Canadian Journal of Learning and Technology
Revue canadienne de l'apprentissage et de la technologie

Cognification in Teaching, Learning, and Training
La cognification dans l'enseignement, l'apprentissage et la formation

Vivekanandan Kumar, Mohamed Ally, Avgoustos Tsinakos et Helmi Norman

Volume 48, numéro 4, 2022

Special Issue

URI : https://id.erudit.org/iderudit/1097225ar
DOI : https://doi.org/10.21432/cjlt28261

Aller au sommaire du numéro

Éditeur(s)

The Canadian Network for Innovation in Education

ISSN

1499-6677 (imprimé)
1499-6685 (numérique)

Découvrir la revue

Citer cet article

Kumar, V., Ally, M., Tsinakos, A. & Norman, H. (2022). Cognification in Teaching, Learning, and Training. *Canadian Journal of Learning and Technology / Revue canadienne de l'apprentissage et de la technologie*, *48*(4), 1–17. https://doi.org/10.21432/cjlt28261

Résumé de l'article

Au cours de la dernière décennie, les possibilités d'apprentissage en ligne ont augmenté de façon remarquable. Les apprenants du monde entier ont maintenant un accès numérique à un large éventail de formations d'entreprise, de certifications, de programmes universitaires complets et d'autres options d'éducation et de formation. Certaines organisations combinent les méthodes d'enseignement traditionnelles avec les technologies en ligne. L'apprentissage hybride génère d'importants volumes de données concernant à la fois le contenu (qualité et utilisation) et les apprenants (habitudes d'étude et résultats d'apprentissage). En conséquence, la nécessité de traiter correctement des données volumineuses, continues et souvent divergentes a entraîné l'avènement de la cognification. Les techniques de cognification conçoivent des modèles d'analyse de données complexes qui permettent à l'intelligence naturelle de mobiliser l'intelligence artificielle de manière à améliorer l'expérience d'apprentissage. La cognification est l'approche qui consiste à rendre quelque chose de plus en plus intelligent, de manière éthique et régulée. Cet article souligne comment les tendances émergentes en matière de cognification pourraient bouleverser l'enseignement en ligne.

CJLT RCAT
Canadian Journal of Learning and Technology
La Revue canadienne de l'apprentissage et de la technologie

Volume 48 (4) Special Issue 2022

Cognification in Teaching, Learning, and Training

La cognification dans l'enseignement, l'apprentissage et la formation

***Vivekanandan Kumar**, Athabasca University, Canada*
***Mohamed Ally**, Athabasca University, Canada*
***Avgoustos Tsinakos**, International Hellenic University, Greece*
***Helmi Norman**, Universiti Kebangsaan Malaysia, Malaysia*

Abstract

Over the past decade, opportunities for online learning have dramatically increased. Learners around the world now have digital access to a wide array of corporate trainings, certifications, comprehensive academic degree programs, and other educational and training options. Some organizations are blending traditional instruction methods with online technologies. Blended learning generates large volumes of data about both the content (quality and usage) and the learners (study habits and learning outcomes). Correspondingly, the need to properly process voluminous, continuous, and often disparate data has prompted the advent of cognification. Cognification techniques design complex data analytic models that allow natural intelligence to engage artificial smartness in ways that can enhance the learning experience. Cognification is the approach to make something increasingly, ethically, and regulatably smarter. This article highlights how emerging trends in cognification could disrupt online education.

Keywords: Cognification, AI in education, Fourth industrial revolution, Educational technology

Résumé

Au cours de la dernière décennie, les possibilités d'apprentissage en ligne ont augmenté de façon remarquable. Les apprenants du monde entier ont maintenant un accès numérique à un large éventail de formations d'entreprise, de certifications, de programmes universitaires complets et d'autres options d'éducation et de formation. Certaines organisations combinent les méthodes d'enseignement traditionnelles avec les technologies en ligne. L'apprentissage hybride génère d'importants volumes de données concernant à la fois le contenu (qualité et utilisation) et les apprenants (habitudes d'étude et résultats d'apprentissage). En conséquence, la nécessité de traiter correctement des données volumineuses, continues et souvent divergentes a entraîné l'avènement de la cognification. Les techniques de cognification conçoivent des modèles d'analyse de données complexes qui permettent à l'intelligence naturelle de mobiliser l'intelligence artificielle de manière à améliorer l'expérience d'apprentissage. La cognification est l'approche qui consiste à rendre quelque chose de plus en plus intelligent, de manière éthique et régulée. Cet article souligne comment les tendances émergentes en matière de cognification pourraient bouleverser l'enseignement en ligne.

