AI for Biotech Futures: Connecting Biotech Companies and Educators to Shape an AI-Ready Workforce

Jon Ashley[1], Dominic Mosses[2], Femi Olorunniji[1], Darren W. Sexton[1], Gavin McStay[1], Baoxiu Qi[1], Mosharraf Sarker[1], Ismini Nakouti[1], Glynn Hobbs[1], Kehinde Ross[1], and Pattanathu K.S.M. Rahman[1]

[1] School of Pharmaceutical and Biomolecular Sciences, HITS, Liverpool John Moores University, 3 Byrom Way, Liverpool, UK L3 3AF.
[2] Protostem-AI, 173 College Road, Liverpool, UK L23 3AT.

Correspondence: j.ashley@ljmu.ac.uk

1 Executive summary

Artificial intelligence is rapidly transforming biotechnology, with applications now spanning drug discovery, protein and molecule design, bioprocess optimisation, quality management, regulatory affairs, scientific writing and diagnostics. As biotechnology becomes increasingly data-driven and computational, graduates entering the sector will need to demonstrate not only subject knowledge, but also the ability to use AI tools effectively, ethically and critically.

This white paper examines the emerging AI skills gap between biotechnology education and industry expectations. It identifies three key stakeholder groups: employers, universities and students. Each group has different expectations of AI use, but greater collaboration between them is needed to ensure that biotechnology graduates are prepared for an AI-enabled workforce.

The paper highlights several challenges facing higher education. First, unequal access to AI tools risks creating an uneven playing field for students, particularly where subscription-based tools offer better performance than free versions.

Second, AI has disrupted traditional assessment methods such as essays, lab reports, literature reviews and online exams, raising concerns about whether current assessments still measure genuine student learning. Third, the ethical use of AI remains unclear for many students and staff, especially in relation to academic integrity, AI declarations, hallucinated references and the limitations of AI detection tools. Finally, there is a subject-specific AI training gap, as many universities provide only general AI guidance rather than biotechnology-focused training.

To address these challenges, the paper recommends that universities provide equitable access to appropriate AI tools for both students and staff. It also argues that assessments should be redesigned either to prevent inappropriate AI use or to encourage transparent and productive AI collaboration. Alternative assessment formats, such as bioprocess design dossiers, industrial case-study investigations, quality-by-design briefs, public-facing explainers and AI-supported data analysis tasks, may better reflect the skills required in biotechnology workplaces.

The paper further recommends that AI ethics and academic integrity should be embedded into student training from the start of degree programmes. Students should be taught how to evaluate AI outputs, verify sources, recognise hallucinated references, declare AI use appropriately and understand the risks of over-reliance on AI-generated content. Staff should also receive structured training so that they can use AI confidently, redesign assessments and support students effectively.

A two-level approach to AI skills development is proposed. All biotechnology students should receive basic AI literacy training, including prompt engineering, literature searching, writing support, revision, scientific image generation, data handling and critical evaluation of AI outputs. More advanced AI skills, such as coding, machine learning, AI model development, large dataset analysis and biotechnology-specific AI applications, should be embedded into specialist modules, practical classes and final-year projects.

Overall, this white paper argues that universities must act quickly to embed AI skills into biotechnology education. By improving access to AI tools, redesigning assessments, strengthening ethical guidance and working more closely with industry, higher education can help close the AI skills gap and prepare graduates for responsible, effective and productive careers in the biotechnology sector.

2 Introduction

2.1. Background

Artificial intelligence (AI) has transformed the way we work and is increasingly being embedded in biotechnology research, development, manufacturing and decision-making. Current examples include machine-learning-assisted drug discovery, automated laboratory workflows and AI-supported diagnostics. These innovations are supporting the biotechnology sector in its move towards data-intensive workflows and computational approaches to research. In drug target discovery, companies such as Insilico Medicine[1] are developing AI platforms to analyse large biological datasets to identify disease mechanisms and therapeutic targets. Other AI tools such as Recursion [2] have also been used to prioritise which drug candidates to synthesise, test and progress through the drug-discovery pipeline. Through a collaboration between Nabla Bio and Takeda, AI has also been used for molecule and protein design by generating screens, optimising candidate molecules, antibodies, enzymes or proteins before laboratory testing [3]. With the introduction of AlphaFold[4], which is one of the best-known AI tools in biotechnology, researchers are now able to accurately predict protein structures and protein-nucleic acid interactions to help power countless applications in biotechnology. Google's DeepMind has also developed a multi-agent AI system based on Gemini called "Co-Scientists" for helping researchers with scientific thinking and hypothesis generation [5].

AI tools are being embedded into the manufacturing of biosimilars. These AI tools are increasingly being used in bioprocess optimisation to precisely control the conditions of fermentation/cell culture in terms of maintaining pH, temperature, nutrients, oxygen and yield [6].

