content prepared by an instructor, they might actually have little interaction with them in online courses. These online one-to-many learning experiences often lack motivation, engagement, and individualized exploration and explanation of the topics that a one-on-one experience provides (van Lent and Schmorrow 2022). In cases where a teacher is available to learners, the load on the teacher in a large, asynchronous, and geographically distributed online class can become overwhelming. Two areas where AI can help increase the student to teacher ratio and support the effectiveness of one-on-one interaction are teacher presence and social connectedness.

In 2016, Georgia Tech's [Design & Intelligence Laboratory](#) developed Jill Watson, the world's first virtual teaching assistant (TA) that automatically answers learners' routine questions anytime anyplace. Jill Watson has been successfully deployed in more than 40 online classes with more than 12,000 students. In Jill's first year as a TA, it answered only routine, frequently answered questions, but did so with more than 90% accuracy and with authenticity such that students did not know Jill was an AI agent. The new Jill powered by ChatGPT (Jill+) will have the capability to directly ingest class documents for answering questions, making it an efficient and scalable tool for teachers and learners (AI-ALOE 2023).

A lack of social interaction is a problem in online education because of the asynchronous and geographically distributed nature of learning. Georgia Tech developed a virtual social agent named SAMI that analyzes learners' posts and extracts information about each learner such as location, interests, and hobbies. It builds a knowledge model for each learner and suggests personalized social connections based on their shared identity. Preliminary evidence indicates SAMI can improve learners' feelings of social connectedness and belonging (AI-ALOE 2023).

### **3.4 Conclusions**

There are many opportunities for AI to enhance the work that students and teachers do together in the classroom. Despite the concerns of student cheating, bias data, or atrophying skills, LLMs will undoubtedly become part of simulation (and all) education. Our challenge is to let go - or brachiate from - our old ways, i.e., take the risk of letting go of our current tether before we reach the next (Schatz and Walcutt 2022). We need to rethink what success in learning looks like, and free ourselves from the narrow definitions of formal education. Learning happens in all places and in many forms, and AI will be part of that future.

## **4 WHAT DOES CHATGPT AND AI TOOLS MEAN FOR THE M&S COMMUNITY (RABADI)**

### **4.1 Observations on ChatGPT, other LLMs, and AI Tools**

As Open AI took the world by storm in late 2022, people including educators have been wondering what this means for their fields, and M&S is one of many. In education and higher education in particular the implications are profound, but essentially, there have been mostly two camps on both sides of the debate. The first camp includes those who are mostly looking at LLMs as cheating tools and have been mostly focused on questions such as: How are we going to know that students are not cheating? How do we know that they are learning what they are supposed to learn? This camp has been busy thinking up strategies on how to neutralize the software or to at least slow it down.

The second camp believes that this is just the beginning, and AI tools such as LLMs are here to stay; therefore, they embrace LLMs and the like as learning tools. While we do share the integrity concerns of the first camp, we tend to belong to the second camp because fighting these tools is not only going to exhaust educators, but it may also not be possible as AI gets better and become more prevalent. Counter AI generative tools are likely to emerge to identify AI-generated contributions (e.g., writing assignments). Antiplagiarism platform Turnitin, for example, claims on its website that it can detect essays generated by ChatGPT. But it is not only essays; ChatGPT can produce code, including code for simulation models, which is not as easy to detect whether written by a human or a computer. Other AI platforms can or will soon be able to generate all kinds of artifacts that currently require skilled humans. Therefore, it might be imperative for educators to rethink the curriculum, students' learning outcomes, and their approach to teaching and learning to accept or embrace this technology while shifting the focus to higher order critical thinking rather than learning the mechanics of executing a process.

But how should educators and education change, and how often? We probably should reverse engineer the question and start with the end goals. That is, what is the end goal of teaching and learning M&S? And if AI can help accomplish this goal, do humans need to worry about the steps in between? Maybe we all agree that the end goal of developing a model for a system, process, or phenomenon of some sort is to understand and/or predict its behavior in a certain environment and under certain conditions. If an AI system can produce such a model with high confidence in its validity, then how it is implemented may not be of interest to the users. Is it possible for model developers and analysts to have a different role to play?