Mots-clés : Cognification ; IA dans l'éducation ; quatrième révolution industrielle ; technologie éducative

Introduction

The agricultural revolution and three subsequent industrial revolutions, aided by advancing communication channels, enabled societies to transform (Yusuf et al., 2020). Their paces of adoption allowed societies to accommodate the disruptive changes that the innovations brought. The agricultural revolution, the slowest one and a precursor to the industrial revolutions, spread as foragers started to adapt the domestication of animals and associated farming methods. The first industrial revolution introduced the mechanization of goods production and spread at a pace afforded mainly by roads and railroads using steam-powered machines. The second industrial revolution brought electrification and assembly-line mass production of goods to societies at a pace associated with electrical connectivity networking. The third industrial revolution electronified and computerized societies at the pace of telephonic and early-Internet communication. The fourth industrial revolution, currently ongoing, percolates our societies at the pace of light, afforded by the Internet aided by Li-Fi and Fibre optic networks, and with the anticipated pace of quantum computational power. The increasing pace of technology adoption across the globe puts societies-at-large at a disadvantage because associated technologies become available and used by certain communities within societies without a proper, commonly understood vetting process. Societies are struggling to grasp, adapt, and accommodate the inventions of the fourth industrial revolution. Governance structures are still being conceived as an afterthought. Ethicality of the fourth industrial revolution is still being studied while the application of the fruits of the revolution are already in the marketplace. These challenges are being felt across several industries, particularly in education.

In recent years, higher education has noticeably felt the influence of the phenomenal growth of the fourth industrial revolution (4IR), aided by the associated technologies and theories that are paving new pathways for educators to conceive novel competencies for learners (Penprase, 2018). Nevertheless, technologically feasible paradigm shifts in higher education will still require thorough analysis of efficacy, ethicality, and merit. This article provides one such analysis. From several points of view, it offers a synthesis to explore a possible marriage of intelligent computing and educational services in a way that properly fuses comparably smart, companion entities to almost everything in human learning. Additionally, this synthesis demonstrates the centrality of data - data about the content, data about the interactions with the content, data on the learning community, and data about the learning outcomes. Rich datasets can be analyzed purposefully and ethically to enrich and personalize student learning experiences.

Cognification in Education

Several trustworthy organizations, media, and individuals (Gysegom et al., 2021; Schwab, 2017) have urged the world of education to explore and accommodate the fruits of the 4IR. They urge educators to prepare learners for a future of cognification. Cognification is a major outcome of the 4IR where just-in-time solutions to day-to-day tasks faced by humans arrive on demand, similar to the way electricity flows instantaneously through wires to places of need. The following two examples of cognification illustrate the changing learning landscape under the influence of 4IR innovations.

Consider the scenario where a student needs to perform a literature review on a certain hypothesis. At present, it is a mundane process of collecting literature manually. The student could either use a script to search various databases for relevant literature or collect literature from other researchers in a research group, who had performed similar manual searches in the past. Subsequently, the student could read through the collected literature, discuss various points of views with other researchers, and eventually arrive at a synthesis. A cognified alternative to this manual process of literature review would comprise of at least the following: (1) a list of relevant literature would be made available on-demand, and scripts that are continually collecting and classifying published literature through a gateway accessible from a globally indexed collection of literature. Thus, the student may be left with only the manual task of picking a subset of the literature. (2) analysis would be conducted on how selected literature relates to the hypothesis created on-demand. That is, relations explored and possibly causated or correlated in individual publications would be selected, collated, and connected with the proposed hypothesis. This would allow the student to manually sift through various classifications of the derived relations and manually select the ones that closely relate to the proposed hypothesis. (3) the student could infer several conclusions and multitudes of syntheses arising from the analyses of the selected literature, on-demand. That is, the conclusions of selected literature and the rigour of these conclusions could be automatically inferred, yielding several potential syntheses. The student could then perform a manual search through these candidate syntheses and select one or more that are plausible. (4) a gap analysis of the hypothesis vis-à-vis the leading-edge of the knowledge frontier could then be derived, on demand. While a synthesis does include substantiation in terms of the validity of the associated relations, the student would be tasked to manually identify a derived synthesis or fuse a subset of candidate syntheses into a derived synthesis. That is, artificially smart technologies could supplement the manual natural intelligence of a researcher, replacing the traditional labor component of collecting, reading, comprehending, and synthesizing the manual literature review with a cognified one (Wagner et al., 2022). The combination would support deeper and richer research exploration. As such, the focus of such a cognified solution would mostly supplement the creative side of natural intelligence, offloading the mundane manual labour imposed on the human brain.

Another example of cognification in education could be a scenario where a student was seeking to develop policy recommendations to a provincial government on a particular communicable disease. In this case, a cognification solution comprised of the following could provide, on demand – the relevant literature, a compilation of hypotheses and relations, plausible syntheses, a comparative analysis of policies on communicable diseases from similar jurisdictions, and importantly, a set of research methods to study the implications of candidate policies conceived by the student. That is, the student would simply be expected to create new policy statements or extend existing policy statements after vetting the intermediate inferences offered by the cognified solution. Further, the cognification solution could offer testable models, verified datasets, and potential conclusions. Thus, cognification could supplement and reduce mundane human work. Relieved of this, the student would be free to tackle larger-scale, creative challenges.

