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Learning theories for artificial intelligence promoting learning processes

David Gibson[1] | **Vitomir Kovanovic**[2] | **Dirk Ifenthaler**[1,3] | **Sara Dexter**[4] | **Shihui Feng**[5]

[1]Learning & Teaching, Curtin University, Western Australia, Perth, Australia

[2]Education Futures, University of South Australia, South Australia, Adelaide, Australia

[3]Learning, Design & Technology, University of Mannheim, Mannheim, Germany

[4]School of Education and Human Development, University of Virginia, Virginia, Charlottesville, USA

[5]Faculty of Education, University of Hong Kong, Hong Kong, China

Correspondence
David Gibson, 28 Chase Road, Berlin, VT 05602, USA.
Email: david.c.gibson@curtin.edu.au

Abstract

This paper discusses a three-level model that synthesizes and unifies existing learning theories to model the roles of artificial intelligence (AI) in promoting learning processes. The model, drawn from developmental psychology, computational biology, instructional design, cognitive science, complexity and sociocultural theory, includes a causal learning mechanism that explains how learning occurs and works across micro, meso and macro levels. The model also explains how information gained through learning is aggregated, or brought together, as well as dissipated, or released and used within and across the levels. Fourteen roles for AI in education are proposed, aligned with the model's features: four roles at the individual or micro level, four roles at the meso level of teams and knowledge communities and six roles at the macro level of cultural historical activity. Implications for research and practice, evaluation criteria and a discussion of limitations are included. Armed with the proposed model, AI developers can focus their work with learning designers, researchers and practitioners to leverage the proposed roles to improve individual learning, team performance and building knowledge communities.

KEYWORDS

artificial intelligence, computational modelling, learning processes

Practitioner notes

What is already known about this topic

- Numerous learning theories exist with significant cross-over of concepts, duplication and redundancy in terms and structure that offer partial explanations of learning.
- Frameworks concerning learning have been offered from several disciplines such as psychology, biology and computer science but have rarely been integrated or unified.
- Rethinking learning theory for the age of artificial intelligence (AI) is needed to incorporate computational resources and capabilities into both theory and educational practices.

What this paper adds

- A three-level theory (ie, micro, meso and macro) of learning that synthesizes and unifies existing theories is proposed to enhance computational modelling and further develop the roles of AI in education.
- A causal model of learning is defined, drawing from developmental psychology, computational biology, instructional design, cognitive science and sociocultural theory, which explains how learning occurs and works across the levels.
- The model explains how information gained through learning is aggregated, or brought together, as well as dissipated, or released and used within and across the levels.
- Fourteen roles for AI in education are aligned with the model's features: four roles at the individual or micro level, four roles at the meso level of teams and knowledge communities and six roles at the macro level of cultural historical activity.

Implications for practice and policy

- Researchers may benefit from referring to the new theory to situate their work as part of a larger context of the evolution and complexity of individual and organizational learning and learning systems.
- Mechanisms newly discovered and explained by future researchers may be better understood as contributions to a common framework unifying the scientific understanding of learning theory.

INTRODUCTION

This paper presents a synthesis of learning theories that support the development of advanced computational resources participating in the processes of distributed intelligence of individuals and groups. Our objective is to develop foundational ideas for a model that can inform the design of artificial intelligence (AI) applications to support learning processes at three levels—individuals (micro), knowledge communities (meso) and cultural groups (macro). Key questions guiding the considerations include the following: How can AI assist individuals in their learning processes? How can AI assist expert teams, collaborative teams and knowledge communities in their learning processes? How can AI assist a larger interdisciplinary culture in its learning processes?

Frameworks for learning theory have been offered from several disciplines, such as educational psychology (eg, behaviourism, cognitivism and constructivism), biology (eg, autocatalysis, evolution, emergence) and computer science (eg, one-shot learning, deep learning, neural networks, infinite mixed membership stochastic blockmodels) but have rarely been integrated or unified within or across disciplines. Among the reasons there are so many theories of learning is that each model only explains part of the story, leading to many overlapping and conflicting ideas. Overlapping ideas, for example, include a common concern for active participation in learning (eg, responses in a behavioural model, neural reorganization in a cognitive model, mental model elaboration in a constructivist model), while conflicting ideas include limitations on agency (eg, behavioural models are restricted to responses to stimuli, cognitive models focus primarily on neural reorganization, constructivist models focus on creating and adapting mental models).

Today, rethinking learning theory in the age of AI is required on several grounds: the partiality of any description, which demands continued openness to new theories and explanations; the lessons of evolution and complexity, which demand continuous coadaptation of theory to reality; and more powerful computational models of learning, which deepen our understanding of prior theories and expand the reach and power of both symbolic and literal human activity. This situation demands that we remain open to new, more encompassing ideas and unifying concepts in the hopes of making progress in the learning sciences. Evolution and its elaboration in complexity theory underscore the natural role of learning as part of exploration and filling niches in a larger environment via incremental steps and leaps of progress. Finally, capabilities of big data, computing power and deep learning models have reached a stage where questions about the roles of AI in society are more salient than ever. Here, we offer a synthesis that illustrates linkages and common processes among learning processes across the micro, meso and macro levels. This synthesis allows a new way to view the potential roles of AI in learning, teaching, research and the education system.

Role of artificial intelligence in learning processes

As many modern fields of inquiry and expression are increasingly underpinned and enhanced by computational resources, there is already an emergent common ground for a unifying framework encompassing AI, learning analytics, educational data mining, machine learning and complexity theory (Dawson et al., 2018; Tsai et al., 2019). For brevity, we will refer to this as a synthesis of theories for 'AI promoting learning processes' or simply'AI' in this paper, by which we mean to include all approaches to AI, including rule-based, machine learning and others, where the aim is to create a high level of agency for independent decision-making by computational agents. With new possibilities for multidisciplinary research on AI in education rapidly evolving, our proposed framework is tentative, aiming to be expansive and inclusive of existing theories to bridge gaps and explore rather than exclude new ideas. The framework is a speculative and suggestive narrative offered primarily as a discussion point and not a definitive answer to all identified challenges.

