Integrating Artificial Intelligence in Healthcare Continuing Professional Development: A Theoretical Framework

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Abstract

Artificial intelligence (AI) enhanced continuing professional development (CPD) has great potential. It promises to transform the learning experience, improve learning outcomes, and ultimately help us improve patient care. Yet, AI is not a magical solution but a new element in the complex socio-technical systems that form our society. We need to understand the system to understand the power of AI. This position paper examines the need for a theoretical framework to help us better understand and guide interactions between AI and healthcare CPD. The 5 step theory construction methodology outlined by Borsboom et al. has been used to create the framework made of six foundational AI pillars: Literacy, Explainability, Ethics, Readiness, Reliability, and Learning Theories, and two complementary theoretical lenses: Complexity Theory and Actor-Network Theory.

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Keywords:
AI, artificial intelligence, AI-enhanced CPD, AI literacy, AI explainability, AI ethics, AI readiness, AI reliability, learning theories, complexity theory, actor-network theory, black box

Abstract

Artificial intelligence (AI) enhanced continuing professional development (CPD) has great potential. It promises to transform the learning experience, improve learning outcomes, and ultimately help us improve patient care. Yet, AI is not a magical solution but a new element in the complex socio-technical systems that form our society. We need to understand the system to understand the power of AI. This position paper examines the need for a theoretical framework to help us better understand and guide interactions between AI and healthcare CPD. The 5 step theory construction methodology outlined by Borsboom et al. has been used to create the framework made of six foundational AI pillars: Literacy, Explainability, Ethics, Readiness, Reliability, and Learning Theories, and two complementary theoretical lenses: Complexity Theory and Actor-Network Theory.

Introduction

Artificial intelligence (AI) applications are increasingly impacting all aspects of the healthcare system, from clinical practice (diagnosis, treatment, prevention) to research, communication, administration, and learning.[1] The super-connected, post-digital nature of our society,[2] where AI tools have access to vast amounts of data, and where the impact of AI can quickly spread globally, amplifies AI's power. AI's rapid evolution is associated with ethical, legal, social, and professional challenges and risks for health and CPD professionals, patients, and the broader society.[3, 4] Therefore, we need to increase our capacity to analyze and improve AI-enhanced socio-technical systems.

Changing Complex Systems

Continuing professional development (CPD) acts as an open, adaptive, complex system.[5, 6] The CPD system is located in a changing healthcare environment, shaped by emerging technologies and clinical practices, and focused on addressing the contextual learning needs of individuals, teams, and organizations. AI adds additional layers of complexity.[7] It provides new variables to the CPD system and connects it more dynamically with the broader healthcare system.

Networked Society – a New Context

Initiatives using AI in education have over a century-long history.[8] From teaching machines in the 1920s to expert systems in the 1970s to 1990s, AI tools existed as (semi)isolated centers, relying almost entirely on rules designed by human experts. Now, our society's super-connected, big-data nature creates a considerably different context. From (semi)isolated centers with limited input of data, AI has become omnipresent and empowered by the global internet of knowledge.

Whether we talk about personalized search findings, text editor suggestions, AI-generated meeting minutes, health monitoring apps, 950 AI-enabled medical devices recognized by the FDA,[9] or learning analytics, or healthcare quality improvement[10] AI tools are here, tightly embedded in our daily practices.

There is Nothing so Practical as a Good Theory

Despite the close relationship between AI, individuals, and society, the research on AI in education and CPD has been mostly technocentric and a-theoretical.[11, 12] Technocentric research may miss the complex interactions between AI, CPD, and broader healthcare contexts.[13]

As we aim to understand how AI impacts CPD activities and the broader socio-technical healthcare system, our focus must shift from the individual phenomena of AI toward the interaction between AI and various phenomena and activities in the complex context of healthcare CPD.[14] Theoretical frameworks help us make that shift, allowing us to understand better and manage interactions between various elements of the complex system.[15]

Kurt Lewin, one of the pioneers of organizational and social psychology, famously noted, "There is nothing so practical as a good theory" and "the best way to understand something is to try to change it."[16, 17] Guided by those maxims, we propose a theoretical framework to comprehend better and guide the integration of AI and CPD. This is a distinct change within the CPD domain; it creates an opportunity to better understand and improve CPD within the broader socio-technical context.[18, 19]

Methodology

We employed the theory construction methodology outlined by Borsboom et al.[20] This process included the following 5 steps:

