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Solving the global STEM educational crisis using Cognitive Load Optimization and Artificial Intelligence–A preliminary comparative analysis

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Abstract
There is a persistent STEM educational crisis exemplified by low student enrolments, and both high failure and attrition rates. ChatGPT is easy to use, however pedagogical quality is not necessarily assured. In one experiment the output had a high cognitive load exacerbated by cognitive gaps making the material hard to teach and learn. ChatGPT is a useful pedagogical technology but not a learning theory. Science, technology and engineering all start by quantitatively modelling systems in order to make accurate and quantitative predictions prior to construction or system modification. By contrast, the current learning theories in use today are based on qualitative soft-science principles, with subjective guidelines that are open to interpretation, which can lead to wide variations in the quality of instructional materials and learning outcomes. Cognitive Load Optimization (CLO) is a new Science of Learning (SoL) theory that quantitatively models relational knowledge as coherent, contiguous, pedagogically scalable schemas optimized for the lowest cognitive load. CLO schemas represent the easiest, fastest and most efficient learning paths and are the fundamental basis of instructional design and teaching. Because CLO schemas are pedagogically scalable it is possible to create CLO schemas that are contiguous across different educational levels (school, college and university) thereby uniquely meeting the goals of the American National Science Foundation SoL ('optimized learning for all') and the Australian Grattan Institute ('optimized learning from pre-school to university'). Using CLO results in significant improvements in STEM learning outcomes but is a detailed methodology that can be time consuming to use. The relative advantages and disadvantages of ChatGPT and CLO are highlighted.

Keywords: AI, ChatGPT, cognitive load optimization, STEM

INTRODUCTION

STEM education has challenges that include low student enrollment and high attrition rates (Sithole, 2017). Educational research is important because of the decline in the uptake of STEM disciplines due in part to the perceived difficulty of these disciplines (IET, 2008). Attempts, such as fun activities and experimentally based teaching, to change this perception are reported to have been unsuccessful (Lyons, 2004). This issue is exacerbated in some developed countries by a continual decline in student performance, highlighting the inadequacies of current educational systems (Timms et al., 2018). The significance of addressing this problem lies in the fact that economic development relies on a well-trained workforce, a goal that cannot be achieved overnight (Australia, 2019).

Furthermore, there are pedagogical issues on a broader scale, manifested in the poor performance of many children who struggle due to a lack of understanding, leading to frustration, disengagement, which hinder future learning. Solutions to this include better quality curriculum.

> 'High quality curriculum can make a real difference, simultaneously reducing teacher workloads and increasing student learning.'

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Contribution to the literature

- ChatGPT is easy to use but pedagogical quality is not assured. In one experiment the output had a high cognitive load with cognitive gaps making the material hard to teach and learn. Arguable it is a useful pedagogical tool but not a learning theory. The current learning theories in use today are based on qualitative soft-science principles, with subjective guidelines that are open to interpretation, which can lead to wide variations in the quality of instructional materials and learning outcomes.
- CLO is a new science of learning (SoL) theory that quantitatively models relational knowledge as coherent, contiguous, pedagogically scalable schemas optimized for the lowest cognitive load. CLO schemas represent the easiest, fastest and most efficient learning paths and are the fundamental basis of instructional design and teaching.
- The paramount basis of CLO is that learning should be easy whilst still fully achieving all learning objectives.
- Because CLO schemas are pedagogically scalable it is possible to create CLO schemas that are contiguous across different educational levels (school, college, and university) thereby uniquely meeting the goals of the American National Science Foundation SoL ('optimized learning for all') and the Australian Grattan Institute ('optimized learning from pre-school to university'). Using CLO results in significant improvement in STEM learning outcomes but is a detailed methodology that can be time consuming to use.

> 'Done well, it can add about four months of additional learning over a single year–and boost students' confidence.'
>
> 'Most teachers are crying out for high-quality curriculum materials.' (Grattan, 2023).

The STEM educational crisis is underscored by the report of the US President's Council of Advisors on Science and Technology that emphasized the imperative for an additional one million STEM graduates and a substantial enhancement in retention rates (PCAST, 2012). The recommendations put forth to attain these objectives underscored the necessity of catalyzing the widespread adoption of empirically validated teaching practices. Moreover, the report called for a transformative change in STEM education, recognizing the critical role this transformation plays in meeting the growing demands of the workforce and ensuring a sustainable pipeline of skilled professionals in STEM. The proposed measures aim not only to address the immediate challenges of enrollment and attrition but also to foster a dynamic and innovative educational environment that aligns with the evolving needs of the global economy.