The use of AI in quality management systems (QMSs) is allowing manufacturers to improve the management of deviations, suggest corrective and preventative actions and assist with audit tracking, risk management, document control and regulatory compliance [7]. AI also has the potential to be used in quality-control inspection such as identifying defects, contamination, fill problems or visual abnormalities in products[8]. In regulatory affairs, AI can also play a role in drafting, checking and standardising regulatory documents, labels, protocols, clinical study reports and suggesting responses to regulators[9]. More generally, in a biotechnology setting, AI is extensively used in scientific and medical writing, where it is accelerating the writing process as well as helping in the drafting of regulatory documents and scientific research articles[10]. However, human oversight is still needed to ensure the accuracy and integrity of AI-generated contents. With the biotechnology sector undergoing these rapid changes, this raises the question of which AI skills are needed to support continued growth .

In biotechnology and in the context of this paper, the three main stakeholders identified when discussing AI skills are industry (employers), academia (education) and the students/graduates (workforce). The expectations of all these stakeholders are distinct and joint consultation between these three main stakeholders is needed to reach a consensus on how to ensure that the current AI skills gap is addressed and enable the biotechnology workforce to demonstrate the use of AI in a productive, responsible and effective manner.

In education, AI is transforming the way tertiary education is being delivered. Students and academics now have access to powerful AI tools which are redefining how biotechnology is being taught and assessed at tertiary level. Large language models (LLMs) have forced academics to reconsider and redesign their assessments to either prevent the use of AI altogether, or to encourage students to use AI in a responsible, transparent and ethical manner. According to a recent report by the Higher Education Policy Institute [11], 95% of students surveyed now say that they use generative AI to help with assessed work, while 12% of students admitted to directly including AI-generated text in assessed work. This represents a marked increase in AI use from the previous year. The use of traditional coursework assessments such as lab reports, essays and literature reviews has now come into question by academics due to their exposure to AI misuse. The integrity of online exams has also come into question.

As such, universities are currently developing new policies or updating existing policies on the use of AI [12]. Current advice for students on the use of AI varies from university to university but the first guidance on the use of AI and assessments came from Monash University in the form of COMPASS [13]. COMPASS is an AI-use permission framework for assessments which allows lecturers to inform students about whether, when, and how to use AI in a particular assignment. The framework is represented by a compass dial with each compass direction representing different levels of permitted AI use.

“N – No AI use” meant that students are not permitted to use AI tools at all for an assessment. “S – Some AI” means that the student can use AI tools but only in some specified ways. “W – Ways of using AI” means that students can use AI in particular parts or processes such as brainstorming, feedback and language support. “E -Every AI” means that any AI tool is permitted for any part of the assessment but should be declared through an assessment declaration. With this framework, the expectations of how AI is used in an assessment are made transparent between the lecturer and students. However, the framework is built on trust with the students.

A more recent policy, which was originally developed as a framework by Manchester Metropolitan University, is the multi-dimensional Model of Assessment (MDMA) [14] which allows lecturers to design (and redesign) suitable AI-friendly coursework assessments. Three zones of AI use were identified: AI-exclusion, AI-collaboration and AI-collusion. The AI exclusion zone is where the use of generative AI is impractical or impossible such as in-person examinations and *viva voces*. The AI-collusion zone includes coursework that is exposed to generative AI and use of AI by students can be easily hidden and may remove meaningful learning opportunities from the student. Assessment types that fit this zone includes essays, laboratory reports and literature reviews. The third zone is AI collaboration which includes coursework where AI could be used to enhance creative and cognitive processes in academic work. This could include assessments such as developing a business plan or pitch for a biotechnology start-up and allows for more transparency for the lecturer while maintaining effective student learning objectives. Once a zone has been defined for an assessment, the authors proposed three steps for redesigning assessments. The first step is to identify the AI-user levels and determine how easily the students can collude with AI. The second step is to identify the assessment parameters and to ask what makes the assessment “AI vulnerable” or “AI resilient”. The final step is to redesign the assessment in order to make it a multidimensional assessment. This would involve combining parameters which encourage AI collaboration.

In the first step, three levels of AI use were identified. User 1: uses a text generator where the student generates the work with little to no editing and where no learning is taking place. User 2: uses a text editor but the work is significantly edited, and some learning is taking place. User 3: becomes a concept curator where the user finds sources and explains concepts. Some text generation is possible but still requires significant curation by the user.

The second step is to identify the key assessment parameters from nine possible parameters which are ranked on a scale of relative significance. These parameters are “structure” and “turnaround” (considered the least significant); “context”, “criticality and reflectivity”, “continuity” and “groupwork” which are (ranked to have higher “relative significance”); and “format”, “foundation and size” (having the highest relative significance). Following these steps will allow for assessments to be redesigned to ensure that they are resilient to AI-collusion and encourage AI-collaboration. Despite these developments in educational policy, there is still some way to go before, AI is fully incorporated into university degree programmes.