1. **Identification of Phenomenon**: We identified AI-supported CPD as a relevant, explainable, and reproducible phenomenon that is rapidly evolving but also stable in terms of its broad and continued impact on CPD. [21, 22]
2. **Drafting Core Principles and Models**: VH drafted core principles to explain the phenomenon and created multiple explanatory models using abductive reasoning (explanatory inference). ChatGPT helped with the initial brainstorming and refining of explanations. This concept were reviewed, refined, and combined, resulting in a draft shared with the author group.
3. **Model Development**: After multiple additional iterations and contributions from all authors, the final model was developed.
4. **Assessment of Explanatory Adequacy**: As the fourth step, we assessed the adequacy of the framework and its ability to explain how AI-enabled CPD can enhance learning.
5. **Evaluation of Theoretical Framework**: We concluded the process by evaluating the value of the constructed theoretical framework through two simulated scenarios.

Complexity-ready lenses

AI-enhanced CPD occurs in the open, adaptive, complex socio-technical healthcare system, where many elements are on the edge of chaos.[23] Working with complex, constantly evolving phenomena requires tolerance to ambiguity, a shift of focus from individual phenomena toward the interaction between multiple phenomena in the system, and unique theoretical tools.[23, 24] Complexity Theory (CT) and Actor-Network Theory (ANT), two different but complementary theoretical lenses, were used to understand the socio-technical healthcare system and the role AI plays in it.

AI-enhanced Authoring

All parts of this article – except the practical examples of framework use - were created by human authors with AI support.[25] For example, summaries provided by ChatGPT influenced initial brainstorming sessions, literature review activities, and validation of the concept logic. Google Scholar was used organically to search for literature supporting or expanding the topics discussed.

AI-enhanced typing assistants (Grammarly, Microsoft, and Google) were used to improve the text's clarity, syntax, and concision (Figure 1) .

Given AI's extensive history in analyzing massive, complex datasets and delivering predictive models,[26] we used two simulations created by ChatGPT 4 to validate our framework. The simulated examples of framework utilization have been AI-generated, human-evaluated, and edited.

The tools (Google Scholar, typing assistants, and ChatGPT) were selected because they are ubiquitous, helpful, and easy-to-use AI-enhanced tools familiar to all authors and the broader healthcare CPD community. That will enable readers to review and replicate processes used while writing this paper.

All selected tools come with significant powers and limitations – most noticeably ChatGPT. For example, ChatGPT imput can be biased, lack deep domain-specific insight, have challenges in making ethical decisions, have a “thinking process” that is not transparent, and can provide ideas without referencing sources and infringe copyright. [10, 27]
To address those limitations, we used iterative, collaborative human evaluation and cross-verification with existing literature. Sources of all concepts presented by ChatGPT have been identified and properly referenced through a search of the literature. So, ChatGPT played the role of an informed friend or librarian we had a chance to chat with.

Abductive validation was used for framework variation. We tested the framework/hypothesis against two AI-generated and human-validated simulated scenarios where ChatGPT acted as a human participant[28]. ChatGPT initially created the scenarios, which the authors later confirmed looked realistic and improved linguistically. Our goal was to ensure that simulated examples are realistic, accurate, relevant to CPD providers, and aligned with the framework.
Abductive reasoning does not provide as strong conclusions as inductive and deductive reasoning. Due to the complex, emerging nature of the investigated phenomena, inductive and deductive reasoning can not work well for this task. Therefore, abductive reasoning was the best option for this task.