In light of these challenges, there is a pressing need for innovative solutions that leverage cutting-edge technologies. This preliminary evaluation seeks to explore the effectiveness of implementing artificial intelligence (AI) and cognitive load optimization (CLO) in STEM education. By assessing the effectiveness of these technologies, the study aims to analyze how they can be leveraged to improve the overall learning outcomes in STEM disciplines with the following deliverables:

1. **Higher pass rates:** AI and CLO have the potential to improve the learning process. By evaluating these technologies, the study aims to demonstrate how improvements in learning outcomes can potentially be achieved.
2. **High-quality learning outcomes:** High pass rates should not be at the expense of the quality of learning outcomes. This can potentially be achieved by creating high quality curriculum materials with high-order learning outcomes supportive of more advanced studies.
3. **Enhancing student engagement & enrollment:**

> Half of Americans think young people do not pursue STEM because it is too hard (Kennedy, 2018).

Achieving the objectives of high-quality learning outcomes and high pass rates has the potential to change student perceptions of STEM education, thereby reducing attrition rates and fostering a more inclusive and engaging learning environment, thereby increasing STEM program enrollment.

The significance of this study lies in its potential to address pressing issues in STEM education, offering practical solutions through the technologies of AI and CLO. The outcomes of this research have the potential to positively impact student engagement, retention, and overall learning outcomes, contributing to the broader goals of advancing STEM education on a global scale.

LEARNING THEORIES & QUALITY OF LEARNING OUTCOMES

Learning theories play a pivotal role in shaping educators' comprehension of how students acquire knowledge. Constructivism, for instance, posits that each student actively constructs their own knowledge

(Piaget & Inhelder, 1969). Constructivism is an established learning theory and the theoretical basis for educational improvement in government schools with the premise that,

> 'Central to constructivism is the notion that learners play an active role in 'constructing' their own meaning. Knowledge is not seen as fixed and existing independently outside the learner' (Peters, 2003).

In contrast, Behaviorist theory, championed by Watson and Skinner in the early 20th century, focuses on modifying student learning behavior through operant conditioning, emphasizing stimulus-response associations (Skinner, 1950, 1958). Meanwhile, Cognitivism, emerging in the mid-20th century and influenced significantly by Piaget and Bruner, delves into how information is received, organized, and stored (Happs, 1985). In addition to learning theories a wide range of methods have been developed to facilitate the educational process, such as variation theory (Cheng, 2016), cognitive maps (Diekhoff, 1983), semantic proximities (Nagy, 1984) etc. These theories and methods are easy to use and well established but are based on qualitative soft science principles, with subjective guidelines that are open to interpretation and hence dependent on the skill and experience of the educator.

Learning outcomes can be evaluated by a learning taxonomy such as the Structure of Observed Learning Outcomes (SOLO) taxonomy (Biggs & Collis, 1982, 1989). SOLO is useful because learning can be ranked according to five different levels with associated evaluation metrics. Excluding pre-structural level 1, uni-structural is understanding based on one element with metrics such a 'identify'. The multi-structural level is understanding based on several related elements with metrics such as 'list' or 'describe'. However, these represent low order learning. High order learning is relational knowledge with many interdependent elements and extended abstract in which knowledge can be generalized to a new subject. Relational knowledge is important for two reasons. Firstly, it confers the ability to understand evaluated by the metric of 'explain', secondly it is the basis of scaffolding in which more complex knowledge is contextualized and acquired. Relational knowledge, is considered the core of higher cognition, highlighting the significance of achieving these higher learning standards (Halford, 2010).

In order to evaluate STEM teaching and learning quality over thirty units across a wide range of STEM disciplines offered by seven nationally accredited institutions (college and university) in two countries were evaluated based on the SOLO taxonomy (Maj, 2021). All the units evaluated were broadly based on Constructivist principles. The findings unveiled considerable variations in pedagogical quality and pass rates. One university unit consistently achieved circa 100% pass rates but was taught and assessed at SOLO multi-structural level–far below any reasonable expectations. Another university unit was taught and assessed at a higher pedagogical level (SOLO relational level) but had consistently low pass rates. This placed the learning responsibility on students rather than how the teacher could improve leading outcomes Anecdotally, academics variously reported that learning should be:

> "challenging, hard, very hard or even a character building 'meat grinder."

It is anomalous that STEM disciplines, grounded in hard scientific principles, are taught based on qualitatively informed learning theories, which may result in a less than optimal learning outcomes. Arguably, a quantitative learning theory is needed.

> "I often say that when you can measure what you are speaking about, and express it in numbers, you know something about it; but when you cannot measure it, when you cannot express it in numbers, your knowledge is of a meagre and unsatisfactory kind; it may be the beginning of knowledge, but you have scarcely, in your thoughts, advanced to the stage of science, whatever the matter may be" (Thomson, 1889).

SCIENCE OF LEARNING

The American National Science Foundation (NSF) initiated the Science of Learning (SoL) program. This program had explicit goals, including the pursuit of '*optimized learning for all*' (NSF, 2013, 2017). Additionally, the Science of Learning Research Center (SLRC) was established in Australia, formulating 12 PEN principles (psychology, education, and neuroscience) (SLRC, n. d.). For instance, PEN principle #1 states, "*Written text and spoken text do not mix*." It is noteworthy that these PEN principles are qualitative in nature. However, despite these initiatives, SLRC, along with many SoL institutes globally, have ceased operations without conclusively addressing the optimization challenge.

