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Assessment integrity and validity in the teaching laboratory: adapting to GenAI by developing an understanding of the verifiable learning objectives behind laboratory assessment selection

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ABSTRACT

Generative Artificial Intelligence (GenAI), such as ChatGPT, is reshaping educational paradigms by offering unparalleled benefits and introducing challenges, particularly academic integrity. This study investigates teaching laboratory practices (traditional, recorded, remote, simulation and virtual), considered an academic safe haven due to its authenticity, and examines how assessments align with learning objectives. This should reinvigorate interest in expanding laboratory learning opportunities. However, unsupervised laboratory reports, a dominant assessment type, present significant cheating risks – intensified by GenAI. Given the scant literature on laboratory assessments and their primary focus on cognitive objectives, little guidance is available regarding how to assess non-cognitive objectives. This studies innovative approach utilises a reflective survey with 134 international academic staff to explore how each assessment type can verify cognitive, psychomotor, and affective learning objectives. We introduce a 'Words of Estimative Probability' heatmap to visualise the likelihood of verifying specific learning objectives, providing a snapshot to guide academics in holistic assessment design. This study advocates for diverse assessments, which mitigate GenAI risks and foster comprehensive skill development. This research equips educators to design secure, effective laboratory education in STEM disciplines, ensuring alignment with evolving academic and technological landscapes by offering a framework for improving assessment validity, integrity, and adaptability.

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1. Introduction

Within science, technology and engineering, the teaching laboratory plays a fundamental role in the skill-acquisition process (Kist 2022; Potkonjak et al. 2016). Through the laboratory, students can acquire and develop various skills, including knowledge & understanding, inquiry, practical, perception, analytical, and social and scientific communication (Brinson 2015). Learning experiences should be both valuable and interesting (Beck, Lazari, and DiBenedetti 2024). The work undertaken and skills needed by engineers are evolving (Crossin et al. 2023), and we must ensure the laboratory stays up to task. One such change is the rise in the use of generative artificial intelligence (GenAI). Research suggests that GenAI will bring about learning and productivity benefits but is also tied to academic integrity risks. Consequently, these concerns may encourage increased usage of teaching laboratories due to the irreplaceable nature of practical hands-on experiences (Nikolic et al. 2023a). Therefore, we must continue to improve our understanding of the contribution laboratories make to learning.

The structure, format and learning pathways of a laboratory can vary (Nikolic 2014). While the laboratory can be implemented using a range of modes, including face-to-face (the traditional approach), simulation, virtual, remote and mixed, the chosen implementation should be aligned with the intended pedagogical approach due to different strengths and weaknesses (Brinson 2015; Gavitte, Koretsky, and Nason 2024; May, Alves, et al. 2023). However, current empirical evidence in holistically understanding those learning differences is somewhat limited (May, Alves, et al. 2023; O'Mahony et al. 2024).

The above observation was best captured by a systematic literature review by Sasha Nikolic et al. (2021a), who found that most laboratory-based studies struggled to use learning as a focal point towards the contribution of their work. Instead, they found the research focus to be on the innovation and implementation, in which student perceptions took centre stage as a measure of success. When learning was analysed, the scope was somewhat restricted, and the learning objective and assessment explanations lacked the detail that others could easily build upon. This led the authors to recommend that '*research be performed to use the assessment types identified in the systematic review and map them explicitly and implicitly to the cognitive, psychomotor, and affective competencies being achieved' (Sasha Nikolic et al., 2021a, 16)*. This study is explicitly built upon that recommendation.

While much is known about the laboratory report, other laboratory assessment methods have not been given much attention (Seery et al. 2017). Additionally, no article could be found that brings together the little collective knowledge of laboratory assessments outside of the laboratory report. As a result, within Section 4, this study makes a major contribution to the field by synthesising current knowledge across all common laboratory assessment types, providing a unique resource to help guide laboratory assessment decisions. However, missing from this synthesis and needed to improve our understanding is the identification of which learning objectives or competencies an assessment task can verify as being demonstrated. Without understanding such connections and through a lack of awareness, the academic community risks missing out on applying the most appropriate assessment method for their targeted objectives.