Cognification is the art of making something increasingly, ethically, and regulatably smart. As discussed, cognified literature reviews can be automated using cognification to relieve the student of the mundane and assist the student to delve deeper into the solution space. Such a solution is expected to (1) increase its scope as required and improve its accuracy with more data; (2) be governed by ethical principles pertaining to that specific activity, particularly in accommodating inferences made by the automation mechanism as it derives relations, consolidates synthesis, performs analyses, and avails an open research space; (3) be regulatable by authorities, in terms of proliferation, contextualization and application, prior to unleashing them to the users. As for the second example, the scope of the policy statement could be expanded across jurisdictions as well as across communities to situate the problem for a deeper and smarter understanding; the associated datasets, current policies, mathematical models, and machine learning models can be vetted for privacy and security concerns before being considered for ethical use; the process of inference, the publication of its conclusions, and the predicted policy implications can be presented to the government as open research, thus imbuing complete control over its proliferation, contextualization, and application.

Overall, the current trends in artificial intelligence (AI) and machine learning point to the inevitability of a 4IR-induced paradigm shift in higher education - the marriage of intelligent computing, instructional services, and learner activities (Zawacki-Richter et al., 2019). What needs our attention is the uniqueness of this revolution, different from the earlier agricultural, industrial, and digital revolutions in fusing a comparably smart, non-living entity to almost everything human. Smart companion entities are increasingly becoming an integral (and compellingly necessary) part of many activities we do, and the way we think and create, supplementing the very essence of humanity. A differing viewpoint might project this companion entity as essential to assist humanity to overcome several atrocious problems plaguing our global and local communities. One must study the balancing of these two viewpoints and the associated ethics and regulation. Keeping in mind the ongoing global effort in cognification, educational institutions need to offer informed guidance to the academics, to the researchers, and to the students to prepare them to adapt to this potential future as it percolates through societies.

The rest of the article discusses cognification from different academic lenses. Since 4IR is just at its inflection point and cognification is a new area of study, arguments are based on the authors' expertise and potential outcomes of contemporary studies. Future studies need to be initiated to investigate the efficacy of 4IR in education.

Cognification in Learning and Teaching – An Example

Modern AI techniques that drive cognification are not perfect. Mostly, the lack of quality data causes failure. Alternatively, failure can come from issues around the quality and richness of models. As the world of education becomes more evidence-based and more data-centric, the application of cognification is expected to yield more trustworthy outcomes.

Recent advances in explainable AI (xAI) could unveil the inner workings of the underlying AI techniques (Arrieta et al., 2020; Xu et al., 2019). Arrieta et al. (2020) define xAI as a system that produces details or reasons to make its functioning clear or easy to understand. Teachers and students already access such open xAI models - for instance, students were able to revise their work based on xAI feedback prior to submitting assignments and teachers were able to subject student responses to automatic evaluation of targeted rubrics. xAI techniques could potentially learn from their own explanations, thus leading to the possibility of an autonomous self-improving system. However, at this time in its development, xAI can provide an acceptable level of application when tuned with a human-in-the-loop approach.

The following example in automated essay scoring (AES) highlights the impact of xAI on cognification. Kumar and Boulanger (2020a; 2020b) describe a way to predict the rubric scores of English essays by applying deep learning techniques over a vast range of writing features. Based on thorough analyses of the distributions of rubric score predictions and distributions of resolved versus the rubric scores of human raters, they contend that the rubric scoring models closely approximate the performance of human raters. Their study reveals that rubric score prediction does not directly depend on a few word-count-based written language features (all word-count features were pruned). Many intuitive features were found and selected by each rubric with no dominant features.

The data for this AES system came from a Hewlett-Packard Foundation funded automated student assessment prize (ASAP) contest (Shermis, 2014). Kaggle[1] collected eight essay datasets of student-written essays (D1 – D8) – which students from Grades 7 to 10 from

[1] https://www.kaggle.com/c/asap-aes

six different states in the USA had written. The essays range from an average length of 150 to 550 words. Each essay was assessed by two human raters. The raters assessed each essay with a holistic score in the range of 0 to 24 and with scores for the following four rubric elements – ideas, organization, style, and conventions. Each rubric was scored in the range of 0 to 6.

The recent version of this AES used the seventh essay dataset (D7) since a) it contained a larger number of sample essays (1567), b) it had a moderate mean number of words (171) reflecting shorter essays, c) it had both holistic (0-30) and rubric level scores (0-3), and d), it had a higher quadratic weighted kappa value (0.72) indicating substantial interrater agreement. D7 included narrative essays on the topic of 'patience'. While the original training set contained 1567 essays with human scores, the original validation and testing set only contained 894 essays without human scores. That is, the holistic and rubric scores assessed by human raters were only available for the original training set that contained 1567 essays. Thus, the 894 essays in the validation and testing set were leveraged for feature selection. This is fine since feature selection must never be informed by the training set to prevent overfitting of the machine learned model.

The essay samples (1567) were processed by the Suite of Automatic Linguistic Analysis Tools (SALAT)[2] which offered a set of 1592 writing features. A subset of these features was used to predict the four rubrics - ideas and content, organization, sentence fluency, and conventions. The resulting performance of this AES is quite comparable to the human rater scores. On average, the human rater scores were identical 63% of times and adjacent (±1) 99% of times. On the other hand, AES predictions on average, after rescaling to a 0-3 scale, were exact and adjacent (±1) 65% and 100% of times, respectively. To the best of our knowledge, only one study attempted to predict rubric scores using D7 (Jankowska et al., 2018), only one study investigated rubric score prediction on D8 (Zupanc & Bosnić, 2017), and very few AES systems in general predict essay scores at the rubric level (Kumar et al., 2017). Zupanc and Bosnić (2017) reported an agreement level (QWK) of 0.70 on the organization rubric (D8).