Based on the examples presented in this paper and in many other sources, this is quite possible on the long run. It is possible for the users just to describe what they want modeled from a platform like ChatGPT, and for the model to self-assemble. In fact, ChatGPT-3.5 can already produce code for models based on description provided by the user. Maybe, models generated for complex systems are less accurate or valid for now, but it is easy to see that they will get better in the near future with more training. Furthermore, ChatGPT has also introduced the capability of installing plug-ins that can extend its abilities. Wolfram Language (used in Mathematica) and Wolfram Alpha tools, for example, have been added to ChatGPT giving users access to all the general computational capabilities and computational knowledge (Wolfram 2023). This means that platforms will have a lot more computational power to solve complex problems. One can imagine that it is a matter of time before another plug-in can produce a complex 3D model that can be easily imported into a VR environment used for simulation training, or providing a discrete-event simulation for decision making. So, the question is what should M&S students and analysts learn?

#### **4.2 M&S Education Future**

It might be too early to make predictions about the future of M&S education (and education in general), but one thing for sure – it will change. The examples presented in this paper by the panelists clearly show that LLMs are capable of producing valid simulation codes, and as these AI tools improve, more complex and optimized simulation model codes will be possible to produce in a few seconds or minutes.

While people have raced to point flaws in some of ChatGPT output, it is a matter of time before many of its invalid answers to be corrected as it learns from its users. Eventually, AI tools including LLMs will be able to quickly and accurately produce many of the components used in M&S processes (e.g., implementing models, creating visualizations, running experiments, conducting statistical testing, tabulating results, etc.). Therefore, it is expected that students (and eventually professionals) will need to learn less of the mechanics and more of the conceptual and critical thinking. Educators may have to shift some of their focus to the ideas themselves and to teach students how to define problems, ask questions, validate findings, and interpret and communicate results. Yet, this still requires that students understand the fundamentals and mechanics of M&S, but maybe spend less time doing so.

One of the biggest challenges is for institutions and educators to adjust quickly. It is not easy for educators to change their course content every semester or month. The world has witnessed this jump in AI almost suddenly, and the step in “intelligence” between ChatGPT-3.5 and ChatGPT 4.0 was significantly



larger, which got everyone wondering whether AI development trajectory has taken an exponential turn upwards, and whether this is the beginning of accelerated path to Artificial General Intelligence (AGI).

## **5 FASTER, BETTER, AND CHEAPER – AND STILL SOLVING THE WRONG PROBLEM: A SYSTEMS THINKING PERSPECTIVE (SCHERER)**

There is considerable uncertainty about the success of AI and diverse perspectives on the efficacy of AI. Regardless of the tremendous press about AI and ChatGPT, “the reality is that just about every successful deployment has either one of two expedients: It has a person somewhere in the loop, or the cost of failure, should the system blunder, is very low” (Brooks 2021). Other experts, such as Yoshua Bengio, believe that progress in AI is limited and not “close to the intelligence of a two-year-old child” (Strickland 2019). Therefore, “the failure rates of big data projects and AI projects remain disturbingly high. And despite the hype, companies have yet to cite the contributions of data science to their bottom lines” (Redman 2019).