Beyond the classroom, this lack of understanding has also limited the insights researchers can deduce on laboratory learning from their studies (May, Alves, et al. 2023). This disconnection is not a unique phenomenon and is not restricted to laboratory learning. A study by Nightingale, Carew, and Fung (2007) suggests that there may be a significant mismatch between the stated learning objectives of subjects and how students are assessed. This mismatch is a substantial limitation in the literature, and when it comes to laboratory assessments, there is little depth in extracting the objectives they measure. Furthermore, with the laboratory report being the most commonly used, GenAI has been found to make cheating easier leading to a substantial assessment integrity and validity risk (Nikolic et al. 2024a). Cheating impacts validity which is required to identify students who have met the standards of a course to an agreed level of performance (Dawson et al. 2024).

Therefore, alternative assessment types should be considered to ensure integrity and validity. The difficult question to answer is which assessment type provides equivalent coverage of the desired learning objectives.

Addressing this information gap provides a significant motivation for this study. This research gap is framed around the research question, '*Which assessment types are best considered appropriate to verify laboratory learning objectives*?' This finding scaffolds to the reflective research question, '*How can we improve assessment integrity in the teaching laboratory?*' The findings from this research will help academics reflect on their laboratory assessment practices, enabling them to align subject learning objectives with the most appropriate and secure assessment. Helping staff to critically think about assessment implementations can transform 'assessment for learning' practices (Reimann 2018). While the scope of the research is limited to the engineering field, the perspectives can provide important insights to those teaching across science and technology. This manuscript commences by providing an overview of laboratory learning objectives. This is followed by a review of the purpose of assessments and the different laboratory assessment types leading to the scientific components of this study.

2. Learning objectives & competencies

Learning objectives are essential in designing an efficient learning system and also in applying an effective system of assessment (Feisel and Rosa 2005). Learning objectives are specific, measurable statements that clearly define what a learner will know or be able to do as a result of engaging in a learning activity (Walther and Radcliffe 2006). For example, 'By the end of the course, students will design experiments to verify *the course concepts*' with the course concepts explicitly defined. Once the objectives have been defined, appropriate learning experiences are designed to achieve them via an observable activity. The learning activities are mapped to specific attributes (competencies) they achieve (Walther and Radcliffe 2006). Within engineering, a typical overarching framework used to determine the attributes/competencies students need to graduate with is determined by accreditation bodies; for example, see Engineers Australia (2008). These competencies can be demonstrated across any mode of learning. Therefore, objectives are more about specific learning outcomes, while competencies focus on applying skills and knowledge in practical situations.

While the laboratory is mentioned within accreditation documentation (Engineers Australia 2008), its explicit reference is limited. Regarding the objectives that should be explicitly developed within the laboratory, most of the direction has come from researchers looking to advance the field. One of the pivotal moments came from a colloquium focused on this topic, leading to the development of thirteen laboratory learning objectives (Feisel and Rosa 2005). These objectives have been used to create awareness of the broader opportunities and learning benefits made available through laboratory work. These objectives have become the foundation of newer instruments, such as the Laboratory Learning Objectives Measurement (LLOM) instrument, which is used to help academics increase their awareness of the holistic objectives and competencies associated with laboratory-based learning (Nikolic et al. 2021a; Sasha Nikolic et al. 2024b). LLOM constitutes 25 learning objectives: nine objectives in the Cognitive domain, nine objectives in the Psychomotor domain and seven objectives in the affective domain. These objectives are listed in Tables 3–5 within Section 6. Such initiatives have been welcomed because it has been recognised that greater efforts are needed to understand and encourage the targeting of a broader range of laboratory objectives than used to date (May, Terkowsky, et al. 2023).