Based on thorough analyses of the distributions of rubric score predictions and distributions of human rater rubric scores, the outcomes of the AES revealed that the rubric scoring models closely approximate the performance of human raters. Further, the AES system can increasingly improve its predictions as more essays are fed to the AES. The AES model is ethically shareable with students after informing the teacher of strict ethical guidelines in receiving student AES usage data, interpreting their writing competency in conjunction with their use of the AES, and assigning grades for students' submissions in the context of a human-in-the-loop approach. Data that are fed to the AES system should also be ethically subjected to commonly used fairness metrics (Majumdar et al., 2021; Mehrabi et al., 2021; Verma & Rubin, 2018) using contemporary AI fairness toolkits such as the IBM AI Fairness 360, Microsoft's Fairlearn, Google's What-If, Aequitas, and Scikit-fairness. Finally, the AES system should be

[2] https://www.linguisticanalysistools.org/

fully regulatable. For instance, when the AES marker's performance becomes equivalent to that of the human raters, the teacher-in-the-loop directive should inject additional rubrics to drive students toward better writing competency as well as drive the AES toward increasing smartness. A long-short term memory recurrent neural network with an attention mechanism (Alikaniotis et al., 2016; Dong et al., 2017) could be trained to locate spots in student essays that influence the AES system's decision-making when assigning rubric scores, thus improving the smartness of the AES.

The black box of each rubric scoring model was scrutinized using an xAI system to determine the features and the degree to which they contributed to the determination of rubric scores. A set of the 20 most important features for each rubric emerged, in which at least 15 features were unique to every rubric and did not significantly contribute to the prediction of the other rubric scores.

Figure 1 highlights the workings of explainable AI. There are two images in this figure, each showing the 20 key writing features. Each feature is represented in abbreviated forms. For instance, the 8th feature from the top represents the word-count features indicating the total number of words in the essay; the 13th feature relates to positive adjectives. In addition, each image shows the level of contributions of each feature to individual essays. For instance, the five squiggly lines (three purplish ones and two reddish ones) in the left image in the figure point to five essays, and the contributions of the 20 features to each essay. Those five lines are wobbly because different features of writing contribute to different degrees. The contributions of features could be positive or negative. If positive, the line would move to the right toward better scores. If not, the line would move to the left leading to lower scores.

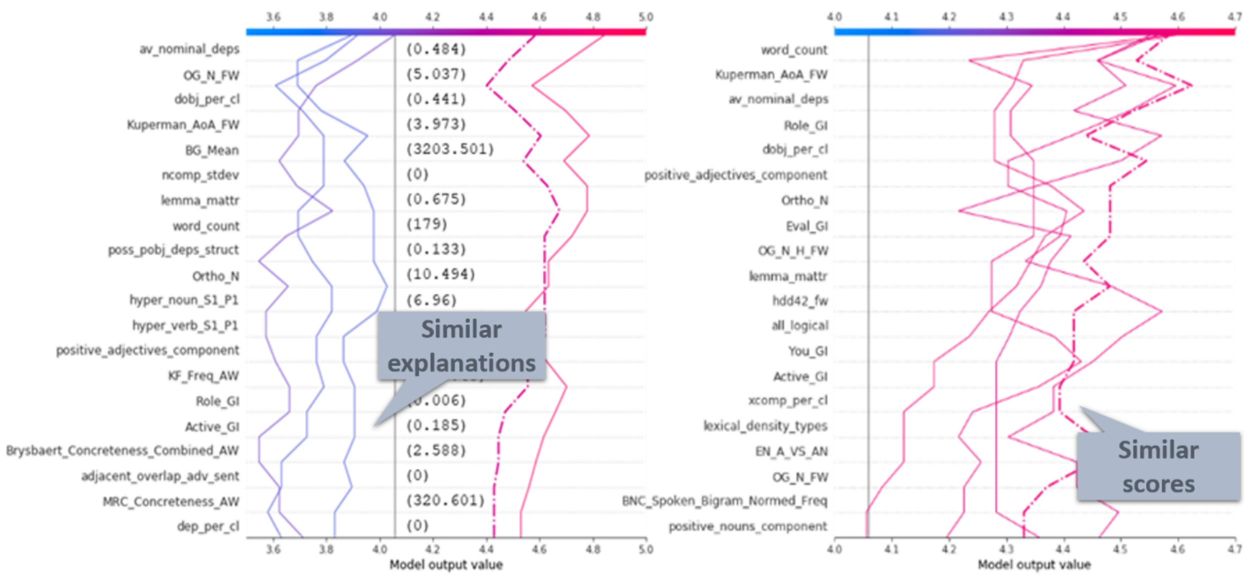
Of the five essays, two of them predict an average score of around 3.9 out of 5.0 while one essay predicts a high score of about 4.8 out of 5.0. Interestingly, these five essays show similar patterns in how features contributed to their predicted scores. One could infer that those students who wrote these three essays have similar writing competencies as well as writing misconceptions. Still, the AES system predicted different final scores for these five essays. Teachers can offer common feedback to such groups and explain how students in such groups can improve their writing competencies corresponding to each writing feature.