In the past few years, the rise of tools like ChatGPT only raised the issues associated with these failures to a new level. Failures for technology approaches such as machine learning and AI are typically not algorithmic failures nor engineering issues, but failures associated with the softer skills required in problem-solving, including the fundamental aspects of systems thinking. Machines via AI may replace part of the work humans are currently undertaking; however, the human elements that are the true value-add of much of these efforts cannot be replaced by AI (Hess and Ludwig 2020). We spend the majority of our efforts in AI on data gathering and cleaning, and we often judge how good an AI or ML system is by the scale of the data used (Bellotti 2021). Perez-Breva states “when our systems aren’t learning as we want, the primary gut reaction is to give these AI systems more data so that we don’t have to think as much about the hard parts of generalization and intelligence” (Schmelzer 2020). This data-driven approach to building AI systems results in training data biases built into the system. And models like ChatGPT are making it harder to detect misinformation (Deen 2023). What is needed to improve these AI systems is a “system thinking” framework. “In system thinking, “antifragile” is a design that not only recovers from failure but is actually stronger and more effective when exposed to failure. When we build AI based on what actually improves decision-making, we create an opportunity for antifragile AI. We know from existing research into cognitive science that good decisions are the product of proactively articulating assumptions, structuring hypothesis tests to verify those assumptions, and establishing clear channels of communication between stakeholders” (Bellotti 2021).

So, what does this all mean for AI-based systems and modeling and simulation? The weakness of the ChatGPT-generated material is a lack of systems thinking and the pitfalls mentioned above. A foundational principle for success is founded in the basic concepts of systems thinking. If you look at the principles of many of the fads/trends in business over the past six decades, systems approach concepts are often fundamental to their core concepts. Thus, the fads often contribute excellent ideas that are typically just a reiteration of basic established systems thinking principles. And you do not need to spend a fortune to get to systems thinking. Unfortunately, a systems thinking framework is absent from an AI-generated solution. Such a deficit will result in models that fundamentally solve the wrong problem and exacerbate solution failures, as we have seen with technology trends from data warehousing to data science and now with AI. This approach of framing it as a systems thinking problem is well beyond prompt engineering.

What are the core concepts of systems thinking? Sound systems thinking results in finding the right problem that is solved for the right reasons. As stated by Russ Ackoff (2003): “It is far better to do the right thing wrong instead than to do the wrong thing right!” The fundamental concepts of systems thinking can be enumerated as follows:

- Top-down, not bottom-up thinking – innovative and creative jumps never begin with iterative improvements of the “as is,”
- Define goals and sub-goals, and identify good metrics for goal measurement,
- Identify the system boundaries – out-scope to validate that the boundary is not artificially limited,

- Identify all systems stakeholders and decision-makers,
- Identify the values components of all stakeholders and decision-makers,
- Identify system alternatives (not tools), using creativity and avoiding the pitfall of group-think and other idea-killing behaviors,
- Identify the critical trade-offs for any system design,
- Using a “model” (from simple to complex, from paper to computer-based) identify all the interactions between system components, including feedback loops, model assumptions,
- Identify the critical lift points - what can be altered in the system that has the most impact,
- Know your history – every system replaces another system and, surprisingly, most issues/problems, etc., have been seen before, and human behavior has not changed, and
- Communicate the results and recommendations of the analysis process in the language, culture, and values of the stakeholders and decision-makers; the best recommendations will not lead to good decisions if they are not understood and accepted by the decision-makers on their terms.

Fluency in these core concepts of systems thinking is the key to not being fooled by AI charlatans or data biases. Such concepts are critical to good modeling and simulation efforts. These concepts permit clarity in the face of the latest fad management process, allowing the systems thinker to see the relevance, if any, of their set of objectives. AI-generated solutions have seen critical failures in identifying values, creating proper metrics, making decision tradeoffs, missing the appropriate boundaries, and a lack of communicating reasoning (O’Neil 2017; Bergstrom and West 2021). The AI-algorithmic-driven extremism that has occurred in recent years from social media is the extreme result of these issues (Ganesh and Bright 2020). Unfortunately, ChatGPT is seen as a force in expanding conspiracy-laden worldviews (Wong 2023).