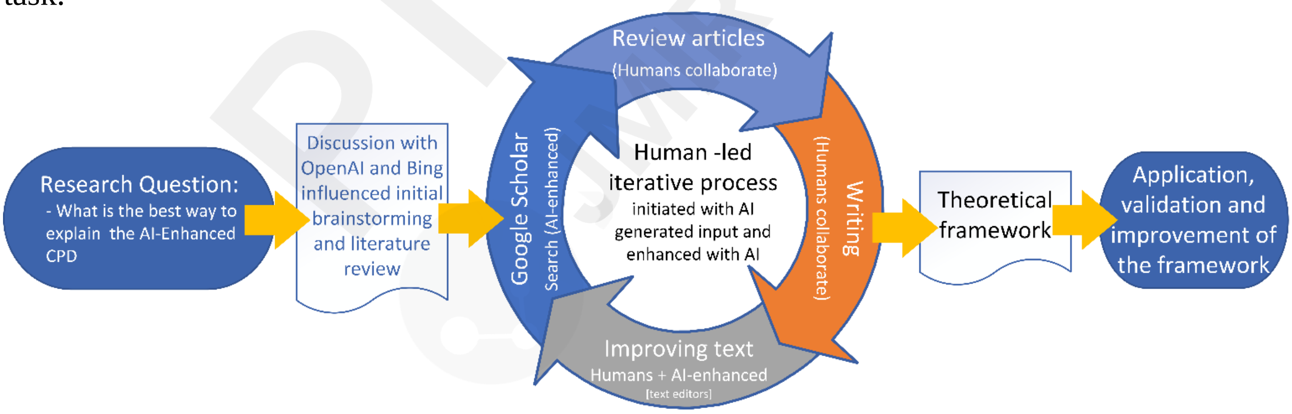

Figure 1. The AI-enhanced writing process of this article

AI and learning theories

Learning theories are crucial in designing AI-enhanced learning environments. For example, Cognitive Load Theory (CLT) and Connectivism can provide valuable insight into using AI to enhance learning activities in different parts of the learning system.

CLT focuses on managing learners' cognitive load to enhance learning efficiency.[29] The goal is to decrease or eliminate extraneous load (e.g., unnecessary examples), adjust the intrinsic load to the learner skill level (e.g., context appropriate to the skill level), and ensure that the remaining work memory capacity is focused on germane load (i.e., cognitive learning processes). Examples of AI-enhanced and CLT-guided interventions are adaptive learning modules, where AI adjusts difficulty based on learner performance,[30, 31] and multimedia learning, where AI optimizes multimedia delivery to optimize cognitive load.[25] [32]

Connectivism emphasizes the role of networks and connections in the learning process.[33, 34] AI and connectivism may facilitate expanding and managing learning networks in the healthcare sector.[35] For example, AI can aggregate and curate up-to-date information for healthcare professionals [36, 37] and suggest learning paths based on individual goals and interests.

The examples above illustrate the interaction between learning theories and AI. Learning theories explain how learning happens, and AI can help us enhance the learning processes described by learning theories. Yet, learning theories do not describe the broader framework of how AI, learning practices, and learning theories interact in the broader healthcare context.

Framework for integration of AI and CPD

The complex interaction between AI, learning theories, and CPD practices introduces the need for a framework to comprehend and guide the integration of AI with CPD for health professionals. We propose a framework made of the six foundational pillars: **A**I **L**iteracy, **E**xplainability, **E**thics, **R**eadiness, **R**eliability, and learning **T**heories, and two complementary theoretical lenses: **C**omplexity theory and **A**ctor-network theory, ALEERRT-CA in short (Figur2).

AI literacy describes our capacity to understand AI's basic concepts and principles, like natural language processing, machine learning, computer vision, and deep data analytics.[38] It also involves the ability to use AI tools and applications in one's clinical practice, such as decision support systems, diagnostic tools, treatment recommendations, patient monitoring, and health education. AI literacy is essential for health and CPD professionals to leverage AI's potential for improving quality and efficiency.

AI explainability (internal logic of how AI makes decisions) and explainability of the impact AI makes on learning interventions (relationship between AI actions and broader socio-technical CPD context) are enablers of AI literacy, readiness, and ethics—understanding how AI-enhanced systems work eases successful implementation of AI.[39-41] However, it seems that trusting that AI is reliable and performs well is more important than having a deep understanding of how AI algorithms work.[42] Very often, we tolerate AI-enhanced solutions as black boxes.

Black boxing is a common process associated with maturation, reliability, and wide acceptance of technology. While the inputs and outputs of the system are known, the user does not understand or is not even aware of the processes inside the black box. Smartphones are a typical example of a black box.[43] As users, we are experienced in inputting and using smartphone outputs. Yet, the average user is minimally aware of the processes in smartphones and how networked and often AI-enhanced apps in the phone interact with external actors. We focus on the service it delivers to us, not on how it works. We trust it works well.

When failures occur or in attempts to improve the system, we need tools to open black boxes of socio-technical systems that utilize AI. It is a process of making internal black box processes visible and ideally understandable to humans.[44] It is an opportunity to examine human and non-human actors in the network of relationships between them and how their interactions deliver desired or, in some cases, erroneous outcomes.

AI ethics refers to the awareness and understanding of AI's ethical, legal, social, and professional implications for healthcare and CPD practice. It involves protecting patient privacy, obtaining informed consent, ensuring accountability, managing bias, ensuring fairness, protecting intellectual property, promoting transparency, and building trust.[45] AI ethics is vital for health professionals to ensure that AI is used safely and responsibly.