The image on the right in the figure points to five other essays where the contributions of writing features on each essay are quite dynamic. That is, the contributions of features are quite varied among the five essays. Despite these variations in contributions of features, these five essays were predicted to obtain a score close to 4.6 out of 5.0. In this case, feedback from the teacher should be more individualized.

Moreover, the study revealed that rubric score prediction does not directly depend on a few features based on word-counts. Many intuitive features were selected for each rubric in the current AES with no specific dominant feature, making it more difficult to trick the AES system. That is, the AES system could identify writing features that students should not ignore. Further, the AES system could also identify to teachers those students who lack competency in these writing features, thus reinforcing the need for a human-in-the-loop approach, and empowering teachers to triangulate their instruction for greater pedagogical outcomes. That is, student essays can be clustered relative to the number of rubric scores, to discover discriminative patterns in the essays that can lead to improved formative and remedial feedback.

Figure 1

Explainable AI in Automated Essay Scoring



Being an xAI-based system, the AES can be applied on a globular scale, across multiple institutions, thus offering a platform for students to compare and/or contrast their performances among a larger group of learners. The AES follows a method that promotes a degree of transparency among users, and an understanding of the AES underlying feature-based deep/shallow neural networks.

Mechanisms to introduce AI accountability and build trust between AI and human agents are crucial for the reliable and large-scale deployment of AES systems.

Theoretical Model on Cognification

Cognification characterizes smart entities that try to become increasingly, ethically, and regulatably smart. The variables contributing to these traits are identifiable and comparable. Accordingly, they arrive at hypotheses that can lead to a theoretical model on cognification. Further, when cognified entities engage with people in a human-in-the-loop approach, variables of collaboration between the human and the cognified entity arise in terms of sense-making and decision-making.

The traits of collaboration of cognified entities include: i) the control of collaborative interactions in terms of autonomy (e.g., active, ethical, co-regulative), ii) theoretical flavours of collaboration (e.g., socio-constructivist, shared cognitive, etc.), and iii) design of collaborative context (e.g., participants, roles, domains) (Kumar, 1996). Sense-making (Abbass, 2019) enables an entity to a) explore data (e.g., create opportunities to collect new datasets), b) derive data (e.g., create new data from existing datasets), c) interpret data (e.g., longitudinal synthesis), and d) share data (ethically and regulatably). Decision-making (Abbass, 2019) enables it to e) assess opportunities and risks in contexts and situations, f) design, plan, and generate courses of actions, g) select and execute one or more actions, h) reason about and explain the choices made (e.g., causal discovery, trust relations), and i) have a degree of autonomy in executing any of these (i through g) traits of the cognified entity. Cognification of an entity resides at the intersection of its traits of collaboration, sense-making, and decision-making.

Literature defines these traits at various levels of granularity. Sheridan (1992) identified several levels of autonomy. Scholtz (2003) arrived at different types of roles for collaborating partners. For example, Scholtz defines "supervisor", "operator", "teammate", "bystander", and "mechanic" as the roles for humans in human-robot interactions. Models of self-regulation, from literature (Winne & Hadwin, 1998), and synthesized from literature (Brokenshire & Kumar, 2009), expand the trait of regulation at several granularity levels. The emergence of trust in collaboration between cognified entities has its own levels of granularity (Abbass, 2019; Mohkami et al., 2015).

In summary, theoretical modelling of 'human in the xAI loop' is essential for the operationalization of cognified entities in teaching, learning, and training. Cognification is liable to suffer abuse, if such models to govern the creation, the application, and the retirement of cognified entities are missing.

Cognification and the Further Democratization of Education

Presently, educational institutions are responsible for teaching and learning. They enact policies and procedures, under governmental regulations and acts, to offer educational and research experiences. The traditional model of education remains mainstream. However, an underlying movement, akin to research pursuits by private institutions, encourages the pursuit of self-learning (what to learn, e.g., OER textbooks), self-teaching (how to learn, e.g., graduate teaching MOOC), and self-research (e.g., crowd-funded research). This movement, representing a new model of learning and teaching, strives to soften the control of the traditional authorities of education. That is, the contemporary educational institutions are urged to consider offering educational credits obtained, in a reliable and verifiable manner, from non-traditional learning and teaching avenues supported by OERs, MOOCs, learning groups, and so on.

This movement offers evidence of learning by capturing detailed intricacies of student learning experiences, rather than aiming at a credential, such as a degree, as the culmination of student competencies. This evidence can originate either in a traditional educational environment or in a non-traditional environment, where the choice of the environment for a particular competency is left to the discretion of the student rather than the institution.

Students could pick and choose their learning experiences from a variety of learning avenues, compile them into a portfolio of verifiable learning evidence, and demand recognition from credit-offering institutions. Thus, traditional institutions would require new roles to verify learning evidence that comes from a wider variety of learning avenues. Educational institutions do offer such services (e.g., Prior Learning Recognition, Credit Transfer Services) but mostly limited to credits obtained from like-minded institutions or institutions that exist within an accrediting organization (e.g., Middle States Commission on Higher Education). All other learning experiences, not including the ones such as the work-integrated learning or the cooperative learning, which are earned from non-traditional avenues (e.g., free MOOCs) are typically excluded.