We will not say that systems thinking is the only approach you will ever need because that would make us sound like the purveyors of all the fads. Systems thinking is hard. A cookbook process is easy, often the underlying core process in automated AI, but also a way to be fooled; hence, these critical concepts are absent from an AI-based solution; fundamentally, the AI-generated solution does not know what it does not know. ChatGPT-type systems implemented in solving M&S problems may be valuable for generating simulation code, visualizations, or data cleaning; however, they will, for the foreseeable future, fail at basic systems thinking. M&S education, while using tools such as ChatGPT for complicated tasks such as coding, needs to also focus on the complex tasks of problem formulation and systems thinking. In the future these are likely to be necessary and sufficient skills: the facile utilization of AI tools will be necessary, but not sufficient for problem-solving. The advantage is that systems thinking trained professionals will retain the advantage over AI for the most critical aspects of problem-solving. This is especially critical in algorithms and analytical models that are at the core of AI.

## **6 STUDENT-MACHINE TEAMING FOR M&S EDUCATION (YILMAZ)**

The fundamental concern about generative AI systems, such as ChatGPT (OpenAI 2023) and Google’s PaLM (Chowdhery et al. 2022), is that they enable academic dishonesty, promote misinformation, and convey the bias hidden in the data (Zhuo et al. 2023). Although ethical concerns (Coeckelbergh 2020) are warranted, a myopic view on misuse can result in overlooking long-term opportunities for reinventing teaching and learning processes. Particularly, in M&S education, a student-machine teaming perspective can offer avenues for exploratory learning while promoting strategic thinking. This section examines (1) the role of generative AI in partnering with students to improve their creative problem-solving skills and (2) the strategies for mitigating potential misuse. The following questions motivate the analysis:

- How does the future of M&S education shape if generative AI systems can compose models, generate simulation code, perform simulation experiments, and analyze results?
- What does it mean to be a good collaborator with AI?

## 6.1 Improving Exploratory Analysis Skills with AI-augmented Strategic Thinking

Understanding the M&S domain and its practices requires characterizing the types of questions of interest to the M&S field, the types of solutions that help answer these questions, the type of evaluation that justifies the validity of results, and the criteria for distinguishing acceptable solutions. M&S skills range from developing effective methodologies for modeling, implementing, and simulating systems, including notations and tools, or qualitative, empirical/predictive, and analytic models. Such solutions are evaluated using formal analysis, validation, and design of experiments or persuasive strategies based on examples and feasibility studies. Given the nature of M&S problems, providing aid in problem formulation, exploratory generation of solution candidates, and evaluation of the solutions can help students, who partner with AI, become increasingly proficient in goal-directed complex problem-solving. Consider the following hypothetical scenario that illustrates interactions with *GPT-n*, a future version of ChatGPT.

**Scenario:** John is a senior-level student taking the Multi-Agent Systems (MAS) course at Auburn University. He needs to complete a project to explore the prey-predator dynamics based on the Lotka-Volterra system of equations. The objective is to demonstrate that the MAS implementation can produce the expected lagged oscillation behavior and exhibit a behavioral pattern predicted by the Volterra principle. The analysis starts with the illustrative student-machine teaming scenario shown in Figure 2. John notices the exponential growth in the prey population and determines that the model does not exhibit the lagged oscillation behavior. He continues to explore by adding a new parameter. Figure 3 presents the interactions that successfully refine the model to produce the desired behavior.

Finally, John decides to broaden the scope of exploratory analysis while deepening the resolution of the model with new environmental factors to test the *Volterra principle*: When prey and predator dynamics are negatively coupled (as confirmed by the previous experiment), injecting biocide (e.g., toxic element) into the environment increases the abundance of the prey and decreases the abundance of the predator. The AI system confirms with high confidence the plausibility of the presence of a biocide in explaining the Volterra principle. Although the interactions depicted by these scenarios are hypothetical and appear to surpass the capabilities of ChatGPT, a more recent experimental version (GPT-4), demonstrates capabilities beyond the mastery of language. The experiments presented in (Bubeck et al. 2023) show how GPT-4 can solve complex and novel problems in mathematics, coding, vision, medicine, and other areas while explaining its reasoning.