This white paper sets out to identify the current benefits and risks of AI in the context of the biotechnology sector, education and regulatory frameworks. The report discusses the current challenges and risks associated with implementing and teaching AI skills in biotechnology programmes. The report will propose strategies for identifying and implementing key AI skills training expected of biotechnology graduates with the goal of embedding AI skills into biotechnology degree programmes across the UK. It will also aim to ensure that the current skills gap between what biotechnology graduates can demonstrate and what skills employers expect of graduates is aligned and adequately provided for by universities.

3 Challenges

3.1 Availability of AI Tools for Students and Academic Staff

According to specialist AI databases [15], the number of available generative AI tools has grown exponentially in the last few years with both generic text-based LLM and specialist AI tools being brought to market. These AI tools are offered to users at different subscription levels based on price, with free versions being offered with use of either older or less capable AI models or through providing user token limits. This “try before you buy” strategy is typically done to encourage subscription to enhanced models or with unlimited token use. Although students can use a variety of AI tools in free versions, the widespread subscription-based pricing can exclude students from disadvantaged backgrounds whose disposable income may be limited. When students use these free versions of AI, they are often unaware that these AI tools are inferior in performance, are more likely to give incorrect information or even hallucinate sources and references. Students may also take the outputs of AI tools at face value without considering the accuracy or precision of the AI tool. Some universities in the US and UK have started to put in place deals with AI tech companies such as “OpenAI” and “Anthropic” for site-wide licences. Site-wide licences are currently expensive and too costly for a lot of universities in the UK.

Due to the packaging of “Copilot” with Microsoft 365, the adoption of Copilot by universities is seen as a cost-effective and convenient way to provide generative AI to staff and students. However, the performance of Copilot AI tools is difficult to evaluate and benchmark against other AI models while at an organisation level, although co-pilot can be linked with OneDrive providing detailed organisational data, the availability of this data for Copilot is limited due to data-protection laws and compliance. Other barriers that may affect access to AI tools include a lack of AI policy by universities in terms of which AI tools are recommended, a lack of devices or connectivity for students, accessibility barriers for students with learning disabilities and English as a second language and a general mismatch of AI training [16]. Students and academics may also have concerns with the environmental impact and sustainability of AI due to the large amount of energy required to power the data centres and scaling of AI, which makes them hesitant to use AI tools [17]. Overall, the variability of performance in AI models and access to AI tools along with concerns that AI will create an uneven playing field for students in assessments and learning opportunities should be the primary and most pressing issue to be addressed by universities, even before considering the redesign of assessments.

3.2 Effect of AI on Student Learning Outcomes

AI has severely disrupted how universities can operate when considering the use of AI tools in assessments, and learning outcomes. In theory, with access to AI tools, student learning outcomes and attainment should increase with fewer students failing modules, grade inflation and increase in first-class degrees being awarded by universities in biotechnology programmes [18]. However, it is still too early to be sure what effect AI use has on student attainment. The opposite effect could be true due to anecdotal evidence that

AI-generated coursework is not necessarily of better quality. This may be due to the inherent bias that some LLMs show to users. For example, “ChatGPT” has been shown to demonstrate bias in its responses towards users, show sycophantic behaviour and even lie [19]. This behaviour can be recognise by experts in the field but not necessarily by students.

Traditional coursework assessment types associated with STEM subjects such as laboratory reports, literature reviews, and final year dissertations are currently at risk of providing little or no effective learning in terms of achieving actual learning outcomes for students.

Some assessment types such as presentations, posters could be exposed to generative AI in terms of using tools such as Canva to design and generate presentation slides or posters or using a LLM to generate scripts for presenters. However, even with this level of AI use, the majority of learning objectives such as how well the students present a slides/poster, demonstrating understanding on a topic and how effectively they handle questions are maintained [20, 21].

The value or validity of online examinations (both closed book and open book) have also been questioned due to the ability for students to use generative AI to answer exam questions off-campus [22]. Universities have started invigilating online exams on campus, but this requires access to extensive IT suites and considerable staff resources [23]. Some university IT resources are not suitable for online assessments with invigilation due to the layout of the rooms, lack of browser limiter software or online admin monitoring software.

Assignments involving group work could also be affected by AI in terms of whether the levels of AI use by individuals in a team may create disparity between individual attainment scores learning scores compared with group scores but key learning outcomes such as teamwork could be maintained even with AI use.

The widespread use of AI tools now means that universities need to control the narrative on how and when AI tools are used in assessment while redesigning assessments to ensure that either AI cannot be used at all during the assessment or where that is impossible, encourage collaborative use of AI, which still results in effective learning outcomes.