A handful of academic institutions have ventured into accepting such learning experiences as micro credentials, but such ventures are still limited to experiences borne out of recognized institutions. Such a restricted credentialing framework is necessitated by the inability of the institutions to verify learning experiences at a global scale in a consistent manner. While there are standards on learner interactions (e.g., xAPI, caliper) and frameworks on experience mapping (e.g., VITAE, ePortfolio), there is no single consistent model that can scale up to verifying learning experiences at a global scale.

Reputation implies higher costs for learners. The average graduate student loan debt balance, as of 2021, is $91,148 among federal borrowers in the United States[3]. The average debt among PhD holders is $159,625; 14% of the average graduate student debt is from the borrower's undergraduate study. The pressure of the cost of education makes quality education unreachable to a significant portion of the global student population. In general, online learning promises to make quality educational experiences equitable but has not measured up, since education quality is still measured mostly in terms of grades and the overall reputation of the institution rather than in terms of quantifiable measures of well-recognized competencies of individual learners. Reputed institutions have a vested interest to maintain the status quo of measuring the quality education. This means that quality education remains accessible to only those students who can afford it, with and without the student debt.

In addition to issues relating to high costs of education, the cognification-based educational movement is further inspired by the fact that traditional ways of teaching, unless carefully crafted, do not naturally inspire creativity, intelligence, and discipline among most students (Astle, 2018). After graduation, student capabilities vary significantly, as the outcomes of education place heavy emphasis on summative evaluation. Formative evaluation captures the process and the experiences of students as they learn and offers a better measurement of learners' capacity than summative evaluations, in general.

---

[3] http://educationdata.org

Blockchain technology can play a vital role in the further democratization of the contemporary education system. Blockchains are immutable ledgers that can record learner experiences at higher levels of granularity, in a continuous manner as and when they arrive. Subsequently, these experiences can be mapped to targeted competencies that match the educational/program/curricular outcomes of students. Employers can seek students targeting specific competencies rather than credentials. Employers can also target self-reliant, lifelong learners. Thus, students can compete on a global scale on specific sets of competencies that interest them, rather than competing to score better grades in tests that offer indirect and abstracted measures of competencies. Because blockchain networks can be reliably shared among all participants, individuals can retrieve past learning activities and continually compile them to expected thresholds. Unlike transcripts, blockchain based learning can continue to accumulate learning credits and growth of competencies as learners progress in the education system. Importantly, privacy and ethical measures on blockchains can be readily enacted through associated technologies (e.g., private blockchains). More importantly, to inspire competition among learners, such a blockchain-based learning trace can be shared publicly, thus helping quality education become truly accessible on a global scale. Institutions can choose to adhere to a blockchain-based framework to supplement existing educational policy frameworks thus accommodating community acceptance of such technologies.

The cost of collecting, analyzing, and maintaining a blockchain-based learning and teaching system is not trivial. At present, the cost of making a transaction in a blockchain is very high. In late 2021, the transaction fee of the Ethereum Blockchain was $2.79695. Blockchain fees depend on several factors including network congestion, transaction confirmation time, and transaction size. Blockchain miners are an important part of this environment, and they stake some of their assets in the blockchain to mine a block. The type of asset depends on the consensus algorithm used by the blockchain in which the transactions are added. Miners are remunerated in the form of block rewards (e.g., new crypto coins) and/or transaction fees to execute a transaction on behalf of the user on the blockchain. For instance, in the Ethereum Blockchain, which currently uses the "Proof of Work" consensus algorithm, miners must solve cryptographic puzzles to mine a block. Once mined, the block can be used to record a learning trace. However, the operation to mine a block requires high-performance computers and a considerable amount of computing power, not to mention the electricity needed to run the high-performance computational devices. The miners must invest heavily to access computational devices. Blockchain is a promising and evolving technology that can record the evidence and the subsequent derivative inferences of learning to further the causes of democratized education provided the underlying cognified operations can ensure consistent improvement, ethical guidelines, and regulatable governance.

Implications of Cognified Education

Cognification is the art of making an entity increasingly, ethically, and regulatably smarter. As the world's complexity grows, humans are discovering that manual methods of the third industrial revolution are inadequate to entirely resolve complex problems, necessitating the need for cognification. Cognified entities are a significant part of the 4IR, especially in the context of education.

Deloitte's fifth annual Global Human Capital Trends report and survey (2017)[4] established that the current half-life of a learned skill, which used to be approximately 25 years, is now roughly 5 years. Deloitte determined that the entire length of a career currently averages 65 years and the tenure in a specific career has reduced to about 4.5 years. That is, people are spending more time in careers and are willing to switch careers more frequently. Accordingly, students need to plan for longer-term learning journeys that continue beyond graduation to reskill and upskill over the course of their conceivably varied careers.