To enhance educational outcomes, the Grattan Institute proposed a comprehensive strategy involving five key changes, including a curriculum overhaul aimed at achieving '*optimized learning from pre-school to university*' (Grattan, 2023). However, the institute did not provide specific details on how this optimization could be realized.

The associated discipline of brain science has recommended various principles and practices for optimizing knowledge construction by means of 'tricks' such as elaboration, retrieval practices etc. {Weinstein, 2018 #1180}. However, they are qualitative.

LEARNING QUALITY WITH ARTIFICIAL INTELLIGENCE

AI is a rapidly developing technology. Generative AI harnesses advanced algorithms to create diverse forms of content, including audio, computer code, images, text, simulations, videos, and more. In the context of natural language processing, tools like ChatGPT specialize in generating human-like text-based interactions. This paper is restricted to text-based ChatGPT.

The integration of ChatGPT in education offers transformative possibilities for enhancing the quality of learning experiences (Cavojsky, 2023; Hassija, 2023; Prentzas & Sidiropoulou, 2023). ChatGPT address cognitive load by using adaptive algorithms based on user input. Student questions can be modified and refined to modify the output.

It is important to note that the responses generated by ChatGPT are not pre-programmed but are instead produced based on patterns and information learned during training. This makes generative AI a powerful tool for creating dynamic and contextually appropriate content across various domains.

ChatGPT 3.5 was asked the following question: What is the difference between a hub and a switch?

Hub

> A hub is a basic networking device that operates at the physical layer (layer 1) of the OSI model. It simply receives data packets from one device and broadcasts them to all other devices connected to the hub. All devices on a hub share the available bandwidth, and collisions can occur if multiple devices try to transmit data simultaneously, leading to decreased network efficiency. Hubs do not have the ability to intelligently manage or analyze network traffic. They are rarely used in modern networks due to their limited capabilities and inefficiency.

Regenerated Output by ChatGPT

> Physical layer device: A hub operates at the physical layer (layer 1) of the OSI model.
>
> It simply receives incoming data packets from one device and broadcasts them to all other devices connected to the hub, regardless of whether the data is intended for a specific device or not.
>
> Broadcast transmission: Hubs have no intelligence to determine the destination of data packets. They blindly transmit data to all devices on the network, which can lead to network congestion and inefficiency.
>
> Limited bandwidth sharing: Since hubs broadcast data to all devices, they share the available bandwidth among all connected devices, leading to slower network performance as the number of devices increases.
>
> Simple and inexpensive: Hubs are simpler in design and less expensive compared to switches.

Switch

> A switch operates at the data link layer (layer 2) of the OSI model. Switches are more intelligent than hubs. They examine the destination medium access control (MAC) addresses of incoming data packets and forward them only to the specific device that should receive them, reducing unnecessary network traffic. Switches maintain a MAC address table (also known as a CAM table) that associates MAC addresses with the corresponding switch ports. This enables them to make informed forwarding decisions. Switches provide dedicated bandwidth for each device, improving network performance compared to hubs. They are capable of segmenting the network into smaller collision domains, reducing the likelihood of data collisions and improving overall network efficiency. Managed switches offer advanced features like virtual local area network (VLAN) support, quality of service settings, and more, allowing for greater control and optimization of network traffic. In summary, while hubs and switches both serve as means to connect devices within a network, switches are much more efficient and intelligent due to their ability to analyze and manage data traffic. Hubs, on the other hand, simply broadcast data to all connected devices, which can lead to network congestion and reduced performance. In modern networking environments, switches are the preferred choice due to their superior capabilities.

Regenerated Output by ChatGPT

> Data link layer device: A switch operates at the data link layer (layer 2) of the OSI model. It is more intelligent than a hub and is capable of making decisions about where to send data based on MAC addresses.
>
> MAC address learning: Switches build and maintain a MAC address table that associates MAC addresses with specific switch ports. This enables them to send data only to the intended recipient, reducing unnecessary network traffic.
>
> Unicast transmission: Switches use unicast transmission, meaning they send data only to the

specific device it's intended for, improving network efficiency and reducing collisions.

Better performance: Switches offer better performance than hubs because they allow simultaneous data transmissions between different devices without causing collisions, resulting in higher network throughput.

More expensive: Due to their advanced features and improved performance, switches are generally more expensive than hubs. In summary, a hub simply broadcasts data to all devices on the network, leading to network congestion and inefficiency, while a switch intelligently manages data traffic by sending data only to the intended recipient based on MAC addresses. As a result, switches provide better performance and are more suitable for modern LAN environments, while hubs are outdated and rarely used in contemporary networking setups.