Before the ideas for our model are laid out, some examples and appeals for new thinking may be helpful as background. Feng and Law (2021) analysed knowledge evolution in AI in education research from 2010 to 2019 and found a wide range of research centered primarily around intelligent tutorial systems and massively open online courses. Neural networks, personalized learning, eye tracking and deep learning were additional trending keywords in the field at that time. As new AI capabilities are becoming available each day, it will not be long before AI systems are commonly used to help write an article or essay, outline a paper, produce an original piece of art or act as a collaborator on an academic research project. With state-of-the-art advances in machine learning, such as large language models (Huang et al., 2022; Zhou et al., 2022), the AI agent may be responsible for most of the 'work' in these activities. These developments call into question longstanding assumptions about learning. Should a higher education faculty grant a degree to someone using such a system? Should an employer hire a graduate based on what they know and know how to do—with or without AI? Would either of these cases be an example of a potential unfair practice or 'cheating?' On the other hand, what should happen if a student gets identified for cheating by an algorithm and an anonymous professor (Hill, 2022)? Who will be responsible if a person is trapped into making important decisions such as college admissions or graduation by intelligent systems that use hidden rules for identifying and addressing people in poverty (Hao, 2022)?

To discuss these cases would venture into prescriptive advice, guidelines or rules, which, while valuable, are beyond our intended scope. The reader is directed to Dieterle et al. (2022) for a discussion of the cyclical ethical effects of AI in education and for advice on creating a virtuous cycle of effects. They discuss five gaps (ie, access, representation, algorithms, interpretation and citizenship) that must be watched as AI is used in education. In addition to the potential harms, educators considering AI may also be vulnerable to the over-hyped potentials and pitfalls of AI in education—'AI theatre' according to Selwyn (2022), perhaps fed in part by 'enchanted determinism' (Campolo & Crawford, 2020)—the sense that technology will somehow rise magically with superhuman powers to address education's shortcomings or save humanity from its own worst impulses. Our narrative will avoid the extremes of wishful thinking or alarmist rhetoric by acknowledging that AI and its global big data foundation are enhancements and distributions of human thinking and performance that magnify human potential.

As a magnifier, AI can make the bad worse or the good better and must be used with that understanding in mind. All tools and artefacts with the power to enhance human potential mediate the intentions of the people employing them. For example, steam engines and later oil and gas burning engines, reduced labor costs for moving vast quantities of earth and made building enormous dams and cities possible. However, they also led to displacements, injuries and unemployment. AI in education is undoubtedly a double-edged sword that can lead to unintended consequences and will likely cause a rethinking of many assumptions about learning, knowledge, skill, performance, creativity and innovation. Critical to its positive use is the intention of whoever wields power, with appropriate caution and watchfulness for consequential impacts. Acknowledging the need for critical review, here we offer a new synthesis framework for thinking about AI at (1) micro level, as a partner in exploration, learning and expression by an individual, (2) meso level, as a creative, collaborative group member in team activities and (3) macro level, as a mediator as well as the initiator of cultural shifts. These roles are possible because AI in education is changing what it means to 'know and do' in concert with intelligent computational resources.

We aim to discuss cross-disciplinary ideas that expand upon existing learning theories and will hopefully shed new light on the nature and roles of knowledge, learner, community and feedback as interacting mechanisms, states and processes in individual and group learning enhanced by AI. We introduce the new model in hopes of leading to a better understanding of the micro, meso and macro levels of AI-assisted learning and its implications as well as the need for researchers and theorists to develop new ways of generating, collecting, analysing and interpreting digital learning experiences when AI is an active coagent of learning. As a coagent enhancing human potential, we view AI as potentially an intelligent partner in improving a learner or group's emotional, behavioural and cognitive capabilities. With these aims in mind, we will introduce agential possibilities of AI in and near key traditional learning theory constructs and leave room for additions, edits and discussion where today we primarily see gaps and a need for a bridge of ideas from intuitions to more firmly established constructs.

To determine which theories to include in the proposed unified model, we adapted Greene's (2022) theory evaluation model. See Appendix A for the 13 criteria a theory should meet for inclusion into the proposed unified model. For example, if a theory does not address the relationship of an entity to a larger encompassing environment, that is, if it is not a *systems theory that includes dynamics*, such as the forces of change that drive the system, then it should be excluded. If the theory is not *concerned with the entity's agency* (eg, individual agency for learning, expert group agency for learning or a larger culture's agency for learning), then it should be excluded. Similarly, if a theory is *irrelevant to the learning processes* of individuals, expert groups or cultures, it should be excluded from the unified model.

Using these criteria, the proposed model combines learning theories to offer greater explanatory power within and across micro, meso and macro levels. The model combines at the micro level Piaget's (1985) theory of learning with Kauffman's (2000) theory of autocatalytic agency and Song and Keller's model of motivation (Song & Keller, 1999). At the meso level, the social learning theory of Dewey (1916) is integrated with the theories of Donovan et al. (1999), and Garrison et al. (1999) to capture human learning as part of a learning group or community. Finally, the foundation for the macro level is cultural historical activity theory (Engeström, 1999), which has roots in the works of Vygotsky (1978) and captures the culturally mediated nature of human activity. The proposed model also has three corresponding role levels for the development of AI: individual (micro), task or field group (meso) and interdisciplinary culture (macro) arranged as a network with nodes and edges for computational modelling of learning processes.

LEARNING PROCESSES AT THE MICRO, MESO AND MACRO LEVELS

The proposed model (illustrated in Figure 1 and elaborated in Tables 1–3) is an integration and expansion of existing learning theories, which we argue can be unified by their literal and functional similarities, despite being drawn from intersecting fields of research implicated in learning, including complex systems, biology, psychology, computer science, sociology and pedagogy. The proposed unification combines three historical sources: Piagetian theory of individual learning enhanced to form a core mechanism for cognitive, affective and behavioural learning theories, a cognitive and social science model of how people learn in teams and knowledge communities and cultural-historical activity theory. The model aims to coherently combine existing levels of learning theories through commonalities within each level and across all levels. In doing so, we can more easily consider AI, in the broad sense of automated cognition with a high degree of independent agency, as a computational partner for inquiry into the leverage points of the system model (eg, where interventions and new information can influence the system).