AI readiness refers to the willingness and preparedness to adopt and implement AI technologies in learning and clinical practice.[46] It involves having a positive attitude and mindset towards AI, being open to learning from and with AI systems, and being able to cope with the changes and challenges that AI brings. AI readiness is crucial for health professionals to embrace AI as a partner in healthcare delivery and CPD. This readiness involves properly implementing AI-enhanced, research, and data-driven care by developing mental models, skillsets, and support systems for healthcare and CPD providers, their teams, and their organizations. Enterprise-wide AI readiness models can be considered to help organize and prioritize the organizational resources for successful implementation of AI technologies.[47-49]

AI reliability is the ability of an AI system to perform consistently and accurately under varying conditions.[50] It is crucial in high-stakes clinical and CPD applications. Yet, it comes with considerable plasticity.[51] AI systems, or humans using AI tools, must be more reliable than humans alone. For example, apps that flag at-risk students or problematic content posted by students may not be as reliable as humans, yet they may reduce the time-consuming task of reading posts and communicating findings, enabling humans to perform much better and faster than they were alone.

Learning theories describe how learning happens and explain where and how AI can improve learning interventions.

Theoretical lenses. CT and ANT are proposed as complementary theoretical lenses, where the CT lens is better suited to deliver a holistic view, while ANT can easily zoom in on a specific part of the system or a specific AI-enabled app and deliver more actionable insight.
CT explains that our world is made of complex, constantly evolving systems. Those systems are open, and they adapt to changes in the context. Complex systems have emerging properties. Therefore, we cannot understand them simply by analyzing their parts.[23] To analyze AI-enhanced systems, we should not focus solely on AI, but on the system and how the addition of AI is transforming the system.

Complex systems are connected, open, and nested. For example, an individual clinician is a system. Yet she is part of the operating room team – a supersystem. Above that, we have suprasystems such as hospital, national, and global healthcare systems.[52, 53] On all those levels, AI can play a role.[54] Furthermore, AI-related improvement in one system, for example, in the operation room, will stimulate changes in external systems such as CPD, administration, and patient communication.

CT theory explains the need for multiple learning theories and the interaction between them. Learning theories observe the same phenomena – learning. However, they observe learning in different parts of nested hierarchies of complex adaptive systems – i.e., different contexts.[54, 55] The CLT, for example, focuses on one individual and learning that happens primarily internally - in a learner's brain. Connectivism, on the other hand, focuses on learning as a global, social, and technology and artifact-enhanced endeavor.

AI can have an impact on all levels of our reality (from individual to global society). Therefore, it is fair to believe that the interaction between AI and established learning theories will be fruitful, allowing us to optimize CPD interventions at every level (individual, team, organization, population, state, and global society).[54]

ANT explains that our reality is shaped through evolving networks of relationships between human and non-human actors.[56] ANT posits that non-human actors, such as text, digital devices (smartphone or electronic health records), software programs, ideas, organizations, or AI tools, have the agency to shape our reality like humans.

ANT can serve as a magnifier for analyzing micro-level networks of non-human and human actors in a specific part of a complex socio-technical system and at a particular time.[56, 57] It is a good lens to analyze the use of a specific AI-enabled app or department using AI.

CT is better suited to the holistic view of the system,[53, 58] such as how AI is changing CPD. While picture created with CT is more inclusive, it is blurry. The macro-system's complex, evolving nature does not allow us to capture all system elements.

As a combination, ANT and CT enable us to observe the big picture and, when needed, zoom and observe a specific part of the AI-enhanced learning healthcare system.

The framework provides tools that can help us open the black box and observe the "main anatomical structures of AI-enhanced CPD" through macro-lens (CT) and micro-lens (ANT).