Analysis

The output was incoherent and discontinuous potentially resulting in a lack of understanding and misconceptions. Not all elements and their relationships are identified, defined, ranked, and sequentially ordered, leading to cognitive gaps. An essential prerequisite, namely Ethernet, is not mentioned. Both hubs and switches are based on Ethernet, a shared communication system connecting multiple PCs. As a shared communication system, there must be a medium access control protocol for controlling bandwidth, but this is not addressed. Referring to a hub as a physical layer device (OSI layer 1) is correct. However, the use of the term 'data packets' is misleading, as a hub operates using bits, not packets, which belong to OSI layer 2 (data link layer). This could potentially lead to misconceptions. The term 'broadcast' is also misleading, as it implies transmitting to all devices except the sender, in contrast to unicast, which is a one-to-one transmission. A PC can unicast to another PC, but a hub transmits it to all PCs (except the sender), sometimes referred to as pseudo-unicast. The text does not explicitly mention the use of the Address Resolution Protocol (ARP), which enables a PC to broadcast. While it correctly states that devices share bandwidth, the core concept of a medium access control protocol determining the use of available bandwidth is missing. Hubs use the carrier sense/multiple access/collision detection (CSMA/CD) control protocol. Stating that collisions can occur, leading to decreased network efficiency, is misleading, as collisions are normal, and the inefficiency is due to the use of the simple but inefficient CSMA/CD protocol.

In the case of a switch operating at the data link layer, the statement is correct. However, the use of frames, which have addresses (source and destination), is only mentioned in the regenerated output. The frames allow the switch to maintain a MAC address table (CAM table) linking switch ports with MAC addresses of PCs, enabling unicast. Although the text implies it, the mention of a switch operating in broadcast mode is missing, which is necessary for ARP to function. The text introduces the term 'dedicated bandwidth' without a clear explanation. The concept of a 'collision domain' is mentioned without clarification, leaving questions about its presence in hubs. The text mentions segmentation without defining it, and it raises questions about whether providing dedicated bandwidth is equivalent to segmentation or creating smaller collision domains. The overall output imposes a high cognitive load with cognitive gaps, posing a risk of student misconceptions. This highlights the importance of exercising caution when relying on AI-generated content for educational purposes, emphasizing the imperative role of human review and correction to ensure the quality and accuracy of information.

ChatGPT 3.5 was asked the following question:

Explain the following equations and the relationship between them:

$$y = Asin(\rho\theta \pm L) \quad (1)$$

$$y = Asin(\omega t \pm L) \quad (2)$$

After defining the variables, the output was, as follows.

Interpretation & Relationship

Eq. (1) is used to describe circular motion. Imagine a point moving around a circle. As it goes around the circle, its vertical position varies in a sinusoidal (wave-like) manner. The amplitude (A) controls how high and low the point goes from its average position. The radial distance (ρ) and angle (θ) determine the location of the point on the circle. The phase angle (L) determines where the motion starts on the wave.

Eq. (2) describes a time-varying oscillation. As time progresses, the point's vertical position follows a sinusoidal pattern. The amplitude (A) controls how far the point moves up and down from its average position. The angular frequency (ω) determines how quickly the oscillation happens. The phase angle (L) still decides where the wave starts.

Relationship Between Equations

Both equations involve the same kind of mathematical behavior: Sinusoidal waves. The difference lies in what is being described. Eq. (1) focuses on circular motion, where the point moves

> around a circle. Eq. (2) concentrates on oscillations that change over time. In both cases, the amplitude, frequency (or angular frequency), and phase angle play important roles in determining the shape, speed, and starting point of the wave.
>
> In summary, these equations represent different contexts–circular motion and time-varying oscillations–but both use the sine function to describe how a value changes in a wave-like pattern. The key parameters in both equations control the characteristics of the wave.

I Analysis

ChatGPT 3.5's explanation of Eq. (1) and Eq (2) presents a clear and coherent representation of mathematical concepts. The explanation adeptly defines the variables, interprets the significance of each equation, and establishes a meaningful relationship between them. However, a notable inconsistency is identified concerning the use of degrees in Eq. (1) and radians in Eq. (2), posing a potential source of confusion that requires clarification. Despite this inconsistency, the output delivers a valuable and well-structured explanation suitable for educational purposes. The integration of a graphical tool enhances the potential for effective teaching, and the acknowledgment of prerequisite concepts demonstrates an understanding of contextual foundations.

COGNITIVE LOAD THEORY

Cognitive Load Theory (CLT) is based on cognitive science principles that include schema, Short-Term Memory (STM), Long-Term Memory (LTM), and Intrinsic Cognitive Load (ICL) (Bannert, 2002; Valcke, 2002). ICL represents the complexity of the knowledge to be taught. Knowledge is represented as a schema, a pattern of relationships between elements, stored in LTM. The process of learning is the construction of schemas in LTM mediated by STM. However, STM (aka working memory) has only limited capacity and retention time and hence can easily be overloaded by curriculum materials with a high ICL. A SOLO relational knowledge schema, which confers the ability to understand and is the goal of learning, has a high cognitive load because it consists of many interdependent elements that cannot be understood in isolation. Understanding an element depends upon understanding the context of pre-requisite elements and their relationships. If instructional materials have missing elements, missing relationships and elements not in the correct sequence this exacerbates the cognitive load.