In an earlier era when computers were new in education, Seymour Papert envisioned computers and programming languages as *mediating tools* that could change how children think, solve problems and construct knowledge (Papert, 1980). We contend that the explanation of that mediating power is now hinged on *complexity theory* and *machine learning*. Complexity theory is viewed as a formal expansion of the theory of evolution (Holland, 2019; Hordijk et al., 2012) while machine learning is understood as a method of data analysis that automates analytical model building. Complex systems concepts are foundational for explaining and probabilistically predicting the adaptive capabilities embedded at every level of hierarchical evolutionary learning systems unfolding over time, within and across the model's levels.

Machine learning concepts, on the other hand, are strongly aligned in our model, via persistent ‘homologous functional’ roles (Aktas et al., 2019), with learning theories that we argue should be considered in the proofs and validations of findings. Persistent homology,

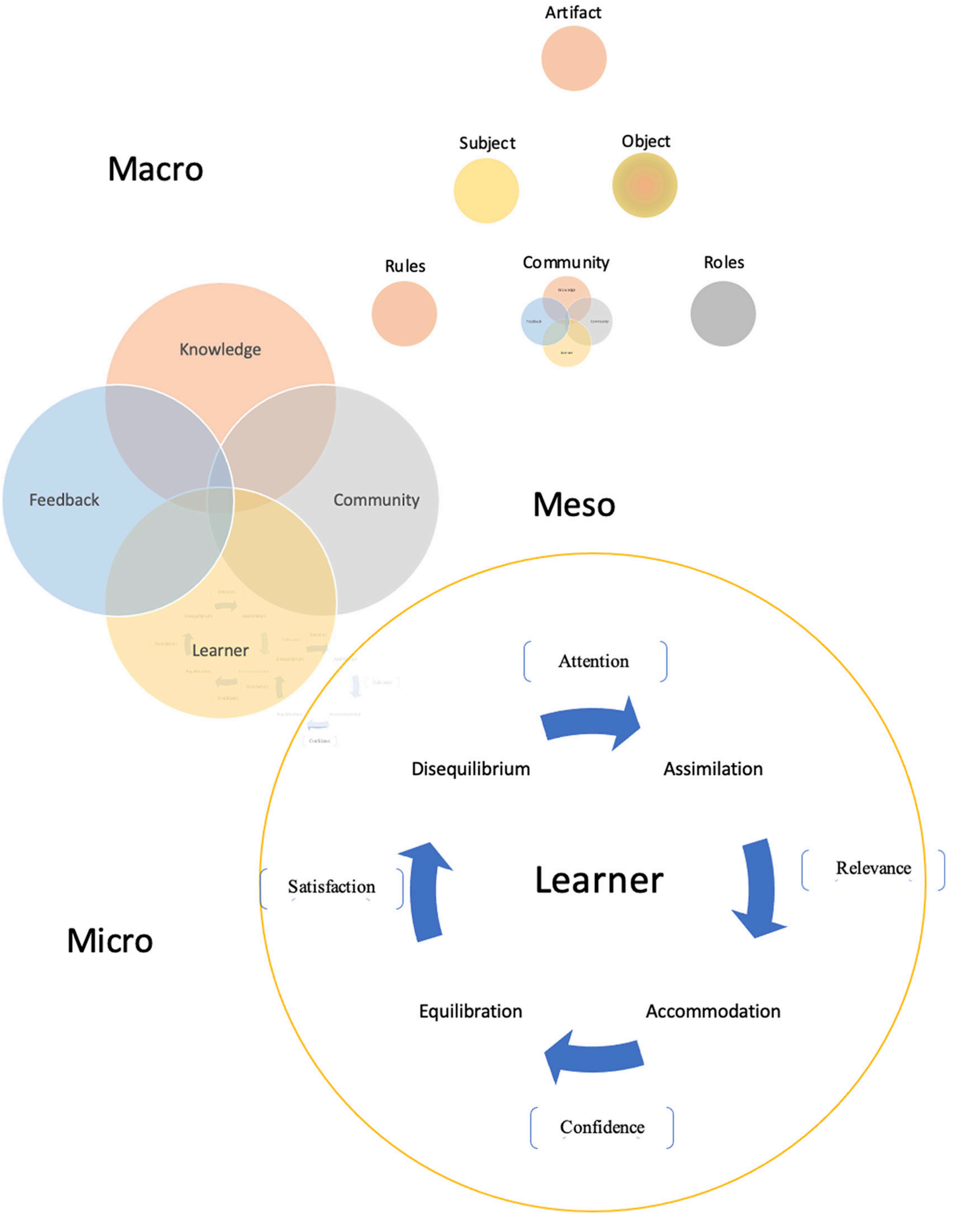

FIGURE 1 A system model for learning theory. The micro-level (individual learner) mechanisms become functionally replicated and multiplied at the meso level (team activity) in an emergent and expanded context of team-based knowledge building. At the macro level, multiple teams become functionally replicated and multiplied into larger emergent cultural entities, such as schools of thought and fields of practice composed of interdisciplinary and international cultures.

according to Aktas, is a mathematical tool in computational topology that measures the topological features of data that persist across multiple scales. For a homologous or similar functional role found in two or more levels, we propose there is a corresponding topological

TABLE 1 Four roles of AI at the micro (individual) level.

Phases or states of Piaget–Kauffman with Keller dynamics	The focus of AI systems co-participating in learning processes
Disequilibration—causes or mediates attention	AI *personalized recommendations*
Assimilation—causes or mediates relevance	AI *learning analytics*
Accommodation—causes or mediates confidence	AI *pedagogical* interventions
Equilibration—causes or mediates satisfaction	AI *formative and summative feedback*

feature of the data space in the modelling environment. We speculate that similar causal loops exist at each of the levels but with different meanings unique to their respective level. For example, one such persistent homologous role is the 'learner' at the micro level, which becomes a 'learning team' at the meso level and a 'learning community' at the macro level. In each level, similar learning processes exist with homologous functions roughly equivalent to disequilibration causing assimilation causing accommodation causing equilibration (eg, of the individual's equilibrium cognitive state, the team's collective intelligence state and the culture's current state of norms). The practical benefit of homologous functions is the transferability of modelling approaches and findings from one level to another. For example, finding that what is true for individuals also has importance at the team or cultural level.