3.3 Ethical Use of AI in Education and Research

Many universities are now allowing the use of AI to help support students' learning and general revision. With the widespread use of AI reported among students, the ethical implications of using AI in student work and teaching AI skills have become blurred [24]. Many universities are relying on trust and transparency between students and lecturers. Policies such as COMPASS have allowed lecturers to dictate how and when AI should be used and this is often communicated by a statement included with the assessment guidelines. General guidance is also given by many universities such as requesting that students include declaration statements on how they used AI in their coursework [25]. However, one issue with encouraging students to include AI declarations alongside their assessments, is that students may be reluctant to include AI declaration statements as they are unsure whether the coursework will be penalised in grade compared to students that either didn't use AI at all or used it and chose to hide their AI use [26].

Despite the guidance and increasing use of AI by students, the number of cases of academic misconduct involving the misuse of AI-generated coursework is increasing. As generative AI improves and the increasing accessibility of new AI tools for students, it is becoming increasingly difficult to distinguish between AI-generated writing and human generated work. Several AI detection tools such as "Turnitin AI-detection tool", "Grammarly AI detection tool" and "GPTZero" have been used by universities to screen student work but the effectiveness of these tools has been questioned and even resulted in false accusations against students [18, 27]. Accusations of inappropriate AI use have been brought by staff based on judgements of tell-tale stylistic indicators of AI-generated writing such as the inclusion of uncommon punctuation marks such as the double em dashes (—), the use of active voice over passive voice and positive language and the lack of variability of length of sentences and lack of specificity in language and topic. These assumptions about AI-generated writing are often speculative and would not by themselves pass the evidence threshold for the misuse of AI. As such, the clearest evidence of AI misuse, is in the reference list and sources or when prompt replies are copied and pasted along with the generative writing. When generative AI first emerged, the models used often produced inaccurate or fabricated citations. With later models, the rate of reference hallucination has decreased [28] and is offered on premium subscriptions. However, since legacy AI models are often offered as the free version and are commonly used by students and premium subscription models still suffer from hallucinations, students may not realise that through the inclusion of references that do not exist, students are committing academic misconduct through falsification of data/misrepresenting the literature rather than inappropriate AI use. In this case the burden-of-proof becomes clear and passes the minimum evidence threshold for academic misconduct regardless of intent by the student. As such, a clear policy on the ethical use, detailed training on how to verify references and find them safely is needed to ensure that students use AI in a safe and ethical way and avoid unintended academic misconduct. These rules can also affect students on PhD programmes as well and may have more serious consequences for research teams.

3.4 The Current AI Training Gap

With the current uptake of AI tools in biotechnology sector, there is an increasing need for graduates with the relevant skills in the use and development of AI. The exact skills needed by workforces can vary from employer to employer and according to business need. Useful AI skills could be separated into two main levels of prompt engineering requirements namely basic AI prompting skills and complex AI development skills.

Basic AI skills would be expected by employers in every Industry, (not just Biotechnology) and would involve being able to effectively prompt everyday tasks using a variety of AI tools to enhance general productivity. These basic tasks would include generating and writing for lab reports, SOPs, grant applications, marketing material as well as brainstorming of research ideas/strategies, searching for papers, and problem solving (**Figure 1**).

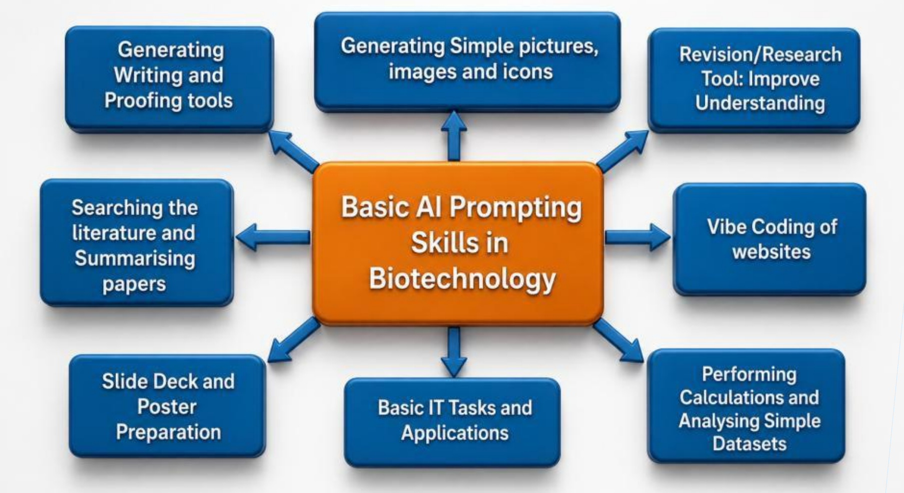

Figure 1: *Basic Student AI prompting skills in Biotechnology.*

In more complex AI applications, advanced prompt engineering in larger tasks such as coding projects or the analysis of large datasets would be expected from biotechnology graduates who have specialised in these types of skills (bioinformatics or AI model/machine learning development) and demonstrated these skills during their dissertation project (**Figure 2**).