The ideal properties of relational knowledge (and extended abstract) are coherence (a unified whole) and contiguity (sequential from the simplest to most complex concept, connected throughout in an unbroken sequence with no cognitive gaps). Scaffolding is the acquisition new, more advanced knowledge. For this new knowledge to be contextualized the underlying knowledge must be resident in LTM.

It is theoretically possible to create relational knowledge schemas that are coherent and contiguous across all educational levels from school to university representative the goals of the NSF SoL (*'optimized learning for all'*) and Australian Grattan Institute (*'optimized learning from pre-school to university'*). However, CLT lacks a reliable quantitative metric for measuring ICL (de Jong, 2010). Without such a metric, these goals are not possible as optimization is a quantitative method. Optimization is essential because creating coherent and contiguous relational knowledge is a complex combinatorial problem involving the identification, ranking, and sequential ordering of many interdependent elements and associated relationships. Failure to achieve coherence and contiguity may result in STEM curriculum materials that are hard to teach and learn.

A range of topics in STEM curriculum materials (science, mathematics, and IT) at school, college and university levels were evaluated. All the materials were, to various degrees, incoherent and discontinuous i.e., non-sequential with cognitive gaps representative of a high cognitive load. Illustratively, at the school level, in the chapter 'understanding networks' hub and switch technologies were explained on p. 56, but Ethernet is not explained until p. 59 (Grover, 2017). Ethernet is a shared communication system that is the basis of both hubs and switches. Furthermore, the explanation of Ethernet is that it uses CSMA/CD to check for collisions. A hub uses CSMA/CD, but a switch has a different medium access control protocol that uses a MAC address table. At college/university level a textbook chapter teaching a single trigonometry waveform ($y = Asin[\omega t \pm \alpha]$) had nine cognitive gaps (Bird, 2014).

Cognitive gaps not only exacerbate the cognitive load but may result in students coming to their own incorrect conclusions called misconceptions.

> "Once integrated into a student's cognitive structure, these misconceptions interfere with subsequent learning. The student is then left to connect new information into a cognitive structure that already holds inappropriate knowledge. Thus, the new information cannot be connected appropriately to their cognitive structure, and weak understandings or misunderstandings of the concept will occur" (Nakhleh, 1992).

Curriculum materials with a high cognitive load and cognitive gaps are not only harder to teach and learn, but also potentially inefficient as cognitive gaps must be identified during the learning process and, if not corrected, may lead to misconceptions, which tend to be cumulative, persistent, hard to correct and may handicap further learning i.e., scaffolding. This may, in part, explain why STEM disciplines are considered difficult.

> "Half of Americans think young people do not purse STEM because it is too hard" (Kennedy, 2018).

COGNITIVE LOAD OPTIMIZATION

Science, technology and engineering all start by quantitatively modelling systems in order to make accurate and quantitative predictions, based on the underlying theory or laws, prior to construction or system modification. By contrast, the current learning theories in use today are based on qualitative soft science principles, with subjective guidelines that are open to interpretation and hence dependent on the skill and experience of the educator, which can lead to wide variations in the quality of curriculum materials and learning outcomes.

CLO, a new SoL theory, is fundamentally different because it is based on quantitatively modeling relational knowledge (and extended abstract knowledge) as a coherent, contiguous whole that is pedagogically scalable across different educational sectors.

CLO relational knowledge is modelled as a concept-attribute matrix. A concept is defined by its essential attributes. A distinctive feature of CLO lies in its reliable, quantitative metrics for assessing cognitive load and its associated detailed methodology and procedures. The simplest metric involves dividing the number of concepts by attribute changes, forming the basis for quantitative optimization achievable either manually or through a software tool based on optmization principles. Hence the CLO concept-attribute matrix can be optimized to create the easiest, fastest and most efficient learning paths. The optimized CLO concept-attribute matrix is then converted into a CLO relational knowledge schema diagram, which is a sequential, structured learning path from the simplest to the most complex concepts with few if any cognitive gaps (**Figure 1**) (Maj, 2020). CLO schemas are the basis of instructional design, teaching and assessment. Hence, during teaching and learning CLO relational (and extended abstract) knowledge schemas are likely to be internalized into student's LTM thereby achieving the goal of learning.

CLO relational knowledge schemas are "agnostic" in nature as they can be the basis of various teaching styles (such as student- or teacher-centered approaches) and assessments (both formative and summative), as well as applications in educational games and eLearning tools.

