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AI paradigms for teaching biotechnology

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ABSTRACT (49 words)
Artificial intelligence (AI) is profoundly changing biotechnological innovation. Beyond direct application, it is also a useful tool for adaptive learning and forging new conceptual connections within the vast network of knowledge for the advancement of biotechnology. We discuss a new paradigm for biotechnology education that involves co-evolution with AI.

KEYWORDS
Education; Artificial Intelligence; Student-As-Partner; Experiential Learning

BIOTECHNOLOGY IS BUILT ON AN INTERDISCIPLINARY NETWORK OF KNOWLEDGE

Biotechnology is broadly multidisciplinary, ranging from the modification and use of biological systems to create new products at one end of the spectrum, to the application of technology towards solving biological problems at the other end. It draws on fields as diverse as bioprocess engineering, "-omics" and gene editing technologies, material sciences, optics and electronic engineering etc. to exploit the potential within biological systems.

Biotechnological innovation depends on drawing meaningful connections within vast knowledge networks via synergistic co-learning, discussions and collaborations amongst inter-disciplinary specialists. The microarray is a canonical example, demonstrating how precision engineering, computing, chemistry, biology, statistics and mathematics can be unified into a practical technology for measuring gene expression. The technology is based on biochemistry fundamental to a cell – that nucleic acids bind very specifically to a complementary version of themselves to form a double-stranded molecule. Theoretically, it is possible to determine global gene expression (i.e. presence of the suite of mRNAs) via this biological principle, but other fields need to come into play. Precision engineering leads towards reproducibly-sized arrays, spotting DNA-based gene probe sequences onto precise chip locations; chemistry contributes to the synthesis of such gene probes and also dye-tags for generating fluorescence corresponding to quantities of bound samples; electrical engineering helps develop sensitive cameras needed to capture the chip image; computing hardware development produces methods for signal extraction (digitize photo-images into intensity-matrices); statistical and mathematical approaches help perform background correction, normalization, identification of interesting signals and mining of significant patterns. Finally, biologists interpret the processed data and, hopefully, unravel the relevant cellular mechanism. The linking of disparate fields for the genesis of innovation is intentional and meaningful.

This process of drawing meaningful links is a critical success formula in biotechnology as seen also in mass-spectrometry proteomics, next-generation sequencing, and synthetic biology. Biotechnologists need to learn not only from many disciplines but also how to make meaningful links. They can get better at this and one way is to innovate biotechnology education itself – by leveraging on one of the most powerful technologies in the toolbox, artificial intelligence (AI).

AI FOR LEARNING

AI describes computational systems that extract signal and learn from input. Today, AI integration with biotechnology is ubiquitous, notably in drug discovery [1].

AI should not be perceived merely as a tool for advancing biotechnology, but also for more *effectively learning* it in two notable ways: facilitating adaptive learning (AL) and helping make meaningful links within knowledge networks (see Table 1).

Individuals have different learning needs. The democratization of knowledge via Massively Online Open Courses (MOOCs) partially addresses this: By making courses freely available, learners can adopt a pick-and-choose strategy. However, this does not address learner-specific knowledge gaps. AL involves constructing personalized learning frameworks (curriculum and learning style) based on a person's learning preferences and prior knowledge. This is especially relevant for practicing biotechnologists, who need to bridge multi-disciplinary knowledge gaps efficiently.

AL is increasingly being driven by AI both "within" and "outside" classrooms. Within classrooms, AI-AL may integrate academic, social, and behavioral data sources to advice on strategic interventions (real-time teaching and curriculum planning). IBM's Watson AI, famously known for its high-profile deployment in pharmaceuticals, can act as an application backend for real-time classroom monitoring [2]. Outside classrooms, AI-AL may manifest as smart online platforms for customized learning, such as Smart Sparrow [3], superseding MOOCs [4].

AI technologies are evolving, and are being taught to "think" without being fed large amounts of data (Table 1) [5]. They can rapidly peruse scientific publications [6], and even generate hypotheses automatically [7]. The implication is that AI can make the links within knowledge networks and then teach this insight to a human learner who now need only to invest significantly less time.