Through this lifelong learning journey, students need to retain traces of their learning as evidence to support their competencies. Such evidence may originate from either traditional and/or non-traditional learning environments. Technologies such as blockchain networks, can assist institutions, employers, and other such agencies to verify the new competencies that students declare. Blockchains networks, while guaranteeing immutability, should be cognified to pave the way for automated mapping of learning traces to estimates of learned competencies. Such a cognified mapping could rely on theoretical support that includes both the human-in-the-loop interactions as well as the supplemental cognification-in-the-loop interactions.

Educational communities in remote and local areas are embracing globalized learning contexts. Consequently, competition for work in geographic locales has become global. Global workspaces expect students to both accommodate cognified tools (as part of their learning journey) and be competent in targeted cognitive capabilities (such as cultural agility and critical thinking).

Research in cognified entities has ventured into several educational areas including AES, software development, music teaching, and industry training. In AES, learners could receive reflective feedback on their drafts and explanation-based feedback on ways to improve their essays. Teachers could personalize instructions targeting writing competencies of specific groups of learners. Institutions could measure overall writing competencies exhibited by learners across different courses, to offer a lens on student writing competencies. Music teaching is increasingly employing cognified entities (e.g., Wirth Method[5]) to measure the impact of teaching music at the school level, classroom level, and individual student level. Energy industries are investing in cognified training programs (e.g., AR/VR immersive training) to empower workers to measure and upskill competencies on their own, in addition to contemporary training requirements of the industry.

---

[4] https://www2.deloitte.com/content/dam/Deloitte/global/Documents/About-Deloitte/central-europe/ce-global-human-capital-trends.pdf

[5] https://wirth-music.org/en/the-wirth-method/

Conclusion

Cognification in learning, teaching, and training raises several important questions. How feasible it is to develop real-world cognified systems for lifelong learning? Could cognification autonomously map learning design and learner activities to an instructional theory such as connectivism? Would the introduction of cognification promote democratization of education? Who owns the copyrights of cognified data as well as cognified models? How intrusive is data procurement in cognified systems? Could cognification offer continuous improvement training to educators? Would cognified tools be accepted in workplaces? What happens if stakeholders do not subscribe to the notion of 4IR in education? Could we truly harness its full potential? How do we transition into a 4IR world while upholding our values on privacy, equality, equity, diversity, and living standards? Currently, cognification lacks the kind of maturity to provide convincing answers to these questions. However, scholars, technologists, and other stakeholders are painting a future of artificial smartness that incorporates human creativity and intelligence, where multiple systems synergize to provide smart support to augmented sense- and decision-making in teaching, learning, and training domains.

References

Abbass, H. A. (2019). Social integration of artificial intelligence: Functions, automation allocation logic and human-autonomy trust. *Cognitive Computation*, *11*(2), 159–171. https://doi.org/10.1007/s12559-018-9619-0

Alikaniotis, D., Yannakoudakis, H., & Rei, M. (2016). Automatic text scoring using neural networks. *ArXiv Preprint ArXiv:1606.04289.*

Arrieta, A. B., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., García, S., Gil-López, S., Molina, D., & Benjamins, R. (2020). Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. *Information Fusion*, *58*, 82–115. https://doi.org/10.1016/j.inffus.2019.12.012

Astle, J. (2018). Do schools really kill creativity? RSA Blog, April 2018. https://www.thersa.org/blog/2018/04/do-schools-kill-creativity

Brokenshire, D., & Kumar, V. (2009). Discovering Causal Models of Self-Regulated Learning. *AIED*, 257–264. https://doi.org/0.3233/978-1-60750-028-5-257

Dong, F., Zhang, Y., & Yang, J. (2017). Attention-based recurrent convolutional neural network for automatic essay scoring. *Proceedings of the 21st Conference on Computational Natural Language Learning (CoNLL 2017)*, 153–162.

Gysegom, W., Houthuys, S., Khanna, S., Migliorini, R., Misljencevic, D., & Robertson, M. (2021). *4IR capability building: Opportunities and solutions for lasting impact*. McKinsey & Company. https://www.mckinsey.com/capabilities/operations/our-insights/4ir-capability-building-opportunities-and-solutions-for-lasting-impact

Jankowska, M., Conrad, C., Harris, J., & Kešelj, V. (2018). N-gram based approach for automatic prediction of essay rubric marks. In E. Bagheri & J. C. K. Cheung (Eds.), *Advances in artificial intelligence* (pp. 298–303). Cham: Springer International Publishing.

Kumar, V. S. (1996). Computer-Supported Collaborative Learning: Issues for Research. *Proceedings of the 8th Annual Graduate Symposium on Computer Science*, University of Saskatchewan, Canada.

Kumar, V. S., & Boulanger, D. (2020a). Automated Essay Scoring and the Deep Learning Black Box: How are rubric scores determined? *International Journal of Artificial Intelligence in Education, 31*, 538-584. https://doi.org/10.1007/S40593-020-00211-5

Kumar, V. S., & Boulanger, D. (2020b). Explainable Automated Essay Scoring: Deep Learning Really Has Pedagogical Value, *Frontiers in Education, 5*. https://doi.org/10.3389/feduc.2020.572367

Kumar, V. S., Fraser, S., & Boulanger, D. (2017). Discovering the predictive power of five baseline writing competences. *Journal of Writing Analytics, 1*(1), 176–226.