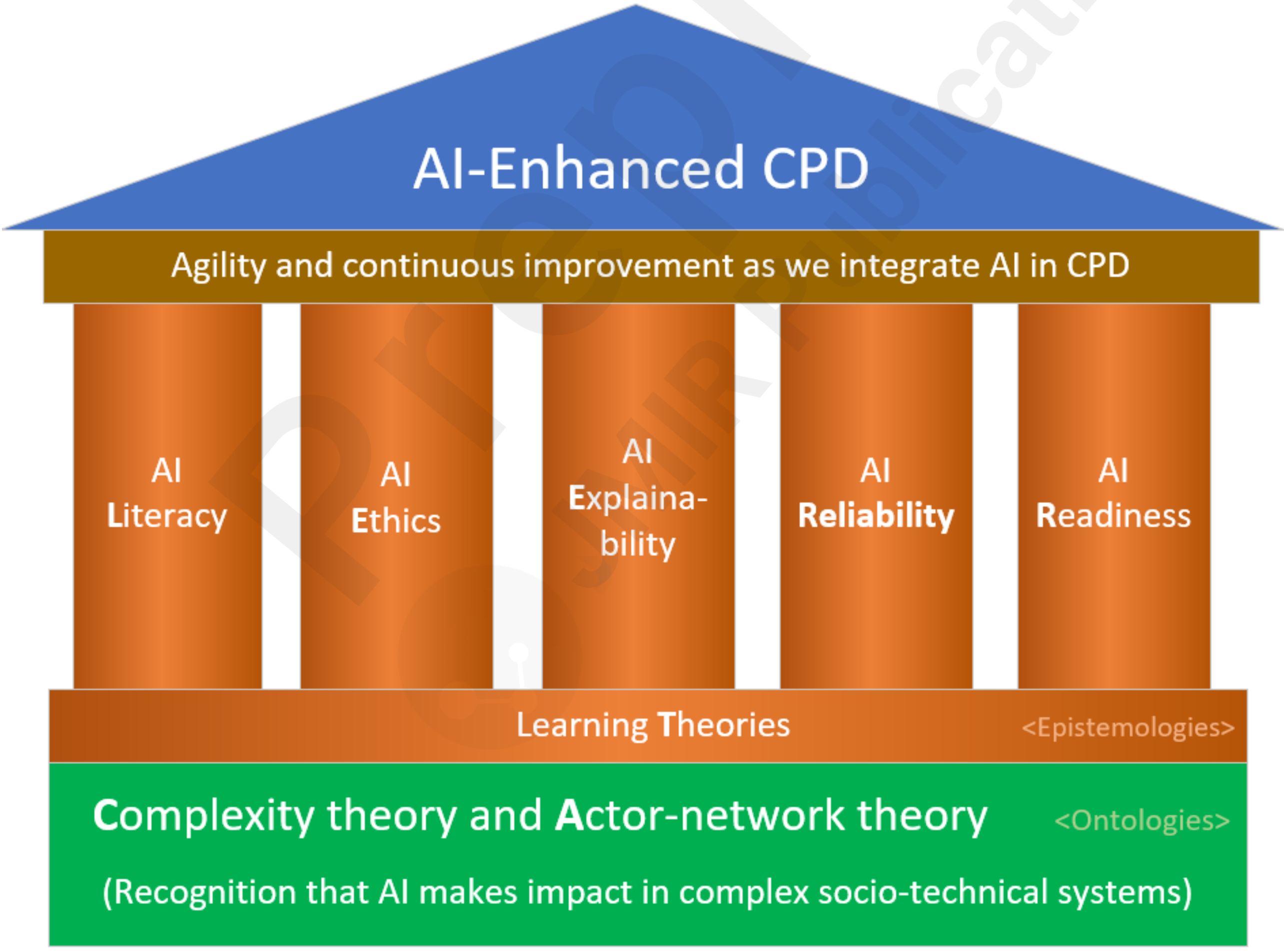

Figure 2 - The proposed framework for integrating AI in CPD - ALEERRT-CA is ade of the six foundational pillars: AI Literacy, Explainability, Ethics, Readiness, Reliability, and learning Theories, and two complementary theoretical lenses to observe system changes associated with AI: Complexity theory and Actor-network theory

Adequacy of the Framework

The proposed framework provides a checklist of 6 building blocks of AI implementation and two theoretical lenses to observe system changes associated with AI. It is a toolset that can help us plan AI implementation and, when needed, open black boxes of AI-enhanced CPD. Therefore, it addresses the criteria of practical application and simplicity (parsimony).[59] CT and ANT, as macro and micro-theories, allow us to observe the system and large-scale structures (CT), and, when needed, focus on the interaction between a small network of human and non-human actors (ANT). The proper theoretical lens for a proper task model aligns with the principle of parsimony.

The framework is rooted in two established theories (CT and ANT) and the literature on AI implementation, which enhances its external consistency and ensures it fits with the broader theoretical landscape of AI in CPD. It appears to provide a good balance of practicality, simplicity, and theoretical robustness, suggesting it can effectively explain how successful AI-enabled enhancement of CPD can occur.

Value of the Constructed Theoretical Framework

The ALEERRT-CA allows us to open the black boxes of AI-enhanced CPD. The black boxes exist on at least two levels. The first level are AI algorithms. That level is not addressed in this paper. On the level above, where this framework is focused on, we have AI-enhanced socio-technical systems and need to understand hidden, complex interactions *between* AI, technical, and social elements that influence learning health system performance and outcomes. The framework describes the main parts - the anatomy - of the AI-enhanced CPD and two theoretical lenses we can use to analyze it.