As outlined earlier, learning objectives must be measurable and linked to assessment. To be effective, the relationship between assessment types and which objectives and competencies are measurable must be known. This ensures validity by correctly identifying the students who have met the standards of a course to an agreed level of performance (Dawson et al. 2024). Therefore, a greater understanding of assessment is needed.

3. Purpose of assessment

Assessment in higher education serves multiple pivotal roles, from shaping learners' educational experiences to guiding pedagogical strategies employed by institutions. It operates within a complex ecosystem influenced by academic standards, educational policies, accreditation requirements and society's evolving needs. The starting point in appreciating the role of assessment is understanding the key connection to conceptual frameworks.

Key conceptual frameworks for assessment include Bloom's Taxonomy, Socio-cultural Theory and Constructivism. The most well-known is Bloom's Taxonomy, a framework that categorises educational objectives into cognitive, affective, and psychomotor domains (Anderson et al. 2001). The taxonomy guides the development of assessment tasks that target different levels of cognitive processing, ensuring that assessments are aligned with learning objectives that span from basic recall of facts to complex analytical skills. Bloom's Taxonomy provides the framework for the Laboratory Learning Objectives Measurement instrument (LLOM) used in this study, discussed in Section 4. Types of laboratory assessment that can be associated with Blooms Taxonomy include:

- **Laboratory Report (Formal Written or Online):** These can be designed to address higher levels of Bloom's Taxonomy, such as analysis, synthesis, and evaluation, especially when students must interpret data, draw conclusions, and discuss implications.
- **Pre-Lab Quiz or Assessment:** These often target the lower levels, like remembering and understanding, to ensure students are prepared with foundational knowledge before experiments.
- **Laboratory Exam (Non-Practical):** Exams can be structured to cover a range of levels, from simple recall of facts (lower levels) to application and analysis of experimental results (higher levels)

Socio-cultural Theory connects the role of language and culture in cognitive development and is connected to concepts such as the Zone of Proximal Development (ZPD) and scaffolding (Vygotsky and Cole 1978). Assessments informed by socio-cultural theory often involve collaborative projects, peer assessments, and interactive feedback mechanisms that leverage social interactions to enhance learning. As the laboratory is a place for such social development, such a theory is relevant. Types of laboratory assessment that can be associated with socio-cultural theory include:

- **Group Presentation and Group-based Laboratory Report:** These assessments promote collaboration and communication among students, aligning well with the Socio-cultural emphasis on learning through social interaction.
- **Demonstration and Interview:** Activities involving social interaction, discussion, and shared problem-solving reflect the social nature of learning as suggested by Vygotsky.
- **Instructor Observation:** This allows the instructor to assess learning processes in a social context, often providing immediate feedback and scaffolding, which are key in Socio-cultural Theory.

Constructivism is the view that knowledge is developed through experiences and interactions with one's environment (Biggs 1996). In this view, assessment is not merely a measure of learning but an integral part of the learning process. Constructivist assessments focus on authentic tasks that simulate real-world challenges, applying knowledge and skills in meaningful contexts. This approach emphasises the importance of formative assessments and feedback for scaffolding student learning. The authentic nature of laboratory work also caters towards constructivist assessment. Types of laboratory assessment that can be associated with constructivism include:

- **Project-based Assessment (Individual or Group):** This type of assessment allows students to engage in learning by doing, reflecting constructivism's emphasis on building personal interpretations through real-world tasks.

- **Lab Notebook Entries:** These encourage students to reflect on their laboratory experiences, document their learning process, and adjust their understanding based on the reflection.
- **Weekly Mini-Assignment or Report:** These can be structured to encourage ongoing reflection and adjustment of understanding, which supports the iterative nature of constructivist learning
- **Laboratory Exam (practical):** This encourages students to apply their knowledge and skills in a real-world or simulated scenario, a core aspect of constructivist learning.