SMARTER TOOLS NEED "SMARTER" HUMANS

While AI-driven education is a powerful paradigm shift, it may raise questions on how teaching practices should co-evolve with (and not merely rely passively on) AI. Bloom's taxonomy (BT), a levelling system for learning outcomes (Figure 1A) – is a useful basis for this discussion.

BT suggests that high level outcomes (create) are built on lower level outcomes (remember). Human work that draws on learning acquired at BT levels 1-3 may be substituted by AI. From the perspective of training novices, AI-AL can help novices scale BT levels faster, since they may, concurrent to their learning at lower BT levels, use AI to perform tasks to generate outputs for higher BT level training. As the learners gain solid foundation (i.e. attained lower BT levels), they can move on to higher-level deployment by synergizing with AI technologies to promote creativity and innovation. By then, they would have sufficient knowledge base to properly evaluate AI outputs for accuracy and value [6, 7]. With this advantage of AI in scaling the lower BT levels, adopting pedagogical approaches that focus more on honing BT levels 4-6 of human capacity is critical towards achieving better synergy with AI-driven education, particularly, to “action-ate” on connections AI makes in the network of knowledge.

The ability to “action-ate” is a skill and can be taught via high impact practices (HIPs) in pedagogy [8]. HIPs focus on creative application of knowledge and self-directed learning. Their minimally didactic frameworks encourage deeper and more meaningful learning through self-acquisition of know-hows, and their simulation of real life practice in a team-based setting allows learners to develop communication/group dynamics handling skills (relevant to BT levels 4-6). We discuss two HIPs: experiential learning (EL) and student-as-partner (SAP) (Figure 1B).

EL reinforces learning from authentic experience through an iterative cycle of reflective observation, abstract conceptualization and active experimentation [9]. Students are put through real life scenarios where they have to problem-solve themselves on a regular basis, drawing on anything and everything deemed relevant (without disciplinary boundaries). An EL course *Fieldwork and Documentation* in Nanyang Technological University, for example, requires students to come up with questions of socio-cultural interest to investigate during an overseas study trip. They therefore needed to conduct interviews of the local community and collate observation, the data of which would be processed and deliberated for presentation via video documentaries or static exhibits. The varied scope of the tasks challenged the students beyond head knowledge and they were highly engaged, gaining considerable competence and confidence in the process [10]. EL projects requiring experimentation to develop products, e.g. mechanical gadgets, culinary dishes, etc. are potentially suitable for biotechnology learners as it layers systematic optimization onto out-of-box thinking and purpose-driven designing that conventional laboratory practicals are unable to [11]. EL brings about a sensitivity towards the interconnectedness of variables and disciplines together with creative “action-ation”, essential traits for co-evolving with AI.

SAP involves co-learning, co-development of curriculum and co-teaching to deepen personal learning [12], as students are coerced into thinking more deeply about the subject matter from a teacher’s perspective. In one example, the Department of Mathematical Sciences, Loughborough University recruited second-year undergraduate students as interns to produce teaching and learning resources for future cohorts of the same level, to redesign two of its historically problematic modules (vector spaces and complex variables) with the aim of enhancing student experience and engagement. The subsequent ethnographic study showed that the interns became significantly more engaged and interested, gaining a deeper understanding of the mathematics they worked on [13]. The “teaching” role forces them to critically examine new knowledge against what they think they know. Achieving learning depth and competency is essential for “action-ating” as it helps build firmer knowledge foundations and importantly, fosters closer working relationships with mentors and peers. In biotechnology education, having senior students teach about technology which may have been relegated in their minds simply as “convenient tools”, e.g. DNA sequencers, can bring about a dimension of complexity in thinking. It may at the same time address the foreseeable pitfall of students blindly relying on AI-driven biotechnology as these become prevalent.

Even with AI-enabling, the gap between theory and action will persist as this ultimately is a human problem. AI can help smoothen learning processes via AL, or provide new ideas. The "step-up" lies in cultivating self-reliant individuals with a penchant for deep learning and creative "action-ation". These are skills teachable via HIPs. EL and SAP are especially invaluable as they elevate student engagement via personalization and ownership with less emphasis on grades and credits [14] amongst other competencies (Figure 2B). These in turn, are relevant towards biotechnology because self-directed learning, creative "action-ation" and aptitude for cross-disciplinary teamwork are crucial in the multi-disciplinary, collaborative, and rapidly changing field of biotechnology.