To illustrate value, we offer two simulated practical examples below:

Example 1 – organization (a macro-example)

A healthcare organization aims to enhance collaboration and knowledge sharing through AI-enhanced CPD (scenario created by ChatGPT 4 on May 4, 2024, and assessed and edidted by authors).
The ALEERRT-CA Framework can support improvements in the following areas:

- **AI Literacy and Readiness**: Assess staff AI knowledge and readiness. Tailored training programs are then developed to bridge any knowledge gaps and cultivate a culture of AI readiness.
- **AI Explainability and Ethics**: Prioritize transparency and ethical guidelines in AI-enhanced content creation. The organization adopts ethical guidelines to ensure the responsible use of AI technologies in CPD initiatives. Guidelines are focused on privacy, data security, and unbiased decision-making.
- **AI Reliability**: Implement quality assurance processes to ensure the reliability of AI-enhanced learning tools and content, mainly in the quality of deliverables, data security, and confidentiality.
- **Learning Theories Integration**: Align CPD initiatives with learning theories, assuring that AI-enhanced CPD practices match the preferences and needs of learners.
- **Complexity Theory and Actor-Network Theory**: The institution conducts a holistic analysis of the interplay between AI tools, healthcare professionals, and organizational systems. This analysis helps identify emergent patterns, systemic bottlenecks, and opportunities for optimization, guiding strategic decision-making in AI implementation.

Outcomes can be:

- **Enhanced Collaboration**: Improved interdisciplinary collaboration and knowledge exchange.
- **Trusted Learning Environment**: Transparent and ethically sound AI-driven CPD content fosters trust and confidence among learners, empowering them to engage actively in their professional development journey.
- **Effective Knowledge Transfer**: Reliable AI-enhanced learning practices facilitate high-quality learning experiences.
- **Pedagogical Excellence**: CPD initiatives aligned with learning theories ensure optimal use of AI-enhanced CPD tools.
- **Systemic Understanding**: Analysis provides insights into healthcare ecosystem interactions, informing strategic improvements.

Example 2 – individual CPD practitioner (a micro-example)

A micro-example example:
CPD professionals use AI to analyze a CPD course evaluation survey responses and plan improvements. Historically, it was time-prohibitive to do a good, deep analysis of extensive survey data. Therefore, quality or analysis was often sub-optimal, and rarely was it convincing and detailed enough to initiate and guide improvement.

- **AI literacy** training informed the CPD professional on AI's practical, safe, legal, and ethical use to analyze survey data.
- **Explainability**: The selected AI tool is set up to explain its decision and reference text used to create themes. CPD professionals can easily review how themes are developed, improve analysis, and confidently present results to all stakeholders.
- **Ethics**: The AI-enhanced analytics prioritize user anonymity and data privacy, ensuring that all learners' consent is obtained before the course begins. Bias-mitigating techniques are employed at both AI and human levels, enhancing the quality of insights.
- **Readiness**: The implementation of AI-enhanced course evaluation analytics is a gradual and transparent process, starting with one course and then extending to others. This approach ensures that all stakeholders are well-informed about the process and results, fostering a positive and accepting attitude.
- **Reliability**. The AI-enhanced analytics have been tested for accuracy and consistency. For Example, CPD professionals continuously monitor output and compare it with manual review.
- **Learning theories** like Cognitive Load Theory and Connectivism help CPD professionals convert insight from AI-enhanced analytics into actionable course improvements.
- **Theoretical lenses**:
    - **ANT**: AI analytics tools are a powerful new non-human actor. They change the established interaction between human and non-human actors (e.g., Online courses, AI tools, learners, and CPD staff) and how decisions are made. CPD professionals use Actor-Network Theory to understand and improve decision-making interactions.
    - **CT**: Fast, detailed analysis of course evaluation data provided by learners—with the possibility to focus on a specific time period—provides insight into the evolution of learners' feedback on learning needs, content, technology, and broader organizational and societal goals and challenges. Complexity theory enables us to understand changes in multiple systems and interactions between those systems. It can help us observe emerging learning patterns and adapt more effectively to the needs of

healthcare professionals and organizations.