Therefore, a diverse range of assessments grounded in different frameworks can be incorporated into the laboratory. Section 4 will provide further details of each assessment type. The question becomes, what purpose do these assessments serve? Assessments serve multiple purposes and include (Adarkwah 2021; Barthakur et al. 2022; Hargreaves 1997):

- **Evaluating Student Learning:** Measuring the extent to which students have achieved the learning outcomes of their courses or programmes.
- **Feedback for Learning Enhancement:** If reflective processes are applied, feedback can be instrumental in identifying areas of strength and areas needing improvement, guiding and motivating students in their learning journey.
- **Supporting Instructional Decisions**: Assessments can help educators identify effective teaching methods and determine where adjustments may be needed if reflective processes are applied.
- **Curriculum Development and Improvement:** Analysing assessment outcomes can identify trends, strengths, and weaknesses in programmes.
- **Accreditation and Accountability:** assessment data can demonstrate an institution's commitment to quality education and confirm standards set by accrediting bodies.

The multiple purposes assessments play in teaching and learning highlights why this is an important research area. At the ground level, assessment motivates students to learn and influences their approach to learning, highlighting that teaching, learning, and assessment are inextricably linked (Hargreaves 1997). As the laboratory plays an important teaching and learning role within engineering and science, bettering our understanding of assessment practice is important. This stems from recent research highlighting that current knowledge of laboratory learning linked to assessment practices is limited (Nikolic et al. 2021a). As a result, there has been an identified need for the community to do more in this regard (May, Alves, et al. 2023). Therefore, it is important to understand what types of assessments are used in the laboratory and how they are used.

However, the value of assessments is limited by their implementation. For example, if the assessment was used to evaluate student learning or capability, it is important to ensure that the measure is true. Regarding engineering accreditation, students must be recognised for the skills verified, as the community does not want unqualified engineers working on tasks that could put the community in danger. This is why assessment integrity is important because we need to ensure that students can demonstrate trust and act honestly. In other words, the goal is to discourage and prevent cheating. Unfortunately, GenAI is a threat to assessment integrity across the most common assessment types used in higher education (Nikolic et al., 2023a). Not only that, but its capability is evolving quickly, and the laboratory report, due to its unsupervised focus, is considered unsecure and highly susceptible (Nikolic et al. 2024a). Therefore, adapting laboratory assessment practices is vital. Understanding which assessments support integrity by being secure or not, is imperative to new university policies that aim to adapt to GenAI, such as that outlined by Bridgeman and Liu (2024).

Academics can support academic integrity by ensuring assessments are secure (the concept of assessment security) by detecting and putting in place measures that help prevent cheating (Dawson 2020). While it may not be possible to stop cheating altogether, strategies can be put in place to help slow it down or discourage it. For example, using assessments that are fit for purpose in ways that cheating would be difficult. This principle is central to the second research question of this study. While the focus of this study is at the assessment level, it is important to recognise that academic integrity requires an institutional strategy covering many layers (Ellis and Murdoch 2024).

4. Laboratory assessments

The systematic literature review by Sasha Nikolic et al. (2021a) uncovered a range of different assessment types used in the literature. A summary of each type is provided, supported by literature from the engineering and science fields. The most comprehensive research studies have focused on the laboratory report, with other assessment types requiring much greater focus (Nikolic et al., 2021a; Seery et al. 2017). Additionally, within the stated use of many assessment types, little is explicitly found linking the assessment type to a specific laboratory objective or competency, hence the growing evidence for the need for this study.

4.1. Laboratory report (individual or group or online)

The most prevalent written assessment type for science and engineering students is the laboratory report, in which students document their experimental work (Parkinson 2017). Laboratory reports fulfil a dual role by instructing students in scientific communication skills and offering a means for academic staff to assess the knowledge acquired during laboratory sessions (Ranawake and Wilson 2016).