Finally, before discussing the details of the three levels, it is important to point out that the model has a network structure with embedded causal mechanisms. The networked structure has embedded motifs (eg, individuals within groups within cultures) and includes an initial definition of the primary nodes and relationships of the network. To add specificity regarding the connections between the model's layers, there is a need to reinterpret micro-level mechanisms from Piagetian and Kauffman terms into more commonly understood terms from collaborative learning (meso) and cultural change (macro). For example, 'disequilibration' at an individual may be understood as an 'anomaly and crisis' at the meso level (Kuhn, 1962) and referred to as 'second-order cybernetics' (Bateson, 1972; Von Foerster, 1979) at the macro level. In this manner, homologous functions exist at three different levels.

We argue that the embedded causal mechanisms operate within each level and across all levels. This implies that any point of observation or analysis (eg, regardless of where a researcher observes a phenomenon) probabilistically *entails* (ie, strongly implies and necessitates) a predicted next step within the level and if the level's process or stage influences another level, that too entails a predicted 'next step' influence within the new level. The separation between the levels is defined in a way that defines both inclusion and exclusion. Learning processes concerning individual learning belong to the 'micro' level. In contrast, processes in which multiple people learn together belong at the 'meso' level. Finally, learning processes that involve other groups of people and other subject area experts exist at the 'macro' level.

A 'dynamic causal network' is a network model (Sugihara et al., 2012) initially developed for testing neural dynamics hypotheses, where nodes represent states and edges represent causal influences. The causal linkages in the model present clear and testable hypotheses needed for developing new computational models and other forms of research. By 'mechanism,' we refer to a natural system of parts and processes (or component entities and events representable as a dynamic network) that brings about and mediates individual and organizational growth and change in some combination of behaviour, emotion and cognition. As the system (ie, learner, group or culture) evolves, the 'state' of the system refers to the simultaneous status of all relevant parts or components, and the 'dynamics or processes' of the system refers to the relationships, transitions or causal influences from part to part and state to state. To illustrate, we have associated one set of theories at the micro level for the states of the learning cycle

TABLE 2 Four role areas for AI at the meso (team or knowledge community) level.

Contexts of Bransford et al. for a novice becoming an expert	AI assisting individual team members	AI assisting the team or community of inquiry
Learner: social status, demographics, characteristic personality, emotional, behavioural, cognitive components, intentions *cause or mediate disequilibration* (or goes unnoticed by the community)	AI *matches individual capabilities to task requirements*—members' strengths, interests and aspirations with each other and toward the shared goal or problem	AI that builds and maintains an individual *learner model* for each community member
Community: the gatekeepers of the fields of knowledge, the community of inquiry *causes or mediates assimilation*	AI nudges the individual to *fulfil collaboration roles*: • Establishing and maintaining shared understanding • Taking appropriate action to solve the problem • Establishing and maintaining team organization (Roschelle & Teasley, 1995)	AI that defines and brings together members and supports the community and manages *human shaping of the field*
Assessment: feedback from novice to expert, admission to the field, determines individual and group fitness and importance to the field *causes or mediates accommodation* (if the learner is accepted along with their contributions)	AI assists in *determining cognitive presence* (Garrison et al., 1999)	AI plays a role in *automated feedback on performance*, testing and certification and also manages the *evidence models* of the field. As evidence models evolve, the field accommodates new knowledge. (cf. Human in the loop research, Wang et al., 2021)
Knowledge: socially constructed, models, hypotheses, empirical, symbolic, semantic. The epistemic experience of field experts builds this knowledge. *causes or mediates equilibration* (if the field of knowledge adapts to or ignores the learner's contributions)	AI nudges the individual to *fulfil problem-solving and knowledge-building roles*: • Exploring and understanding • Representing and formulating • Planning and executing • Monitoring and reflecting (Mayer & Wittrock, 1996)	AI finds new links and connections within the field of knowledge, suggests new lines of research and defines legitimate *task models* in the field

TABLE 3 Six roles of AI at the macro (cultural) level.

Entities in cultural historical activity theory	The focus of AI systems co-participating in cultural intelligence
Artefact: includes tools, systems, symbols, language, devices, and in general, computationally enhanced cognitive extensions and intelligence distribution. Artefacts join with *Rules* and *Objects* to form the *Knowledge* of the community	AI *intelligent tools and resources generate novel ideas* for creating narratives, rationales, empirical tests, visualizations and other learning artefacts
Object: an aim or goal of using a mediating artefact to accomplish something joined with *Rules* and *Artefacts* to form the *Knowledge* of the community	AI *enhances goals and planning* to clarify objectives and find routes toward achieving stated aims
Subject: synonymous with the Bransford meso learner and the Piaget–Kauffman–Keller micro-learning agency, in Activity theory, the Subject may join the *Community* and *Roles* to form *Feedback* for self and others	See AI roles in the meso and micro levels above
Community: includes and expands on Bransford community into a larger global and historical, multicultural, geosocial world—for example, the global community of a field of knowledge is an agency unto itself when it is a field (community of inquiry) relating to the rest of the world and as a Bransford community. The *Community* joins with *Subjects* and *Roles* to form (expert) *Feedback*	AI *helps cross-cutting communities form and evolve* and helps the expert community *integrate with other fields of knowledge* via innovation and collaboration
Roles: differentiate community members who inhabit specialized niches of performance according to their Piaget–Kauffman agency or expertise. Roles join with the *Community* and *Subjects* to form *Feedback*	AI *helps members fulfil their community roles* (eg, publishes, peer reviewers, new member support services, field historians and theorists)
Rules: include membership rules, norms and practices of the global community; includes rules of entry into the community and the rule of entry of new knowledge into the field. Rules join with *Objects* and *Artefacts* to form the *Knowledge* of the community	AI systems *remember, maintain and mirror algorithms as research test beds* for empirical, intuitional, creative and hypothesis-driven approaches.

(ie, nodes)—Piaget–Kauffman—and another for the motivating influences (ie, edges)—Song–Keller—detailed below.

For example, if an individual is in a state of *disequilibrium* (a Piaget–Kauffman node), then a highly likely outcome is that the individual's *attention* (a Song–Keller edge) will be drawn to whatever initiated the disequilibrium. Similarly, in the state of *assimilation* (a Piaget–Kauffman node), the individual creates *relevance* (a Song–Keller edge), while in the state of *accommodation* (a Piaget–Kauffman node), *confidence* (a Song–Keller edge) is created via new knowledge and skills. Finally, in the state of *equilibration* (a Piaget–Kauffman node), the learner has reached *satisfaction* (a Song–Keller edge).