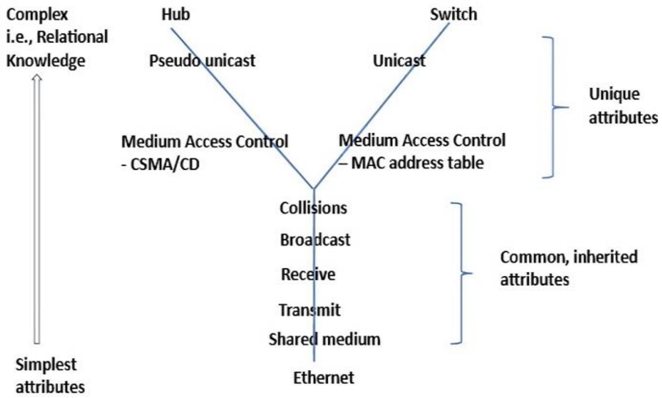

Figure 1. CLO relational knowledge schema of hub & switch (Source: Author's own elaboration)

Notably, when employed as the foundation for an eLearning tool called state model diagrams, CLO has demonstrated accelerated learning outcomes achieving significant improvements in learning outcomes achieved in considerably less time (Maj et al., 2004). The quality of CLO based learning was evaluated six weeks after the final exam and student responses matched those of someone with expert knowledge (Maj et al., 2005). Networking professionals undertaking advanced studies were given a one-hour lecture on spanning tree protocol using only CLO state model diagrams. All five students responded positively, best exemplified by the response of one student who wrote,

> 'Yes, I have learnt more in this period than the whole of the semester.'

CLO relational knowledge schemas support scaffolding in which students can build upon and extend their existing knowledge (Maj & Veal, 2007).

Remote, online based learning can be a challenging mode of teaching. According to a national report on online learning 29% of respondents complained about lack of engagement and 34% complained about lack of/inadequate academic interaction. Furthermore, a number of students did not think they were getting 'value for money' with requests for refunds (TEQSA, 2020). Teaching engineering mathematics based on the CLO method in remote access mode resulted in excellent student feedback, 100% pass and retention rates whilst still achieving the learning objectives (Maj, 2018).

Because CLO schemas are coherent and contiguous, they are pedagogically scalable whilst still maintaining relational knowledge integrity. Hence it is possible to create a single, coherent, contiguous CLO schema that spans different educational levels (school, college, and university) thereby meeting the NSF SoL and Australian Grattan Institute goals of optimized learning for all.

Illustratively, CLO was used to teach IT at school level resulting in significant improvements in learning outcomes (Maj, 2021). The same CLO schema taught at school level, is also taught at college and university level

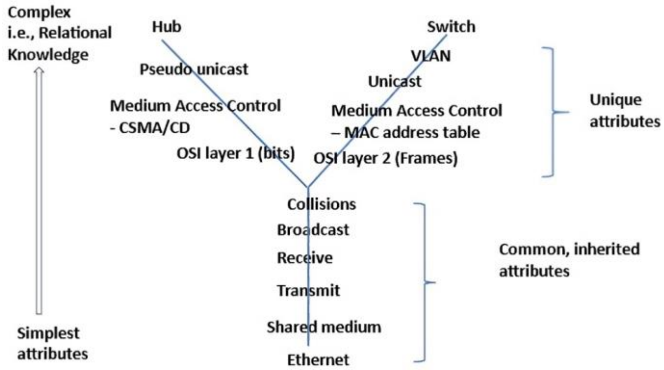

Figure 2. Extended CLO relational knowledge schema of hub & switch (Source: Author's own elaboration)

but includes more advanced attributes. For instance, CLO diagram suitable for schools (**Figure 1**), would be taught at a faster pace and more advanced attributes added (**Figure 2**). The attribute of OSI layer 1 (bits) may be added as a hub attribute; and the OSI layer 2 attribute (frames with MAC addresses) added as a switch attribute. A switch attribute of VLAN can be incorporated, reflecting the switch's capability to create separate broadcast domains.

Because of the property of scalability, CLO may be used to teach Business studies students who are specializing in IT management requiring student to study STEM units such as cybersecurity, computer and network systems, IT systems etc. However, not untypically business students may not have a strong technical background. Arguably, the objective of learning should be not to turn business students into technical experts, which is neither desirable or attainable, but to achieve a standard of relational knowledge learning that is relevant to employer expectations and supportive of further, more advanced studies i.e., relational knowledge in LTM. The quality of learning of 64 undergraduate Business studies students who had passed three STEM IT units was evaluated by ten simple relational knowledge questions–all students scored zero (Maj & Nuangjamnong, 2020). In this experiment, a cohort of 33 students whose first language was not English were given three lectures in remote online mode on computer technology, network technology and cybersecurity using CLO based materials and the relative advantages of CLO versus traditional teaching evaluated. The results indicated that learning based on the standard method was superficial low order learning (SOLO multi-structural with understanding based on several related elements with metrics such as 'list' or 'describe') that is unlikely to be resident in LTM. This explains student comments that included:

> 'Know but not understand, cannot apply to actual work' and 'It does not have explaining in each, how it works.'

> 'But lack of deep understanding of each topic. Sometime you do not really know your understanding is correct or not.'

When asked if they would remember what they were taught in three months' time, responses included,

> 'Not remember at all.'

> 'Only for short term'.