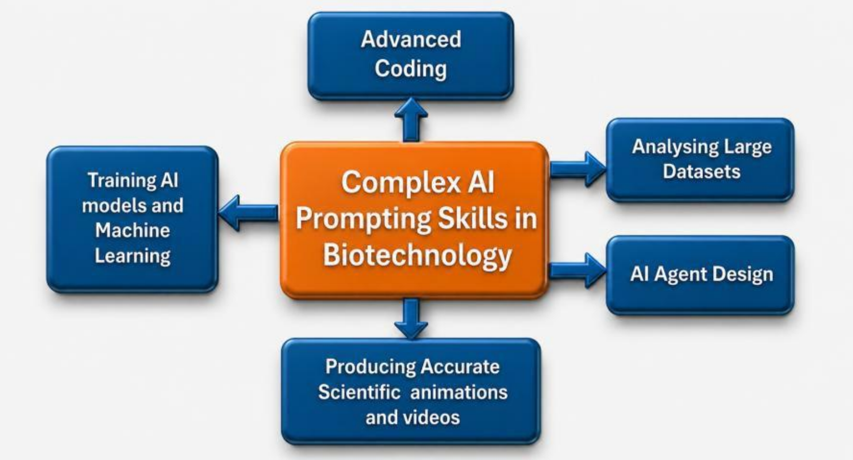

Figure 2: *Complex Student AI prompting skills in Biotechnology.*

Another current challenge is the lack of dialogue between academic institutes and industrial employers. Because the exact details of AI workflows by the biotechnology industry can include proprietary and intellectual property, the exact tailoring of teaching of general and more specialist AI tools required by industry is not clear. Furthermore, the frequency, quality and details of in-house training given in AI by employers is not well documented. This lack of dialogue between academia and industry has slowed the adoption and embedding of AI skills into degree programmes.

Many Universities have started providing AI training for staff and students, but this varies from institution to institution and is limited to general use rather than subject specific training. Incorporating AI into subject-specific programmes is more complex and slower due to the university governance and academic frameworks that are in place for changing assessments.

Although students and staff have started using AI routinely in an educational setting, the differences between these two users can raise issues regarding how effective AI is as a productivity and learning tool.

The unique timeframe of AI technology means that there are generational differences between students and staff in terms of attitudes to AI, understanding of the technology, usefulness and threats posed by the technology. For instance, staff that have gone through their formal education before 2023 have developed the expertise and background to allow them to effectively analyse, check accuracy, recognise biases, and generally evaluate the quality of outputs from generative AI. However, students may not have yet developed these critical thinking skills, meaning that any answers given by AI would be taken at face value by students. Students may also use AI purely as a writing tool rather than a revision tool, or to augment and develop their skills. The quality of support from AI is still being discovered. Students may not be aware of the capabilities and limitations of AI and may not be aware of the accuracy of AI to the same extent as experienced professional users, which could lead to issues in terms of academic integrity.

4 Recommendations

4.1 Addressing the Availability of AI Tools for Staff and Students

There is a pressing need to ensure that students and staff have access to the same AI tools to ensure a level playing field in terms of student attainment and fairness. This would mean that universities need to make a significant investment in access to AI tools, not just in generative LLMs, but specialist AI tools for literature searching, generating scientific diagrams, summarising papers, revision tools for exam preparation and proofreading tools. In order to ensure fairness, students need to be given access to the same tools meaning that dedicated university AI tools deployed at university level and if possible, provide students from socially disadvantaged backgrounds, more financial support to access AI tools.

Staff must also be given adequate training in the use of AI either during their formal teacher qualification or at the start of their contracts to ensure that they can use AI tools confidently, redesign assessments and ensure that learning objectives for students are still achieved.

AI has created further opportunities to develop and redesign lecture content, generate blended learning resources in Biotechnology (through vibe coding) and inform curriculum design which would help support student learning [16]. The use of vibe coding to develop blended learning resources provides opportunities for universities to develop bespoke in-house resources that complement student learning which in turn removes the need for specialist third-party service providers and could save costs for universities.

However, more investment in staff resources which can facilitate these blended learning resources is needed such as web hosting services or improved integration with virtual learning environments. AI could also be used in marking assessments and enhancing exam questions, although the use of AI in assessments may be considered deeply unpopular amongst students [22].