Individual learning: The micro level

At the micro level—individual learning—Piaget's theory (Piaget, 1985) is unified with and interpreted broadly with Kauffman's theory of autocatalytic agency (Kauffman, 2000), which defines four states that are dynamically linked with Song and Keller's ARCS model of motivation (Song & Keller, 1999). These elements are integrated to form a ubiquitous engine of learning with Piagetian–Kauffman *states or phases* of the transformation of energy into information and action (disequilibration, assimilation, accommodation and equilibration) and Song–Keller *relationships or dynamics* powering those transformations (ie, attention, relevance, confidence and satisfaction).

Besides explaining the internal states and processes of individual learning, the model also explains the outcomes of learning, which can be classified as *internal structures and representations* such as mental models, schemas, memories, automatic skill complexes, habits and so forth (Ifenthaler et al., 2011; Ifenthaler & Seel, 2012) and *externalizations* such as traces, produced artefacts, as well as tools and symbols used during problem-solving. We can compare this to the recent paper on *generative agents* (Park et al., 2023) where the structure of agency uses the plan-do-study-act cycle and includes memory. The micro level thus defined contains a *causal model of learning* that provides a framework for understanding how AI can be integrated to support individual learning (Table 1).

For example, the causal loop can be described by starting from learning analytics assisting assimilation (other narratives could start from any node or relationship in the model). Trace data are captured by information systems and, together with learning analytical techniques, can be used to extract subtle, hidden patterns of an individual's learning behaviour. Those patterns can be used to assess theory-informed concepts of interest in presenting and adapting a learning design (Ifenthaler et al., 2017). The informed patterns, together with real-time input from students, can be further used to support the development of personalized recommendations, which AI can adroitly align with a learner's prerequisite knowledge and current performance to facilitate effective new learning.

At this micro level, psychological, cognitive and brain-based theories of learning are treated as aggregation or dissipation sub-models (Prigogine, 1976), quasi-homomorphisms (Holland, 1998, 2019) or persistence homologies (Aktas et al., 2019) of the Piaget–Kauffman–Keller model of individual learning. The concept of *dissipation* was defined by Ilya Prigogine as structures in thermodynamic systems far from equilibrium, a discovery that won him the Nobel Prize in Chemistry in 1977. A dissipative system is open to an environment and operates far from equilibrium, in essence, to gradually transform energy from a raw form to some transformed form. In learning, transformed forms of experience include the learner's memories, mental models, performance actions, knowledge, skills and capabilities.

AI as a partner in individual exploration, learning and expression

Four AI roles are aligned with the micro-level phases to help an individual through the processes and stages of learning (Table 1). AI can make personalized recommendations that stretch the learner's knowledge and capability boundaries and suggest the next best strategic moves by applying machine learning to user attributes and activity data (Pea, 2014). AI can bring up a new idea or observation, drawing attention to something not noticed before, or the learner might prompt the AI to look for and then share something new to consider (Montaner et al., 2003). Related examples include an 'alerting dashboard' for improving scientific inquiry (Dickler et al., 2021) and research on knowledge tracing of attention (Rodrigues et al., 2022).

During the assimilation phase of integrating something new into what was already known, AI can provide information for analysis by learners to help them meet their needs—*learner-centered learning analytics*—allowing someone to see, for example, where they stand in relation to others or their past, and making clear the current goals and paths forward (Shum et al., 2019). For example, AI might detect deep versus surface learning strategies used by the learner (Gasevic et al., 2017). Another approach of AI assisting assimilation and future accommodation is providing visualized model-based feedback, in which concept maps are offered that are structurally and semantically like expert solutions (Ifenthaler, 2011).

Building confidence in what one knows requires accommodating new knowledge into existing habits, skills and practices often assisted by tutors, which today can be offered automatically by empathetic pedagogical agents (Sabourin et al., 2011). Historically, research on such intelligent tutors has envisioned selecting a teachable moment and influencing the learner at that moment (Shute & Psotka, 1994). Recently, improvements in AI interactions can also flag the urgency of instructional interventions with promise for automated tutors (Yu et al., 2021). Other *pedagogical interventions* support study success (Ifenthaler et al., 2019) and provide data and evidence from virtual practicums, games and simulations for learning (Gibson & Jakl, 2015). Finally, aggregating from a common learner model across multiple learners opens an influence channel to the meso level, for example, by informing a dynamic version of instructional design (Lockyer & Dawson, 2012).

In the phase of return to equilibrium, making AI explainable via *feedback to the learner* is seen as key to making lasting impacts (Khosravi et al., 2022) since the learner's understanding of feedback is crucial in taking informed action and next steps. AI can also accumulate evidence over time and create linkages and analyses in relation to standards and outcomes of interest, including by using advanced natural language processing (NLP) along with deep learning techniques to interpret texts, images and transcripts to infer levels of knowledge and capability.

Social learning: The meso level

At the meso level (team or community), the micro-level mechanisms are combined with social network theory and social psychology to render what (Dewey, 1916) noted as a communal process of inquiry and Donovan et al. (1999) and others have elaborated as the social context of a learning community (Bransford et al., 2000; Donovan et al., 1999; Pellegrino et al., 2001). In educational research, this level has been described as a critical community of inquiry enhanced by technology (Garrison et al., 1999).

Table 2 outlines two scenarios of learning with AI at the meso level. First, the column 'AI assisting individual team members' shows the individual's role in team learning and performance in the face of a task or challenge. Similarly, the column labelled 'AI assisting the team or community of inquiry' shows a team or community of inquiry that addresses its mission, goals and tasks and is motivated to attract new members and stimulate new knowledge, tools and processes. The community of inquiry scenario is most often researched from the standpoint of public discourse, which may play a homologous or functionally similar role to the individual's self-talk at the micro level. Evidence of a crosswalk and embedding from the private individual learning model to the public team or community learning space is apparent, for example, in the descriptors of cognitive presence. Given the crosswalk between the system levels, using AI to support learning at the meso level also requires significant sharing of learners' micro-level data. Data sharing brings challenges around ethics, data privacy, consent and transparency (Gašević et al., 2016; Pardo & Siemens, 2014) and raises the question of who owns such AI systems and what the system knows about individual students.