Majumder, S., Chakraborty, J., Bai, G. R., Stolee, K. T., & Menzies, T. (2021). Fair enough: Searching for sufficient measures of fairness. *ArXiv Preprint ArXiv:2110.13029*. https://arxiv.org/abs/2110.13029

Mehrabi, N., Morstatter, F., Saxena, N., Lerman, K., & Galstyan, A. (2021). A survey on bias and fairness in machine learning. *ACM Computing Surveys, 54*(6), 1-35. https://doi.org/10.1145/3457607

Mohkami, M., Noorian, Z., & Vassileva, J. (2015). Dynamic credibility threshold assignment in trust and reputation mechanisms using PID Controller. In N. Baloian, Y. Zorian, P. Taslakian, & S. Shoukouryan (Eds.), *Collaboration and technology, 9334* (pp. 148–163). Springer International Publishing. https://doi.org/10.1007/978-3-319-22747-4_12

Penprase, B. E. (2018). The fourth industrial revolution and higher education. In Nancy W. Gleason (Ed.), *Higher education in the era of the fourth industrial revolution* (pp. 208-229). Palgrave Macmillan. https://doi.org/10.1007/978-981-13-0194-0_9

Scholtz, J., & Bahrami, S. (2003). Human-robot interaction: Development of an evaluation methodology for the bystander role of interaction. *SMC'03 Conference Proceedings. 2003 IEEE International Conference on Systems, Man and Cybernetics. Conference Theme - System Security and Assurance (Cat. No.03CH37483)*, *4*, 3212–3217. https://doi.org/10.1109/ICSMC.2003.1244385

Schwab, K. (2016). *The fourth industrial revolution* (First U.S. edition). Crown Business.

Sheridan, T. B. (1992). *Telerobotics, automation, and human supervisory control.* MIT press.

Shermis, M. D. (2014). State-of-the-art automated essay scoring: Competition, results, and future directions from a United States demonstration. *Assessing Writing*, *20*, 53–76. https://doi.org/10.1016/j.asw.2013.04.001

Verma, S., & Rubin, J. (2018). Fairness definitions explained. *Proceedings of the International Workshop on Software Fairness*, 1–7. https://doi.org/10.1145/3194770.3194776

Wagner, G., Lukyanenko, R., & Paré, G. (2022). Artificial intelligence and the conduct of literature reviews. *Journal of Information Technology*, *37*(2), 209–226. https://doi.org/10.1177/02683962211048201

Winne, P. H., & Hadwin, A. F. (1998). Studying as self-regulated engagement in learning. In D. J. Hacker, J. Dunlosky, & A. C. Graesser (Eds.), *Metacognition in educational theory and practice* (pp. 277–304). Routledge.

Xu, F., Uszkoreit, H., Du, Y., Fan, W., Zhao, D., & Zhu, J. (2019). Explainable AI: A brief survey on history, research areas, approaches and challenges. In J. Tang, M.-Y. Kan, D. Zhao, S. Li, & H. Zan (Eds.), *Natural language processing and Chinese computing, 11839* (pp. 563–574). Springer International Publishing. https://doi.org/10.1007/978-3-030-32236-6_51

Yusuf, B., Walters, L. M., & Sailin, S. N. (2020). Restructuring educational institutions for growth in the fourth industrial revolution (4IR): A systematic review. *International Journal of Emerging Technologies in Learning, 15*(3), 93–109. https://doi.org/10.3991/ijet.v15i03.11849

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – Where are the educators? *International Journal of Educational Technology in Higher Education*, 2–27. https://doi.org/10.1186/s41239-019-0171-0

Zupanc, K., & Bosnić, Z. (2017). Automated essay evaluation with semantic analysis. *Knowledge-Based Systems*, *120*, 118–132. https://doi.org/10.1016/j.knosys.2017.01.006

Authors

Vivekanandan Kumar is Professor and Associate Dean of Research and Innovation in the Faculty of Science and Technology at Athabasca University in Canada. His research interests include artificial intelligence in education, cognification, fourth industrial revolution, and learning analytics. http://vivek.LearningAnalytics.ca. ORCID: 0000-0003-3394-7789 Email: vivek@athabascau.ca

Mohamed Ally is Professor in the Faculty of Humanities and Social Sciences at Athabasca University in Canada. His current areas of research include mobile learning and use of emerging learning technologies in education and training. https://news.athabascau.ca/research/athabasca-university-professor-named-commonwealth-of-learning-chair/ Email: mohameda@athabascau.ca

Avgoustos Tsinakos is Professor in the Department of Computer Science of International Hellenic University in Greece. His research interests include mobile learning, technology-enhanced learning, intelligent tutoring systems and internet applications of AI. http://de.teikav.edu.gr/tsinakos/. ORCID: 0000-0001-5043-0226 Email: tsinakos@cs.ihu.gr

Helmi Norman is Associate Professor of the Faculty of Education, Universiti Kebangsaan Malaysia (UKM) or the National University of Malaysia. He is also the Deputy Director of Instructional Technologies of the Center for Teaching and Curriculum Development, UKM. He currently drives the e-learning transformation in the university. His research interests are in the field of digital and futuristic education. https://www.helminorman.com/about Email: helmi.norman@ukm.edu.my