4.2 Ensuring that Student Learning Outcomes are Achieved in an AI Enabled World

Currently, policies are in place such as COMPASS which help set lecturer expectations in coursework assessments and MDMA which allow for the effective redesigning and stress testing of existing coursework. However, to ensure that student outcomes are valid, biotechnology programmes should implement coursework that either encourages collaborative use of AI or prevents AI use. Types of assessment which are sheltered from abuse by AI include the use of closed-book, in-person examinations, mini-vivas , presentations and practical exams. While these assessments are resistant to AI collusion, AI tools can aid students as a revision tool and exam practice medium [29]. Where it is impractical to use AI-resistant assessments, coursework assessments should be redesigned to encourage collaborative working with AI, make assessments industry focused and ensure that learning objectives, academic standards and fair assessment are maintained. It is also worth mentioning that if these AI skills are to be routinely used by employees to generate reports, lab reports and SOPs, the question remains as to what the overall worth of scientific writing is as a core skill at university level. Therefore, moving away from traditional academic scientific writing assignments to more assignments that simulate tasks performed in a Biotechnology setting, unlock more high order student active skills and encourage AI collaboration would help maintain effective learning. **Table 1** shows a series of traditional coursework types and examples of alternative assessments with learning objectives.

Table 1 Examples of Pre-AI assessments and alternative assessments in the context of Biotechnology with learning outcomes.

Pre-AI assessment	Alternative assessment	Description	Learning outcomes
Lab report	Bioprocess Design Dossier	Students design an upstream and downstream process for producing an enzyme, recombinant protein etc.	Short technical dossier including: • Organism or cell factory choice Feedstock choice • Fermentation mode • Key process parameter • Downstream recovery steps • Contamination control

Table 1 Continued

Standard essay or Literature Review	Industrial case-study investigation	Students investigate a real or realistic industrial biotechnology problem	Students produce case study with: • a root-cause analysis • a fault tree or fishbone diagram • suggested experiments • process data they would collect • possible corrective actions a short management summary
Standard report	Quality-by-design brief	Students are given a target product profile and asked to define critical quality attributes, critical process parameters, and a control strategy	Outline that includes: • product purity requirements • host-cell protein limits • endotoxin or contamination risks • process parameters affecting quality • analytical tests • batch release criteria • documentation requirements
Literature Review	Public-facing Explainer	Students explain an industrial biotechnology topic to a public audience, policymaker, school group, or local community	Students could submit either • Short article • infographic, • podcast script • video storyboard • public briefing note.

Table 1 continued

Calculations worksheet	Design a coding programme for analysing large Biotech data sets	Students use “vibe coding” to design and carry out computational tasks using python	Students produce the python file and excel summary that includes: • Statistical analysis Summary of data

These alternative assessments aim to align more with the skills needed by Biotechnology employers and encourage AI collaboration over collusion. However, it is important to note that the implementation of new assessments requires considerable work and academic regulatory approval and to address the fast pace at which AI tools increase in terms of functionality and performance, a fast tracking in academic regulatory approval process is needed for assessments.

With the widespread use of AI by students in their coursework, a question remains as to whether the current grading system also needs to change. Students in the UK are graded independently meaning that potentially 100% of the cohort can technically achieve the highest grade possible. In countries including the US and Singapore, a bell-curve grading [30] is often used where students are awarded grades based on how well they do on a bell-curve distribution graph. This effectively means that students are awarded grades based on their relative performance against the rest of the cohort. A bell-curve grading marking system would effectively consider any AI use by students meaning that marks could be awarded based on how well the student utilised the AI tool. bell-curve grading rarely used in UK universities and changes to grading may need to come from an institute and national level.

4.3 Ensuring the Ethical Use of AI

With the increasing number of academic misconduct cases seen in universities recently brought about due to the misuse of AI, universities should consider moving away from a “ban or detect” model and adopt a transparent, teachable assessment-led model to ensure that students use AI appropriately while still proving their own learning. Ethical use of AI should not only be linked to academic performance but extend to and align with the expectations of industry and regulatory bodies.

Policies such as COMPASS already help define expectations regarding acceptable AI use but general training on the ethical use of AI would also help create clear boundaries of what is acceptable use of AI such as making it clear that AI can hallucinate references which would make the student liable for academic misconduct under “false data”. Encouraging students to include an “AI declaration statement” can help create transparency and avoid ethical traps, but there also needs to be clear differentiation in terms of how the inclusion of a declaration affects the grading for the coursework and if and how to differentiate the marking for those that used AI and declared it from those that did not use AI at all or failed to declare the use of AI.

The use of AI detection tools to detect inappropriate use of AI in writing are not currently fit for purpose and should be avoided in proving unethical use of AI in writing until their effectiveness is demonstrated. Integrating ethics into basic AI prompt training at the start of a degree programme would help set expectations and avoid issues with academic misconduct. Clearer university policy on the ethics of using AI, would also lead to fewer cases of academic misconduct and both providing specialist training on misuse of AI and benchmarking evidence thresholds in academic misconduct panels would prevent students from being wrongly accused of academic misconduct. Overall, these recommendations will help promote appropriate and ethical use of AI by students well beyond their studies

4.4 Addressing the AI Training Gap?

As set out earlier, AI applications in Biotechnology can be split into two main groups based on the complexity of AI use.