Perception and awareness in the individual have a functionally similar impact on a team or community in the form of disequilibration of a team or community's status quo. In addition, applicability at the individual level maps to assimilation processes in a team or community, whereas conception and ideation in the individual map to the accommodation of new ideas in a team or community. Finally, experience and practice building up into a stable base of knowledge in the individual maps to equilibration of the team or community in the sense that the newly accommodated knowledge bridges from ideation to its realization to the satisfaction of team or community members. In this example, we see the private world of Piaget–Kauffman–Keller micro level in an individual reflected in the public team or community space of the meso level, where functionally similar roles are carried out in the body politic.

In the second scenario, the team or expert community is the primary agent at the meso level and provides induction that inculcates new members in the community's knowledge and ways of knowing (Brown et al., 1989; Csikszentmihalyi, 1996). Formal professional feedback by the community is ideally guided by evidence-centered models that organize the knowledge domain, characteristic tasks and expected capabilities of practitioners in the field (Mislevy et al., 1999). Informal forms of feedback include signals of social acceptance, pats on the back, critical questions involved in collaborative inquiry and so forth. Socially constructed knowledge and expertise are thereby both replicating and evolving through contributions by existing and new community members. The dynamical model of the meso level contains state and process combinations formed into dynamic clusters or motifs composed of aggregations and dissipations from the micro level. The states and processes from the micro level may be viewed at the meso level as latent variables, emergent roles and underlying driving mechanisms for processes. For example, a single learner at the micro level becomes a member of a team or group at the meso level. A novice who is not yet a member of the expert community might introduce a new idea that causes disequilibration, and the community must assess whether to assimilate the new person and knowledge. If the community opts to do so, then the new knowledge and person must be accommodated, and when that has been accomplished, equilibration returns. Thomas Kuhn (1962) noted this level's entities and processes as the core of scientific revolutions.

At the meso level, the roles of AI become more complex, and new functions emerge because the roles need to balance (i) tracking and responding to everyone simultaneously within a focus of collaboration during team problem-solving and knowledge building and (ii) assisting the team in working within (or breaking tradition with) a larger community of inquiry or field of research knowledge (Table 2). If the former does not happen, then the team or the teamwork is more likely to fail, and if the latter does not happen, then the team's work will not be accepted by or related to a community of inquiry or authority of experts.

AI assisting individuals as team members

AI assistance to the individual shifts the focus from acquiring and practicing knowledge and abilities to fulfilling social roles in collaboration. For example, AI can help match individual capabilities to task requirements, using the individual's strengths, interests and aspirations with task conditions such as the shared goal or problem. AI can nudge the individual to help establish and maintain the team or community's shared understanding, take appropriate actions and help maintain the team's organization (Roschelle & Teasley, 1995). AI can assist in determining an individual's cognitive presence, which is crucial to self-assessment and self-regulated learning (Garrison et al., 2009). Cognitive presence was initially derived from transcript analysis of group discussions by teams of researchers and can now be researched with the aid of NLP algorithms (Litman, 2016) and large language models such as ChatGPT (Sagar, 2020) that rely on the semantic structure of meaning.

Ongoing research will also likely tie NLP to evidence-centered design (Behrens et al., 2011; Mislevy, 2011) and social epistemic network signatures (Gašević et al., 2019). A set of signatures of interest in understanding individual learning in a team or community context are problem-solving and knowledge-building roles that can be nudged by AI, including *Exploring and understanding*, *Representing and formulating*, *Planning and executing* and *Monitoring and reflecting* (Mayer & Wittrock, 1996).

AI assisting a team or community of inquiry

We propose four mechanisms that fulfil the organizational role: maintaining learner models, shaping the field of knowledge, managing evidence models for the field's assessment and feedback processes and recommending new lines of research and development. Aligned with the organizational role of maintaining learner models, AI can help cluster people together to solve problems and address challenges. For instance, AI can support finding someone with the right expertise to fill a competence gap in a group activity or a compatible group of people for a creative project. This same function, operating at the macro level, has been explored for tracing the development of research ideas globally and finding promising new avenues for research.

AI itself can be a creative and cooperating partner in collaborative activity, making unique contributions in terms of ideas, processes, artefacts and search results. It can also detect and act on group process stages. For example, AI can help identify when the group conversation is drifting away from its stated goals and objectives, helping assess the potential pros and cons of contemplated actions. In this way, AI can help the team stay organized and productive by monitoring and characterizing individual contributions to collaboration (Kerrigan et al., 2019).

Learning analytics at the meso level may include its role in (1) guiding reform activities in higher education and (2) assisting educators in improving teaching and learning (Siemens & Long, 2011). In our model, these functions belong to the organizational side of the meso-level role (ie, Assisting the community of inquiry, including moderators and mediators in Table 2) and are distinct from its potential role in assisting individual learners with collaboration.

Finally, AI can participate in distributed knowledge networks (eg, building, searching, maintaining and creatively accessing them to solve problems) by assisting teams in problem-solving. This includes exploring and understanding ideas, images and semantics (Egozi et al., 2011; Ifenthaler, 2010), representing and formulating creative new representations, planning and executing team actions (Wang et al., 2021) and assisting the team in monitoring and reflecting on progress and achievement (Gao et al., 2018).

Sociocultural evolution: The macro level

At the macro level, we introduce the concept of ‘group of groups’ by which we mean to encompass cross-disciplinary activity, international activity, and broadly, the level of complexity where culture is influential and evolves. At this level, Cultural Historical Activity Theory (CHAT), as expanded by Engeström (1999), is used as a six-node network model for understanding the larger sociocultural systems involved in learning (Table 3). The four-node meso-level network participates partially in some of this level's entities. For example, Artefacts, Objects and Rules at the macro level are unified into Knowledge at the meso level. At the same time, Community, Role and Subject combine to partially form both global Community and Feedback processes, which at the meso level inculcate a novice into becoming an expert and, at the macro level, influence the development of new fields of knowledge. Depending on the context of the inquiry, the Subject at the macro level may be an individual from the micro level, a group of learners from the meso level, or an emergent new interdisciplinary ‘group of groups’, such as biologists and chemists working in the biochemical domain.