By contrast for CLO based teaching student comments included:

> 'Know in-depth details and easily apply in life.'

> 'It focuses on understanding.'

> 'I have a full understanding to the topic'.

Regarding knowledge retention in three months' time, responses for CLO based learning included,

> 'Of course I will.'

> 'Sure, I prefer this method because I can have a full understanding. I like the way I can think of something not remember it'.

The last comment is indicative of relational knowledge resident in LTM. The majority of students (99%) preferred learning based on the CLO method. The behavioral intentions of a cohort of 210 business studies graduate students, evaluated by both the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), found a significant effect on students' behavioral intention to adopt/use CLO (Nuangjamnong, 2022).

The challenges of remote access learning are potentially exacerbated when instruction is in English to students whose first language is not English. A cohort of 30 Chinese business studies graduate students were taught IT based on CLO principles in remote online mode and the results evaluated using descriptive statistics factors that included: Performance Anticipation (PA), Effort Expectancy (EE), Relative Benefit (RB), and Adopt Cognitive Load (ACL). The responses to all factors were either high or very high. Illustratively for Relative Benefit

> 'Adopting cognitive load optimization in STEM with teaching in the project management course by the lecturer, this technique has more advantages than other teaching techniques because the contents in the course will focus only necessary knowledge in-depth', had a mean of 4.09 with a standard deviation of 0.739 (Nuangjamnong, 2023).

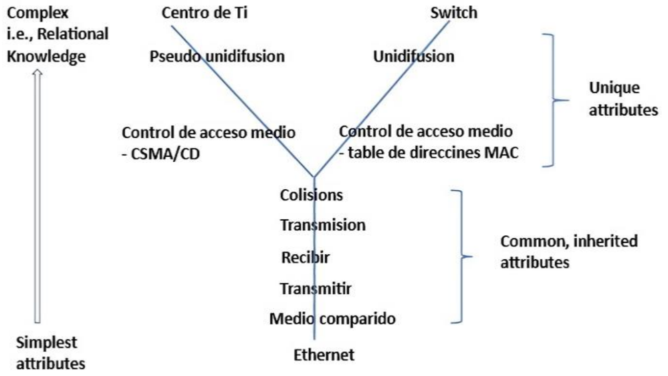

Figure 3. CLO relational knowledge schema of hub & switch in Spanish (Source: Author's own elaboration)

Additionally, CLO relational knowledge schemas can be translated into different languages, thereby enhancing their accessibility and applicability globally (**Figure 3**).

CLO has been evaluated across all educational sectors (school, certificate, diploma, undergraduate and postgraduate) for a wide range of STEM disciplines (engineering drawing, cybersecurity, project management, medical informatics, electrical principles, industrial applications of IT, network engineering etc.) in both face to face and remote delivery modes. In all cases CLO consistently achieved high pass and retention rates (typically 100%) coupled with exceptionally high positive student satisfaction feedback (Maj, 2022).

CLO uniquely meets the goals of the NSF SoL ('*optimized learning for all*') and Australian Grattan Institute ('*optimized learning from pre-school to university*'). However, CLO is time consuming to implement. A strong case can therefore be made for economies of scale i.e., CLO STEM curriculum developed for a large number of schools and colleges.

CLO LEARNING THEORY VS. AI CHATGPT

1. *Nature:* CLO is a new SoL theory and educational technology, while AI ChatGPT is a useful educational technology but not a learning theory.
2. *Practical application:* CLO is a practical learning theory and methodology with rules for creating optimized CLO relational knowledge schemas. AI ChatGPT is a useful and easy to use educational technology.
3. *Concept representation*: In CLO relational knowledge is modelled by concepts that are defined by attributes, which are identified, defined, ranked, and sequentially ordered. There is no assurance that all elements/relationships are identified, defined, ranked, and sequentially ordered in AI ChatGPT.
4. *Relational knowledge optimization:* Relational knowledge is quantitatively optimized from simple to complex in CLO, whereas questions can be refined to get easier or complex responses with AI ChatGPT, but not quantitatively defined.
5. *Cognitive load:* CLO optimally minimizes cognitive load, in contrast to AI ChatGPT, where cognitive load may be high.
6. *Learning paths:* CLO schemas are provable the easiest, most efficient and fastest learning paths.
7. *Knowledge coherence:* Relational knowledge is coherent and contiguous in CLO, whereas relational knowledge may be incoherent and discontinuous in AI ChatGPT.
8. *Misconceptions:* Few, if any, misconceptions are associated with CLO, while AI ChatGPT may result in misconceptions.
9. *Pedagogical paths:* Because CLO schemas are coherent and contiguous, they are pedagogically scalable whilst still maintaining relational knowledge integrity. Hence it is possible to create a single, coherent, contiguous optimized CLO schema that spans different educational levels (school, college, and university). AI ChatGPT is applicable to school, college, and university educational sectors, but the output is not necessarily coherent and contiguous. Further work is needed.
10. *Instructional design:* CLO schemas serve as the basis of curriculum design, teaching, and assessment. Further work is needed regarding the role of AI ChatGPT in instructional design and assessment.
11. *Learning outcomes:* Significant improvements in STEM learning outcomes are achieved in considerably less time with CLO. Further work is needed to determine AI ChatGPT's impact on learning outcomes.
12. *Disciplinary applicability:* CLO works for all STEM disciplines and is theoretically applicable to other disciplines. AI ChatGPT works for different disciplines, but further work is needed.
13. *Alignment with goals:* CLO meets the objectives of the both the Australian Grattan Institute ('*optimized learning from pre-school to university*') and NSF SoL (*optimized learning for all*). No data are available on AI ChatGPT's alignment with specific educational goals.
14. *Visualization:* CLO schemas are diagrammatic, allowing relational knowledge to be viewed concurrently; however, AI ChatGPT is text-based.
15. *Schema variability:* CLO schemas do not vary, but regenerated output varies with AI ChatGPT.
16. *Internalization of knowledge:* CLO-based teaching is likely to result in CLO relational knowledge schemas being internalized into student LTM,