While the expected learning benefits of the report are documented, there is some debate on its ability to foster critical thinking abilities effectively or to spark student interest and excitement in their learning (Chen et al. 2018). The work of Lal et al. (2017) discussed the potential of lab report bias towards applying or reinforcing concepts already taught in lectures and upon a student's report writing skills against laboratory learning. Additionally, they can be time-consuming to mark, impacting the benefits of timely feedback (Hoffa 2006). As students can work on some experiments in groups, some coordinators encourage further collaboration and reduce marking time through the use of a group report (Abdulwahed and Nagy 2011).

Laboratory reports generally follow an introduction, method, results, and discussion structure (Ranawake and Wilson 2016). Beyond the lengthy traditional report, a concise synopsis format is also used. Research has suggested that the synopsis format saves time for students and markers and is linked to similar learning outcomes (Hoffa 2006).

A systematic literature review found that laboratory reports are extensively used as a medium to measure learning (Nikolic et al. 2021a). For example, Uzunidis and Pagiatakis (2023) used laboratory reports to measure the success of a new online laboratory implementation using a ten-point rubric to assess a student's ability to describe the experiment, apply the methodology, describe conclusions and demonstrate correct measurements and calculations. Laboratory reports also measure ethical behaviour, allowing students to demonstrate that they can record and publish erroneous results even if they contradict theoretical expectations (Nikolic et al., 2024b). Research has also suggested that adding a peer review component can enhance student awareness of the value of technical writing, encouraging them to focus more on their writing skills to effectively communicate their thoughts and experiences to peers and instructors (Alba-Flores 2018; Andersson and Weurlander 2019).

The online laboratory report provides hybrid capability with media-rich functionality, meshing quizzes and report-like capabilities (Spanias et al. 2000). At the completion of experimentation, students are guided to provide an account of their activities and observations and answer targeted questions. They can also upload files, graphs and code. The advantage of such an approach is marking automation, providing faster feedback to students.

4.1.1. Assessment integrity

The laboratory report, while popular, has always had some integrity risks as it is an unsupervised and unsecure assessment. If the student had access to experimental data (for example, a team activity), it could be easily given to a contract cheater to write, or a student could use paraphrasing tools on another student's work (especially if the experimentation had been completed before). Therefore, as found in Nikolic et al. (2023a) it is no surprise that GenAI could be used to help students write the laboratory report. Its ability to write more of the report is only growing (Nikolic et al. 2024a). What could not be found in the literature and is worthy of further research is whether a group report would increase assessment integrity. The hypothesis being that peer pressure from other group members not wanting the risk of being penalised would encourage original work.

4.2. Weekly mini-Assignment or report

While the traditional, formal laboratory report is generally used towards the end of a module, the timing and delay in providing feedback can eliminate the opportunity to correct errors and inform student development (Felder and Brent 2005). An alternative approach is to use smaller, frequent assessments such as mini-assignments or reports that provide students an opportunity to reflect on past mistakes and successes, improving motivation and confidence (Watson and Knight 2012). Such a feedback loop is at the heart of formative assessment (Sadler 1989). While such practices can add workload, the extra effort may not necessarily translate to the students in need taking advantage of the available feedback (Hargreaves 1997). An example of using weekly assessments that scaffold to a major laboratory report is outlined in Rodgers et al. (2020).

4.2.1. Assessment integrity

The integrity risk is determined by the submission. If the students work on the activity at the end of the scheduled laboratory, under supervision and submit it before leaving, it can be considered a secure assessment. While there may be elements of plagiarising experimental data or information from other students, time factors supported by supervision would limit the risk/reward ratio, leading to better security. However, if the mini-assignment or report is submitted later, the same assessment integrity risks as outlined for the laboratory report hold.

4.3. In-class activity/questions

In-class activities and/or questions are an assessment method used throughout the experiment to provide feedback on skills and/or solutions and support scaffolding (Vojinovic et al. 2020). There are multiple strategies for such an implementation.

The work of Lal et al. (2017) described the use of guided question sheets used in a group structure. The question sheets comprised a template structure to guide data collection and computation and questions to guide data synthesis and inference of concepts. Interestingly, they found a considerable inconsistency between the in-class marks and other assessment tasks, noting the caveats of group assessment vs individual.