CONCLUDING REMARKS

AI is more than just a tool for driving biotechnological innovations, but is also useful for learning it. While AI can help ease learning processes, co-evolution with high-impact teaching practices will create significantly better returns on innovation.

CONFLICTS OF INTEREST

The authors declare no conflicting interest.

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Table 1 How AI can make biotechnologists “smarter” (Note that AI-led education is still developing, and the examples shown are instances of meeting a specific “smart” learning requirement, these are not exclusively biotechnology learning examples)

Requirement	What it is	Relevance to Biotechnology	Institutional adoption example	Technology deployed
Adaptive Learning (AL) Aided by: AI-driven adaptive learning technologies (The use of advanced data analytics to profile users, predict behaviours, and provide specific mitigations for altering behaviours towards desired outcomes)	AL collects real-time information on the learner’s engagement with the teaching material. It then provides personalization of the learning experience depending on one’s prior knowledge, learning style, real-time performance on assignments, etc. The personalization aspect could involve dynamic difficulty adjustment of the source material for online-based learning.	Biotechnological innovation is multi-disciplinary --- we are limited by our ability to learn as much and as quickly as possible At the trainee level, this can help improve efficiency in both depth and width of learning in our training programs. AL also has implications for practicing biotechnologists: New technologies and knowledge paradigms emerge quite rapidly. It is may play a role in helping experts stay relevant, and improve quality of biotechnological innovation	Pearson Education Nanyang Technological University (Lee Kong Chian Medical School)	IBM-Watson (Element and Enlight) [2] https://www.ibm.com/watson/education What it is: Tools for real-time classroom monitoring and curriculum planning with an AI backend
			University of New South Wales	Smart-Sparrow [3] https://www.smartsparrow.com/ What it is: Adaptive online learning platform for providing customized learning experience via their adaptive pathways, feedback and analytics modules
			University of Arizona	Knewton (Alta) https://www.knewton.com/ What it is: An integrative platform that consolidates data science, statistics, psychometrics, content graphing, machine learning, tagging, and infrastructure to enable upscaled personalized learning
			Colorado Technical University	Intellipath What it is: A smart learning platform that allows students to direct their learning, while also capable of strengths analysis and ‘change’ how the course progresses in order to best address those personal learning needs
Forging links within knowledge networks Aided by: Reinforcement Learning (Learning that does not require perfect or	These are advanced technologies that may be deployed for the purpose of mining information and drawing meaningful links amongst different fields	Biotechnological innovation is driven by creating a “network of knowledge” from different fields Given today’s big data landscape, effective	Non-institutional specific	Semantic Scholar [6] https://www.semanticscholar.org/ What it is: It is an AI-powered search engine that reads, extracts information and categorises findings from published research papers. It is meant to provide meaningful evaluation of a paper’s worth via meta-analysis. It is hoped that it would become advanced enough to become a

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<td rowspan="2">large amounts of data)

Deep Learning (Facilitates complex decision-making by modelling AI as neural networks, not unlike the neural connections found in the human brain)</td>
<td rowspan="2">Such technologies may also be used for knowledge discovery within existing datasets, such as those containing metrics on learning performance. These algorithms may then make predictions and identify patterns from such data</td>
<td rowspan="2">knowledge discovery via smart data mining is a necessary step forward.
Furthermore, making predictions and drawing inferences from big data is beyond the cognitive abilities of the average human brain. We need to co-evolve with AI to drive future biotechnological advancement</td>
<td></td>
<td>hypothesis engine that can guide scientists towards the bigger picture or to adopt alternative perspectives towards problem-solving</td>
</tr>
<tr>
<td>Non-institutional specific</td>
<td>Knowledge Integration Toolkit (KnIT) [7]
https://dl.acm.org/citation.cfm?id=2623667