Universities will need to ensure that biotechnology students have a basic level of AI training in the use of AI in terms of effective prompt engineering, ethical considerations and critical analysis skills. Based on the basic AI skill applications identified in **Figure 1**, examples of the core AI skills, student tasks and expected learning outcomes of a basic AI training workshop are detailed in **Table 2.**

Table 2 Examples of core skills, active learning tasks and expected learning outcomes for a basic AI training workshop

Core AI skill	Task	Expected learning outcomes
Generating writing and proofreading	Use AI to generate and edit a short piece of writing and assess the: • Accuracy • Quality of the response	Students can construct basic prompts and evaluate the accuracy and suitability of AI-generated responses.
Searching the literature for sources	Students look up a list of references on the journal website, with some being hallucinated by AI.	Students will recognise the ethical implications of using AI.
Generating images using AI	Students are given a description of an image/animation and ask the AI image using a prompt.	Students are able to prompt engineer scientific diagrams, images and animations.

Table 2 continued

Using AI as a revision tool	Students will be asked to generate an exam question based on the content of the module. They then answer the question and use AI to analyse their answer.	Improved student learning and understanding of core biotechnology concepts.
Training in IT applications	Students will be given a set of data in a software format that they are not familiar with (Excel sheet, ImageJ) and ask them to use AI to learn the software and process the data set.	Statistical analysis, improved IT skills and data quality control.
Vibe coding a website on biotechnology	Students use AI tools to code a basic website on Biotechnology .	Basic vibe coding (programming) in biotechnology context.
Business pitch	Students use AI to develop a biotechnology startup idea.	AI prompting Image and slide generation.

This training in AI must be provided to students at the start of their studies through workshops and active learning rather than simply giving lectures.

More complex AI skills can be embedded into specialist modules, practical classes and final year projects as a specialism. For example, students could develop or evaluate AI models for biotechnology applications such as genomic analysis, protein structure prediction, image analysis, bioprocess optimisation or drug discovery. This would allow students with a stronger interest in computational biotechnology to develop deeper technical expertise while still ensuring that all graduates have a baseline level of AI literacy.

Staff must also be given adequate training in AI skills to redesign, and competently use in education, either during their formal teacher qualification or at the start of their contracts to ensure that they can use AI tools confidentially, redesign assessments and ensure that learning objectives for students are achieved. Due to the fast pace of AI, regular consultation with industry, external examiners, and professional bodies would also allow for alignment of course content, assessments and learning outcomes and help prepare graduates for a career in biotechnology.

Overall, these measures would help address the AI skills gap, align expectations between students, staff, employers and professional bodies, and better prepare biotechnology graduates for future employment.

5 Conclusions

The emergence of AI tools such as LLMs and AI agents has transformed and disrupted the biotechnology sector, providing both opportunities and risks. Universities have struggled to keep up with current AI developments and need to redesign both curricula and assessments to ensure that curricula and assessments remain valid and continue to support student learning. Ultimately, we need to provide adequate training in AI skills to our graduates in order to ensure that graduates are prepared for their careers in biotechnology. The ethics of AI use is still blurred and unclear with different expectations seen for students when compared to researchers and academics. A much clearer ethical framework is needed for all stakeholders.

In this white paper, we discussed current policies on the use of AI in industry and in education. We discussed the current challenges in terms of the availability, ethical use of AI by both students and staff, ensure that assessments still provide effective student learning and addresses the current gaps in graduate training. We also proposed some recommendations which will address these current challenges such as proposing and embedding basic AI training workshops into all biotechnology degrees, ensuring that both students and staff have access to the same AI tools and to ensure that assessments can still produce effective learning outcomes for students where AI use is collaborative and not collusive.

6 Acknowledgements

The authors gratefully acknowledge the funding support of the Industrial Biotechnology Innovation Catalyst Networking/Clustering Funding Scheme Application Ref: IBIC-NET-002

7 AI Declaration

AI was used to brainstorm ideas for this white paper and generate the executive summary and enhance Figure 1 and Figure 2