**Implications of the scenario:** The scenario highlights hypothetical interactions that can assist a student in developing exploratory analysis skills. To support a student in conducting exploratory analysis, generative AI accesses other systems, generates and compiles code, composes visualizations, explains its reasoning, performs statistical reasoning, summarizes data, stratifies results, and learns from student feedback. During such interaction, students can shift their focus to generating hypotheses, adapting to emergent information in an evolving analysis, and learning to ask better questions to improve information gain. In the past, by abstracting away from machine instructions to assembly code and using domain-specific simulation programming languages, M&S students and practitioners could focus on the essential aspects of a problem while avoiding mundane, platform-specific incidental tasks. A similar shift can occur with the introduction of generative AI tools. Students can gain deeper insight into context-sensitive strategic thinking, which focuses on creative searching and formulating hypothesis-driven inquiries to reveal useful information.

On the other hand, abstracting away the intricate details of the underlying platform and algorithms can be detrimental to the ability of students to customize generic algorithms to fit the requirements of a particular problem. Such ability is critical in understanding what methods work, when, and why. To mitigate this concern, student assignments can be reframed so students continue to pay attention to requisite algorithmic and procedural problem-solving skills. Instead of banning generative AI tools, students can be encouraged to use them to improve strategic thinking and exploratory analysis skills. Instructors can stimulate critical thinking by requiring students to provide a brief essay to reflect on their interactions with AI, explain the rationale for choosing specific questions, and perform diagnostic analysis on the AI's recommendations. Moreover, to motivate students to participate in the creative economy, the assignment

**John:** Please generate a NetLogo model that simulates two interacting species by using roughly the steps listed in the attached file. The model should capture the prey-predator dynamics based on Volterra equations. **GPT-n:** I found a NetLogo Wolf-Sheep Predation (WSP) model with a structure similar to your proposed specification. Can we start with it? **John:** Yes. **GPT-n:** The Lotka-Volterra equation model requires you to specify the following parameters: ..... I can apply them to the WSP model to generate a customized version. **John:** Please use the following parameters and range of values for each parameter: ..... **GPT-n:** The model is ready for simulation. Which experiment model and performance criteria do you need to apply? **John:** Apply Latin Hypercube Sampling to both design and scenario parameters. Then, apply a full factorial design over the design and scenario space to test designs over the scenarios with 30 replications. Collect the results and show the visualizations of the prey and predator count trajectories over time. **GPT-n:** Do you need the combined trajectories over runs or each individual run? **John:** Aggregated results would be sufficient.

A visualization emerges on the screen:



Figure 2: Hypothetical interaction scenario for discovering mechanisms that generate lagged oscillation behavior in prey-predator dynamics.

**John:** Add a food source named grass with a growth rate ranging from 0.3 to 0.7 so the prey population stays over a threshold allowing predators to find them. Rerun the simulation using the grass parameter with the same parameter levels from the previous experiment. **GPT-n:** Updating model.....Performing simulations..... Analyzing results.....I performed time series analysis on the trajectories produced by the new version. The analysis confirms the lagged oscillation behavior at the 95% confidence level. Would you like to see the new plot. **John:** Yes.

A second visualization is displayed on the screen:

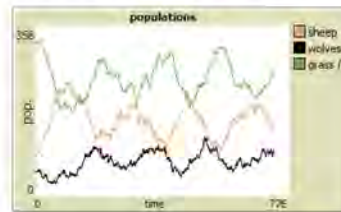


Figure 3: The refinement of the conjectured mechanism by introducing a new factor to improve the model.