Outcomes:

- **Improved decision-making**: AI-enhanced analytics enable timely, data-driven CPD program improvement
- **Enhanced trust**: The transparent, ethical, and result-focused use of AI fosters trust among all stakeholders, encouraging engagement and support for AI-enhanced CPD initiatives. Learners appreciate the stronger and faster link between their feedback and the improvements that follow.
- **Effective Learning Design**: Better and faster feedback loops, enhanced with learning theories and theoretical lenses, help CPD professionals to learn what works well and optimize learning design

The examples show that the ALEERRT-CA framework can be equally beneficial for organizations as it is for CPD professionals.

As a relatively simple but inclusive and complexity-ready model, it can serve as a starting toolset that will help us with the integration of AI in CPD. It can support interdisciplinary collaboration between medical, engineering, social, ethical, and legal domains and help us shape human-centric AI-enhanced CPD.

As with physical toolsets, it is not necessary to use all tools. For some tasks, we may need only one or two tools. Also, it is possible to add additional tools to the toolset or replace existing tools with new ones. For example, CT and ANT are good theoretical tools for this task. Yet, it is possible to add new theoretical tools to the toolbox – especially if they match a specific need or authors have more experience with them.

The complex, constantly evolving nature of AI in our society necessitates agility and continuous improvement. Therefore, we propose this framework as a work in progress and a position on the direction we, as the CPD community empowered with AI tools, may take.

The iterative nature of the framework allows us to improve how we use the framework and the framework per se. In the same manner, repeated empirical validation will help us confirm its value.

Conclusion

Integration of AI into healthcare CPD is reshaping a complex system, demanding a deeper understanding and strategic application of available resources. Just like with the reconstruction of a house, we need tools for this task. The proposed ALEERRT-CA framework can serve as a needed toolkit to help us navigate the first steps of this transformation.

We hope that this paper will add to the discussion on the role and capacity of AI in the CPD of healthcare professionals and stimulate innovation and further research in the emerging field of AI-enhanced CPD.

Lessons for practice

- AI-enhanced tools have become part of our daily life. It is not about whether we are using AI or not but how well we use it to enhance our CPD practices.
- AI makes an impact in complex socio-technical systems. Therefore, AI-enhanced CPD interventions should be designed to foster beneficial interactions between AI tools, healthcare

professionals, and the broader healthcare system.

- Theoretical tools, such as ALLERRT-CA, can increase our ability to open the black boxes of AI-enhanced CPD systems, and understand and improve how AI is used in CPD, ultimately improving the impact of CPD.