while students are guided to construct their own relational knowledge schema with AI ChatGPT.

17. *Integration levels:* CLO quantitatively integrates instructional design, teaching, and assessment levels, whereas no data are available on AI ChatGPT's integration levels.
18. *Teaching styles:* CLO schemas are agnostic and can be used by different teaching & learning styles (e.g., student-led, teacher-led). Further work is needed to evaluate AI ChatGPT's adaptability to different teaching styles.
19. *Language adaptation:* CLO schemas can be converted to different languages. AI ChatGPT is multi-lingual.
20. *Software tool:* There is a software tool available for CLO, continually improving, while AI ChatGPT is an easy-to-use software tool.
21. *Learning process:* CLO is a new learning theory with a detailed methodology and principles that must be understood before schemas can be created; conversely, AI ChatGPT is easy to use and does not require an extensive learning process.

CONCLUSIONS & RECOMMENDATIONS

The goal of learning is relational knowledge (and extended abstract) resident in LTM. Relational knowledge is important because it confers the ability to understand and is the basis of scaffolding in which more complex knowledge is contextualized and acquired. Current learning theories and methods are easy to use and well established but are based on qualitative soft science principles, with subjective guidelines that are open to interpretation and hence dependent on the skill and experience of the educator. This may result in considerable variations in pedagogical quality and pass rates. Furthermore, such curriculum materials may have missing elements, missing relationships and elements not in the correct sequence representative of a high cognitive load–which makes the material hard to teach and learn. This problem is compounded by cognitive gaps in the materials, which exacerbate the cognitive load and may result in students coming to their own incorrect conclusions called misconceptions, which may handicap further learning. This may be one reason why STEM disciplines are considered difficult with the associated low retention and pass rates.

This paper evaluates two possible solutions to this problem–AI ChatGPT and CLO. ChatGPT is easy to use and works for a wide range of STEM disciplines and educational levels but there are two potential problems–it is an educational technology but arguably not an educational theory and there is no assurance of pedagogical quality. However, further work is needed.

It is anomalous that STEM disciplines, grounded in hard scientific principles, are taught based on qualitatively informed learning theories, which may result in a less than optimal learning outcomes. The need for a quantitative approach to learning has been identified by the NSF SoL objective ('*optimized learning for all*') and Grattan Institute goal ('*optimized learning from pre-school to university*'). Optimization is a quantitative method that mandates the need for measuring cognitive load.

In the Constructivist learning theory learners play an active role in 'constructing' their own meaning. Knowledge is not seen as fixed and existing independently outside the learner. In effect students are guided to construct their own knowledge–which may be inefficient and error prone. By contrast, in CLO the core principle is that the relational knowledge to be taught is defined and must first be quantitatively modelled and optimized for the lowest possible cognitive load with no cognitive gaps. The resultant CLO relational knowledge schema diagram thereby represent the easiest and most efficient and fastest learning paths, which are the basis of curriculum design, teaching and assessment. Furthermore, these schemas are 'agnostic' and hence may be used as the basis of different teaching and learning styles. There is some evidence that during the teaching and learning process these CLO schema diagrams are internalized into students' LTM, which may facilitate scaffolding in which more complex knowledge is contextualized and acquired. However, further work is needed. Because CLO schemas are coherent and contiguous, they are pedagogically scalable whilst still maintaining relational knowledge integrity. Hence it is possible to create a single, coherent, contiguous optimized CLO schema that spans different educational levels (school, college and university). Work to date has demonstrated that using CLO can result in significant improvements in STEM learning outcomes and all educational levels (school, college and university). However, CLO is a new learning theory with a detailed methodology (procedures, metrics etc.) that is time consuming to use. Further work is needed to address this issue. CLO provides a quantitative learning taxonomy and hence it may be possible to evaluate ChatGPT output and then optimize it based on CLO principles in order to reduce curriculum development time. However, further work is needed.

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