AI as a mediator and initiator of cultural shifts

AI at the macro level considers the embedded influences from micro and meso levels, focusing on knitting together separated communities of inquiry that might not otherwise find each other or work together. Examples at this level include bibliographic network analysis that leads to new lines of research, tracing the global spread of ideas and finding solutions for out-of-field problems. For instance, there is often a significant amount of time between discovering mathematical ideas and their practical adoption, typically only after society has evolved to use those ideas (Feng et al., 2017). The mechanics of the macro level are exemplified in AI today by deep learning and the unusual generalizability of large language models. For example, symbolic embeddings of expert language may include cultural and semantic markers that help convey meaning beyond the surface level of the words themselves. These markers may include references to specific traditions, customs or historical events that are important within a particular community of practice, as well as linguistic nuances and technical terminology that are not commonly used in everyday conversation. By incorporating these cultural and semantic markers into their language, experts can communicate more effectively with one another and create a shared understanding of complex concepts and ideas.

Boundary crossing between the micro/meso/macro levels carries replicated submodels or *persistence homologies* (Aktas et al., 2019) of the lower levels. For example, the meso level of group learning contains multiple micro-level instances for each learner in the group. Some dynamic influences are expected to persist from the micro to the meso level, such as individual learner characteristics known to influence group roles. At the meso level, each community of inquiry or field of knowledge and practice influences upward into the macro level and downward into the micro level. Whether the influences from one level to another are dynamic summaries (eg, running averages within time windows, phase portraits, vector space as a context) or generative sparse representations (eg, used for prediction, elaboration, sensor network construction) depends on many factors including the node's current role in a function, the context of the function and the causal role of the function.

The theory expands on the typical idea of 'context' by fully defining the boundary of context as the remaining two levels from any entity in its level in the network. To support this conception of context, the theory requires that each node of the relevant network at each level has semipermeable boundaries via polysemantic nodes to allow multiple-model participation (ie, probabilistic composition context information comes from elsewhere in the hierarchy and influences are both received by and sent to other nodes or levels). The neuroscience concept for this phenomenon is 'reentrant processing' (Edelman & Mountcastle, 1982).

The partial boundaries within each level (eg, nodes acting in their causal role or as mechanisms in one context and states in another) participate in both composition and influence. The machine learning literature has explored the *superposition* of polysemantic nodes (Elhage et al., 2022) and models (Cheung et al., 2019) as a network mechanism for multiple encodings. The proposed theory must make use of such a mechanism of superposition to unfold the appropriate sub-model or polysemantic node within a specific context. For example, prompts given to a large language model shape a context for appropriate vector selection and interpretation of inputs during a process such as a 'chain of thought' (Wei et al., 2022). When a context demands it, semantic shifts to another embedded model become more probable.

Taken together, these characteristics of the macro level—embeddings, boundary crossings, contextual adequacy and partial membership of network nodes needed for multiple interpretations—need significant future research. For example, how can individual learner characteristics be used to inform group roles and team productivity? How can communities of inquiry be designed to facilitate influences and interactions across the levels?

LIMITATIONS

It should be noted that the proposed theory does not account for all areas of research and practice that interest education. The current theory narrowly focuses on learning processes used by individuals, expert learning communities and larger interdisciplinary and cultural groups. By defining the three-level model (ie, individual learners, expert groups and broader cultures), we assume a specific structure of the contexts for the chosen learning processes. We recognize that not all learning contexts are covered by the model, and we invite thoughts and discussions about its applicability in other contexts.

By narrowly focusing on learning processes at the three specified levels, our strategy for selecting which theories to include was straightforward (see Appendix A). However, we recognize that the choice of included theories might be limited in some way that we have not considered. If there are such theories that we have not considered, then our model may be limited by a lack of scope or critical ideas that ought to be considered. We invite the reader to be in contact with us to enlighten or challenge us and expand our thinking.

In addition, some features of the learning processes of the three levels have not been explicitly called out and discussed. For example, the emotional and affective processes of an individual at the micro level or of peer and expert interactions at the meso and macro levels have not been called out. Understanding to what extent such processes are already included or implied in our theory is a current limitation and a question needing further research. For example, one such expert is the teacher, who may play a critical role in facilitating and supporting the learning process and may benefit from AI in the supporting roles we propose. As a second example, we note that analysing a psychological model such as the COPES model of self-regulated learning (Winne & Hadwin, 1998) shares several features with our model. For example, the COPES framework makes central the issue of a 'task' (what we would call a meso-level requirement placed in front of the learner) and describes both cognitive (C) (micro) and external (meso) 'evaluations' (E) made by the learner during task completion. Additions to our core model can define new entities and relationships bringing a sharper focus to a research question and aiding in understanding phenomena. We hold that such additions should ideally relate to the proposed framework's entities and relationships wherever possible, allowing a parsimonious foundation in learning science to evolve. In other words, when a new concept needs to be introduced to better understand or describe a learning process of an individual, expert team or a larger culture, it should be described in relation to the defined micro, meso or macro levels, their entities and relationships to the greatest extent possible.

A third limitation is that we have left undefined and undiscussed many potential refining ideas about the network relationships and have only prescribed causation as fundamental to individual learning and its functionally similar roles in the meso and macro levels. This leaves open secondary and derivative influences of many kinds and allows other causal explanations to evolve. Concerning future derivatives, we have asserted that the causal role of aggregations (ie, entities and processes brought together) and dissipations (ie, energy or information used to enact and make impact)—as intended by Prigogine, Kauffman and complexity scientists who deal with social phenomena—will continue to be found as primary mechanisms at every level. Hypotheses that test this idea would start with the assumption that forms of agency at the three levels (eg, individual agency for learning, team or expert group agency for knowledge creation, and interdisciplinary agency for a cultural change) will exhibit a similar structure to the proposed causal cycle and motivational influences of the micro level described here.

Finally, a fourth limitation concerns a broader scope of the discussion that could not be addressed due to space limitations, that is, the introduction to the various disciplines unified by the presented theory. For example, we did not provide a compelling reason why a causal model of the emergence of agency for learning should be examined alongside the theories from computational biology, complexity science and developmental psychology into a unified model. Similarly, while the three broad groups of learning theories (ie, behaviourism, cognitivism and constructivism) are often referenced, a proper discussion of their differences and critiques warrants a lengthy discussion that others have already covered (Cooper, 1993; Ertmer & Newby, 2013; Liu & Matthews, 2005) and which, due to space limitations, could not be included here. For the same reasons, there is a limited discussion of the research implications of the proposed theory and how implications at one level of the theory affect understanding on other levels (eg, how does understanding of learning at the micro level affect understanding of small team learning). A follow-up paper or series could begin to address these limitations and assist in reaching out for comments and engagement regarding the theory.