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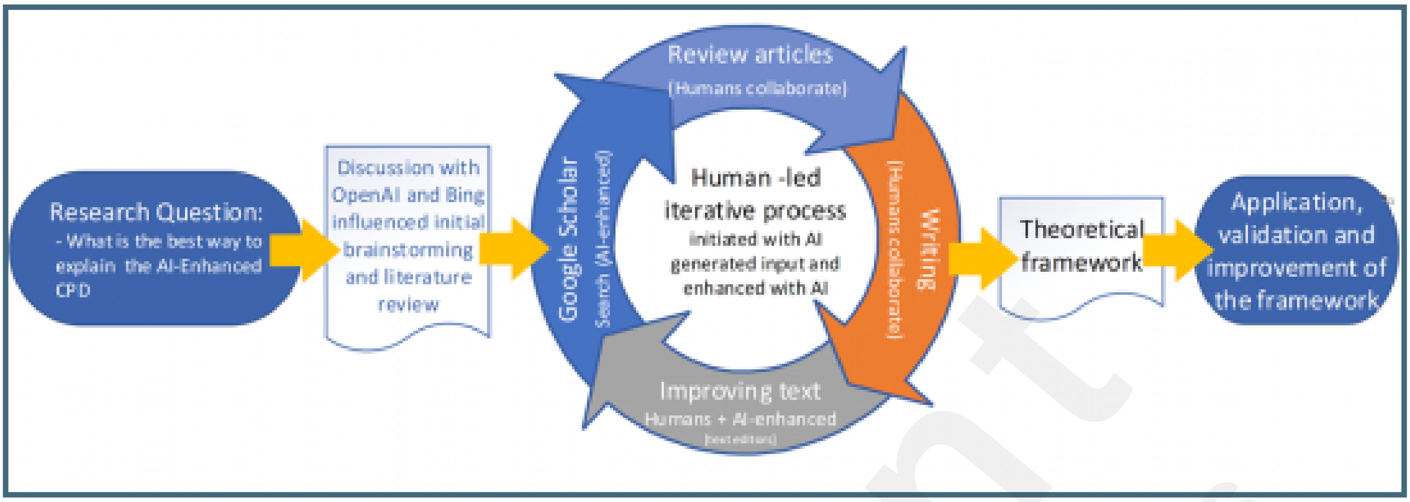
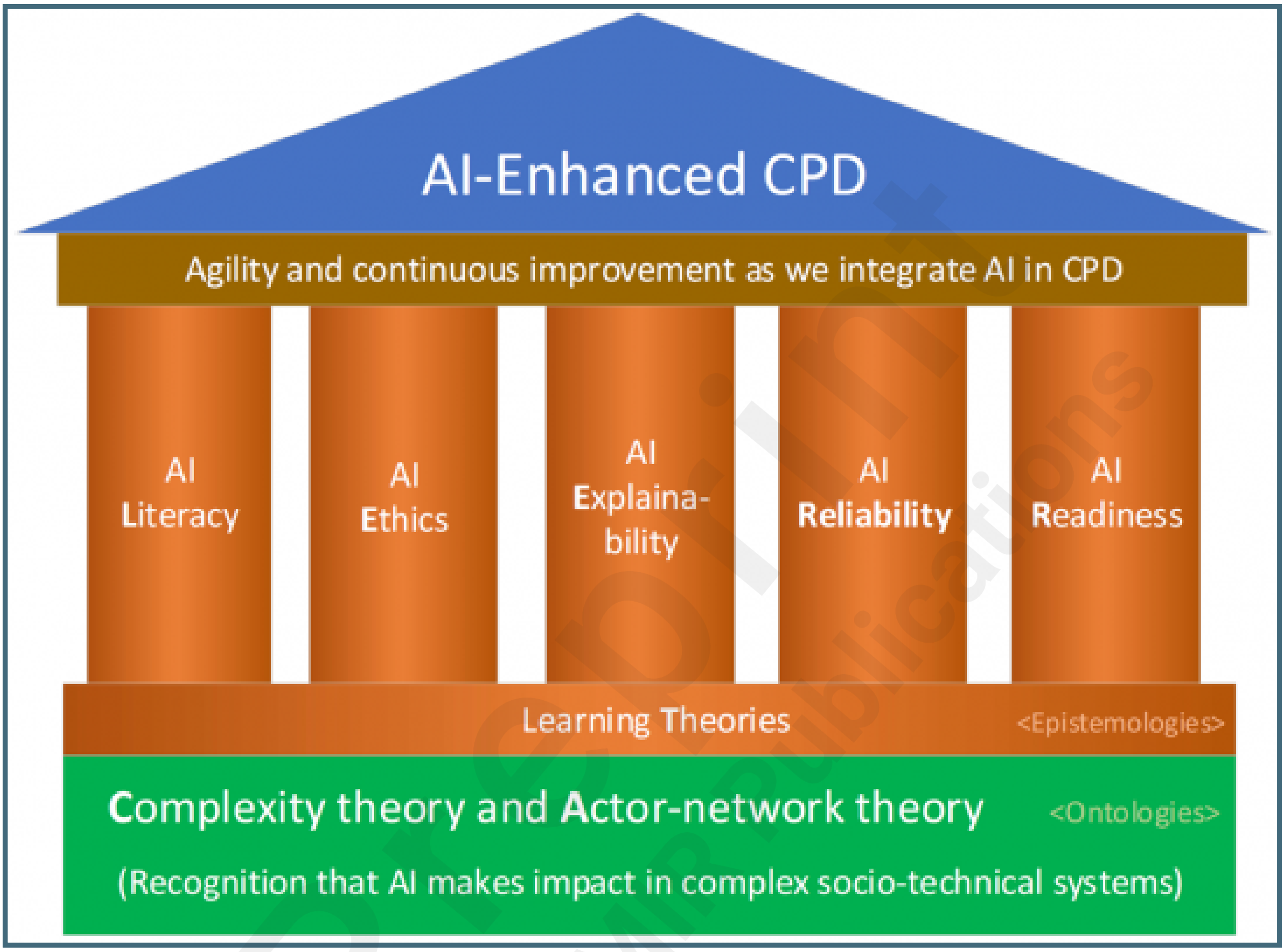
Supplementary Files

Figures

The AI-enhanced writing process of this article.



The proposed framework for integrating AI in CPD - ALEERRT-CA is made of the six foundational pillars: AI Literacy, Explainability, Ethics, Readiness, Reliability, and learning Theories, and two complementary theoretical lenses to observe system changes associated with AI: Complexity theory and Actor-network theory.



TOC/Feature image for homepages

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