What it is: It is an automated hypothesis generator (from text-mining of scientific literature) and is based on IBM Watson. One of its earliest (and promising) deployments is in predicting links and interactions between proteins via data-mining. This accelerates work on understanding the functional properties of proteins without excessive involvement in reading the literature or performing experiments</td>
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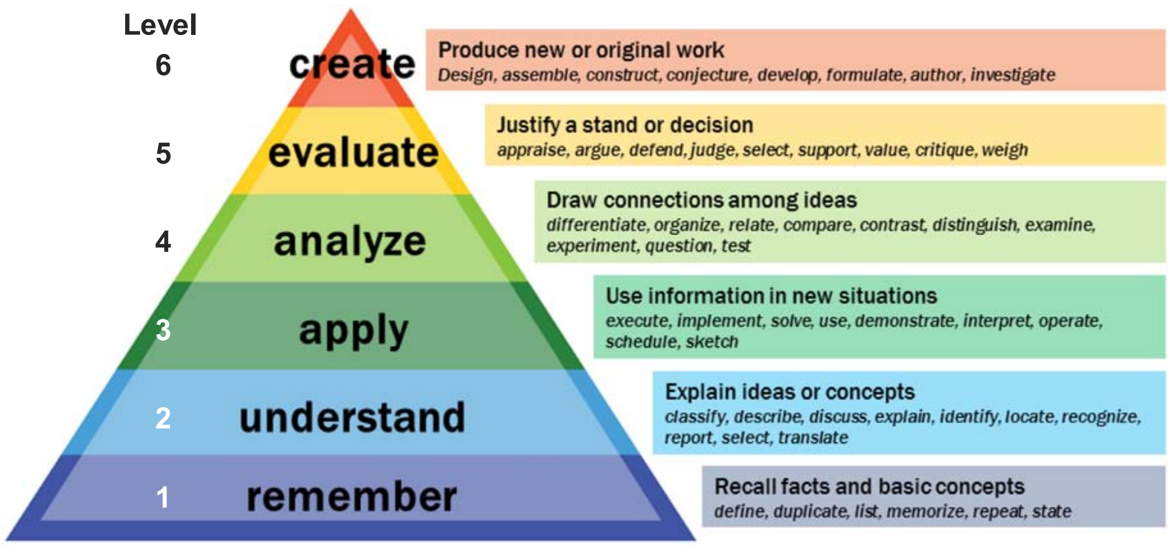
A



B

Learning outcomes	Competencies met by experiential learning (EL)	Competencies met by student-as-partner (SAP)	Relevance to biotechnology education
Increase student engagement via personalisation and ownership	Projects are student-led and self-initiated	Students create their own "ideal" teaching material based on pre-set learning objectives	Biotech innovation is driven by active engaged individuals
Increase motivation for self-directed learning	No exams. Informal learning context. Freedom.	Encouragement, mutual respect and empowerment	Creating new ideas requires acquiring inter-disciplinary knowledge
Enhance skills, knowledge, self-confidence	Students find ways to solve their own project-specific problems	Students must achieve critically "deeper" understanding of subject matter	Essential for putting theory/ ideas into practice/ materialization of new tech
Build meaningful mentor-learner relationships	Students are required to stand on own two feet and are facilitated	Students are facilitated. Build an informal working relationship with mentor	Deeper interactions produce better learning and work outcomes
Build teamwork and leadership skills	Students are required to work in teams and coordinate their activities	Students work in teams and engage in peer-to-peer teaching/mentoring	Biotech creation requires inter-disciplinary teamwork

Figure 1 ***A****: Bloom's Taxonomy is a ranking of learning outcomes from foundational (Remember; level 1) to deep (Create; level 6) (Image credits: Vanderbilt University Center for Teaching).* ***B****: Learning outcomes met by experiential learning (EL) and student-as-partner (SAP) pedagogies, and how these apply towards biotechnology education. Both EL and SAP attains level 6 of Bloom's Taxonomy (c.f. 1A) in the sense that both requires students to create a final product based on their initiative and creativity, building on prior acquired knowledge. Without delving too deeply, we briefly explained how each of the outcomes are met by EL and SAP in terms of execution respectively.*