CONCLUSION

We have discussed a three-level model (ie, micro, meso and macro) of learning that synthesizes and unifies existing learning theories, which we argue may benefit computational modelling to further develop the roles of AI in education. The proposed causal model is seen through micro-, meso- and macro-level lenses to explain how knowledge is aggregated or brought together, as well as dissipated, or released and used, within and across the levels. The model was defined and elaborated, drawing from developmental psychology, computational biology, instructional design, cognitive science and sociocultural theory.

We defined the micro level as the core and minimal mechanism of learning in an individual—a model that progresses through four stages with four linking dynamics. Many other factors exist, both internal and external to the individual learner. When those factors are external, then the meso or macro levels of the theory apply, a practical result of which is that measurements of parts of the system can be understood within a holistic context. When those factors are internal, we propose that they form additional sub-models that either bring together or release and use the energy and information of individual learning, with a practical benefit resulting in an improved unification of learning theories.

We define the meso level as the social environment of a learning team, focusing on learning via shared problem-solving, including creative activity, building things, addressing common problems and facing challenges. There are many other reasons to participate in a pair or team (eg, finding a mate, being part of a family or tribe) that are more distally related to learning, and as in the micro level, those factors can be internal or external to the meso level. When they are external, we propose treating them as coming from either the micro or macro level, completing a model of context that may benefit future research. Similar to the micro level, when the factors are internal, we propose they form additional sub-models that either bring together or release and use the energy and information of team learning.

Finally, we define the macro level as an interdisciplinary, cross-cultural space where groups of groups interact and work together to build knowledge and develop skills for the future. Aligned with this landscape, we outline several roles for AI systems to engage in the learning process at all three levels, spanning both individual and organizational learning. We have thus proposed a potentially unifying structure for learning theory that is cognizant of the computational requirements and possibilities of AI and capable of helping organize a wide variety of theories involved in the micro, meso and macro levels of learning.

Armed with this framework, learning designers can explore new ways to design and implement effective learning environments. Researchers and data analysts can take advantage of the interconnectedness of the levels for creating and studying learning process interventions and predictions. Finally, practitioners can leverage their knowledge of the AI roles to improve individual learning, team performance and building knowledge communities.

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ORCID

David Gibson https://orcid.org/0000-0003-1053-4690

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APPENDIX A

THEORY EVALUATION CRITERIA ADAPTED FROM GREEN (2022)

Internal criteria	Micro	Meso	Macro
Scope: The theory addresses a wide range of phenomena while also being appropriately constrained by them	Learning processes that are internal to an individual and nothing more	Learning processes arising between two or more individuals and nothing more	Learning processes arising in group-to-group relationships and nothing more
Unification: How well the theory incorporates different phenomena and areas of knowledge	Unifies Piaget, Kauffman, Song and Keller; integrates external context from meso and macro	Uses Bransford et al. unification of cognitive, social science; integrates external context from micro and macro	Uses Engestrom et al.'s unification with Vygotsky; integrates external context from micro and meso
Parsimony: How well the theory represents phenomena and their relations in the simplest ways possible	Proposes a causal model of individual learning (agency forming) processes. Proposes a completeness hypothesis with meso and macro frameworks	Incorporates the micro as an agent-based multiplier and adds causative implications (eg, what happens if knowledge community, knowledge or assessment) is absent or weak?	Incorporates the meso as an agent-based multiplier and adds causative implications (eg, what happens if roles, rules, cultural community, subjects, objectives or artefacts are absent or weak?)
Plausibility: Descriptions and consequences of the theory seem likely, given the related literature	Descriptions and consequences are aligned with the literature. New consequences arise from a more substantial causal theory, new linkages among interoperating theories at the micro level and limitations from the meso and macro levels	Descriptions and consequences are aligned with the literature. New consequences arise from embedded causality and limitations from the micro level and limitations on context from the macro level	Descriptions and consequences are aligned with the literature. New consequences arise from embedded causality from the micro level rising through the meso level and limitations on context from both the micro and meso levels
Fruitfulness: The theory suggests new research questions, hypotheses and practical applications	Four specific AI applications are outlined with a focus on each of the nodes and relationships of the micro network	Four additional AI applications are outlined with a specific focus for each of the nodes and relationships of the meso network	Six additional AI applications are outlined with a specific focus for each of the nodes and relationships of the macro network
Accuracy: The evidence supports representations of the theory's phenomena and their relations	Untested as yet	Untested as yet	Untested as yet

(Continues)

APPENDIX A Continued

Internal criteria	Micro	Meso	Macro
Internal consistency and coherence: The phenomena and relations addressed by the theory do not contradict one another	Theoretical coherence within the levels is established via historical literature; multilevel coherence needs to be empirically established in future research. Computational modelling and experimental validation are needed to further test the theory		
Mechanism: The theory provides a clear, precise description of how phenomena come about	The theory has directionality (causal implication)	Introduces causality from the micro level into the meso level	Introduces causality from the micro level via the meso level into the macro level
Testability: The predictions and explanations of the theory can be verified or disconfirmed in a convincing manner	Higher probabilities are predicted for closer stages in the causal chain and processes leading to those stages	To be developed	To be developed
Specificity: The theory explains what it is supposed to explain and is not so vague that it can survive any empirical result	See 'Scope'		
External criteria (same across all levels)			
External consistency or coherence: The theory coheres with other established theories	The theory offers a computational framework for learning theory consistent with computational biology, complexity, cognitive science and cultural-historical activity theory		
Analogy: The theory has similarities to other accepted theories	Network theories have been multiplying across several scientific areas since Euler introduced graph theory in 1736. Our application to learning theory involves and allows networks scoped to micro/meso/macro levels and their interactions, with a defined vocabulary of entities as the nodes and at the micro level, with defined (directed graph or causal) relationships on the edges. We have applied the network analogy to common issues in the learning processes of individuals, expert groups and larger cultural configurations		
Practicality: The theory is relevant, available and valuable to society	The 14 AI application recommendations provide theory-based guidance for research and development processes		