**John:** Add a biocide component that can be consumed by both the wolf and sheep agents to reduce their growth rate in proportion to their population size at each simulation step. Report the average count of both types of agents and compare them to the average population sizes in the previous experiment. Test the results at 99% confidence level. **GPT-n:** The mean level of reduction in the predator population sizes over the two experiments (with and without biocide) is 70. The difference is significant at 95% but not at the 99% level. I need additional X replications to test at the 99% level. Do you need me to rerun the experiments? **John:** No. 95% confidence is sufficient. Tell me which of the parameters is most significant in explaining the variation in the reduction of predator population size. **GPT-n:** I performed Feature Scoring over the design parameters [D] and scenario parameters [S]. The factors that have the highest scores are wolf-reproduction rate and biocide level.

Figure 4: Broadening the exploratory analysis to account for the Volterra principle.

may require groups of students to produce a podcast, which is challenging to plagiarize. Peer review of such podcasts can also be required to facilitate community building.

## 6.2 Student-Machine Teaming: Learning to be a Good Collaborator with AI

One of the benefits of using generative AI in an educational setting is providing students with the experience of collaborating with AI to solve complex problems. Students could learn to effectively combine human intelligence, particularly flexibility, and adaptability, with machine performance, such as speed and accuracy. With the immersion of autonomous elements in complex systems, there is an increasing demand for skills that involve specifying complex goals using language that adapts to emergent information.

## 6.3 Recommendations

Given the evolving nature of generative AI technology and the currently limited understanding of its impact on higher education, instructors can continue to develop better awareness by participating in the conversation: (1) What do I need to know about AI as an M&S instructor? (2) What are the ethical considerations of AI in M&S education and research? (3) What is learning, and how will AI tools affect the courses I teach? (4) How are students using AI tools, and how can I partner with them? (5) What do I need to rethink about the exams, papers, and projects I assign? (6) How do I (re)design my courses in the wake of AI disruption? (7) What other AI tools and developments are coming, and how do I design for them? (8) What conversations need to happen in my department or discipline, and what is my role?

## 7 SUMMARY AND CONCLUSIONS

Obviously, the M&S education community is not the only community concerned with this kind of questions. For discussions in related fields, see, among others, for the engineering domain (Qadir 2022), and for the more general education domain (Kasneci et al. 2023). As discussed in the contributions of the panelist, ChatGPT has the potential to become a powerful tool when applied within the validity constraints, and understanding these constraints must become part of the M&S education.

When testing out the capability of ChatGPT, such as described in (Goode 2023), it proves to be very good at replying to factual questions. As this equals looking up the main data points for which the system was trained, this is not surprising. Even if there are small variances in the question, correct answers can be generated. That is also the reason why ChatGPT is doing well on related tests. In the moment more than interpolation between data points and generating answers using statistical knowledge of the underlying language is needed, the quality of answer decreases rapidly. The reason for this is that LLMs are models of the language describing a domain and not a model of the problem domain itself (Mitchell and Krakauer 2023). This difference may result in plausible sounding but nonsensical solutions, and M&S education must enable simulationists to identify nonsensical answers. Like a math student using a calculator must recognize when a result is flawed, so an M&S student must recognize flaws in ChatGPT solutions.

ChatGPT contributes to the category of *generative AI*, i.e., the objective to produce AI generated content (AIGC), as discussed in detail in (Zhang et al. 2023). This generated content is not intentional by itself; there is not good or bad AI. ChatGPT needs to be applied by users like any other tool, and they have to know its validity domains. However, in recent years, AI moved from the laboratories into the daily life of people and from the research groups into the classrooms, so it becomes pivotal to better understand the positive and negative potentials (Littman et al. 2022). In addition to technical skill and understanding how to use AIGC, students need a strong ethical foundation, as it is the tradition of engineering education, within a broader AI framework as envisioned in (Floridi et al. 2018).


To support the productive use of ChatGPT in M&S education, not only the curricula have to change. The training of faculty is important as well to communicate chances and challenges. Similarly, M&S professionals will need training in how to use ChatGPT in practice as well. Knowing what this tool is best useful for as well as its application limits shall be in the center, and with thousands of programmers working on the improvement of these family of tools, this will not be a one-time requirement but requires life-long learning and participation of M&S professionals in industry, academia, and government.


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