8 References

1. Medicine, I. *Insilico Medicine*. n.d. 27 May 2026]; Available from: https://insilico.com/.
2. Recursion. *Pioneering AI Drug Discovery*. 2025 27 May 2026]; Available from: https://www.recursion.com/.
3. Nabla Bio, I. *Designing Better Medicines*. 2025 27 May 2026]; Available from: https://www.nabla.bio/.
4. Jumper, J., et al., *Highly accurate protein structure prediction with AlphaFold.* Nature, 2021. **596**(7873): p. 583–589.
5. Gottweis, J., et al., *Accelerating scientific discovery with Co-Scientist.* Nature, 2026.
6. Helleckes, L.M., et al., *Perspectives for artificial intelligence in bioprocess automation.* Current Opinion in Biotechnology, 2026. **97**: p. 103392.
7. Klyushnichenko, V. *A Vision for Artificial Intelligence in Biopharmaceutical Quality Management Systems*. 2025 8 July 2025 27 May 2026]; Available from: https://www.bioprocessintl.com/information-technology/a-vision-for-artificial-intelligence-in-biopharmaceutical-quality-management-systems.
8. Vora, L.A.-O., et al., *Artificial Intelligence in Pharmaceutical Technology and Drug Delivery Design.* Pharmaceutics, 2023. **10**((7)): p. 1916.
9. Somara, S., et al., *Artificial Intelligence in Biotechnology and Pharmaceuticals: Evolution, Applications, and Regulatory Frontiers.* Current Stem Cell Reports, 2025. **11**(1).
10. Fingerhut, A. and D.C. Winter, *Artificial intelligence and medical writing: where are we going?* Br J Surg, 2023. **110**(8): p. 883–884.

11. Stephenson, R., *Student Generative AI Survey 2026*. 2026, Higher Education Policy Institute.
12. Atkinson-Toal, A. and C. Guo, *Generative Artificial Intelligence (AI) Education Policies of UK Universities.* Enhancing Teaching and Learning in Higher Education, 2024. **2**: p. 70–94.
13. Network, A.i.H.E. *1 May 2024: Gen AI in assessment: institution and program tactics*. [Assessment in Higher Education Network] 2024 27 May 2026]; Available from: https://ahenetwork.org/1-may-2024-gen-ai-in-assessment-institution-and-program-tactics/.
14. Dorobat, C.-E., et al. *Generative AI & Assessment Design in Higher Education*. n.d. 27 May 2026]; Available from: https://aiinhighered.com/assessments.
15. n.d. *There's An AI For That*. n.d. June 3, 2026]; Available from: https://theresanaiforthat.com/.
16. *Assessing the Extent of Utilization and Availability of Artificial Intelligence in Teaching and Assessment of Students by Lecturers in University.* Asian Journal of Assessment in Teaching and Learning, 2024(14): p. 87–95.
17. Tanveer, M., S. Hassan, and A. Bhaumik, *Academic Policy Regarding Sustainability and Artificial Intelligence (AI).* Sustainability, 2020. **12**(22): p. 9435.
18. Chaka, C., *Detecting ai content in responses generated by ChatGPT, Youchat, and Chatsonic: The case of five ai content detection tools.* Journal of Applied Learning & Teaching, 2023. **6**(2): p. 94–104.
19. Black, J., *Can AI Lie? Chabot Technologies, the Subject, and the Importance of Lying.* Social Science Computer Review, 2025. **43**(6): p. 1147–1158.
20. Chen, J., et al., *AI-Assisted Enhancement of Student Presentation Skills: Challenges and Opportunities.* Sustainability, 2023. **15**(1): p. 196.
21. Huo, H. and F. Wang, *A Study of Artificial Intelligence-Based Poster Layout Design in Visual Communication.* Scientific Programming, 2022. **2022**(1): p. 1191073.
22. Babitha, M.M., C. Sushma, and V.K. Gudivada, *Trends of Artificial Intelligence for online exams in education.* International Journal of Early Childhood Special Education, 2022. **14**(01): p. 2457–2463.
23. Gopane, S. and R. Kotecha. *Enhancing monitoring in online exams using artificial intelligence*. in *Proceedings of International Conference on Data Science and Applications: ICDSA 2021, Volume 2*. 2021. Springer.
24. Safdar, N.M., J.D. Banja, and C.C. Meltzer, *Ethical considerations in artificial intelligence.* European journal of radiology, 2020. **122**: p. 108768.
25. Garcia Ramos, J., *Development and introduction of a document disclosing AI-use: exploring self-reported student rationales for artificial intelligence use in coursework: a brief research report.* Frontiers in Education, 2025. **Volume 10 - 2025**.

26. Gonsalves, C., *Addressing student non-compliance in AI use declarations: implications for academic integrity and assessment in higher education.* Assessment & Evaluation in Higher Education, 2025. **50**(4): p. 592–606.
27. Chaka, C., *Reviewing the performance of AI detection tools in differentiating between AI-generated and human-written texts: A literature and integrative hybrid review.* Journal of Applied Learning & Teaching, 2024. **7**(1): p. 115–126.
28. Chelli, M., et al., *Hallucination Rates and Reference Accuracy of ChatGPT and Bard for Systematic Reviews: Comparative Analysis.* J Med Internet Res, 2024. **26**: p. e53164.
29. Firat, M., *How chat GPT can transform autodidactic experiences and open education.* Department of Distance Education, Open Education Faculty, Anadolu Unive, 2023. **2**.
30. Corcoran, S., *Beyond the Bell curve.* Journal of Psychologists and Counsellors in Schools, 2024. **34**(2): p. 212–222.