A possible drawback to in-class activities is when the implementation requires substantial effort to mark and record progress. To combat such issues, digital solutions have been designed and are recommended (Ross 2017). Particularly in software engineering, automation tools that provide instant feedback on progress are important to ensure efficiency (Garcia et al. 2005).

4.3.1. Assessment integrity

While undertaken in a supervised environment, the pressure to obtain marks can result in plagiarism or fudging of experimental data and written discussions when the laboratory demonstrators are not in close proximity, and the activity is carried out throughout the available class time (Nikolic et al., 2024a). The likelihood of this occurring would be a factor in the risk/reward ratio and the setup. Similarly, GenAI could help students with such activities and questions if access to GenAI technology within the laboratory was available, including on personal devices (Nikolic et al. 2024a). If the activities/questions were hand-written, copying text from a screen would be more noticeable to observe. However, if students needed to answer questions at the end of the laboratory, under supervised conditions, it would be harder to access GenAI technology.

4.4. Lab notebook entries

As students complete laboratory experimentation, it is common practice for students to record all their experimental data and observations in a notebook, be it physical or electronic (Ogot, Elliott, and Glumac 2003). In a project setting, Laverty et al. (2012) used the evaluation of the notebook to focus on students' ability to replicate lab work, emphasising logical organisation and recording key observations. Marks were also given for neatness and quality of writing and diagrams, albeit to a lesser extent. Similarly, Samah et al. (2014) described collecting and grading the log book entries on a weekly basis, but the pedagogical reasons were not outlined. Research on this assessment type is limited.

4.4.1. Assessment integrity

Assuming handwritten lab notebook entries, GenAI cannot help with neatness and the quality of writing and drawing diagrams. Beyond that the same security principles outlined for in-class activity/questions apply. Regular interaction by the teaching staff throughout the project can help develop an understanding of student capability, flagging any anomalies.

4.5. Project-based assessment (individual or group)

The classical pedagogical format of laboratory learning is where students follow a structured format of completing a series of experiments that combine to create a final product that achieves specific aims (Lal et al. 2017). Laboratory projects have greater scaffolding and encourage students to be creative and synthesise knowledge from previous learning experiences (Laverty et al. 2012). Project-based assessments tend to be multi-faceted in that the key assessment is an analysis of the final outcome but is also supported by many other assessments that encourage and support the necessary scaffolding. For example, the project may require a written report, periodic demonstrations and interviews.

The assessment of a computer engineering project by Kellett (2012) was based on a demonstration that showcased that the project was functioning as per requirements, together with a written report that outlined the design and provided the results of output confirming that the project functioned as required.

4.5.1. Assessment integrity

As project work scaffolds across multiple assessment types outlined in this study, the overall integrity will be a factor of the weight and selection of the individual assessments, and how they combine to evaluate the final product. For example, via demonstration or interview, while not foolproof, can be a more secure option to confirm a student's understanding of the work (Nikolic et al. 2024a). Integrity can be enhanced if the final product is meant to be unique, showcasing the knowledge and creativity of the student/s. Security would be lower if all students worked on the same project, and the final output is expected to be the same. GenAI can possibly assist students in some parts of a project, which parts will be determined by the design of the project work. Regular interaction by the teaching staff throughout the project can help develop an understanding of student capability, flagging any anomalies. This may be more difficult to do for a group project, however, pressure to be more ethical in a group laboratory setting may be interesting to investigate.

4.6. Pre-lab quiz or assessment

A pre-lab quiz or assessment is an activity conducted before students start experimentation. Either directly before commencement or sometime before. While recent literature is filled with examples of quiz-based pre-lab assessments (Cann 2016; Kollöffel and de Jong 2013; Vial et al. 2015), some older literature has explained the use of a synopses-based activity (Rollnick et al. 2001). The primary motivator of pre-lab assessments is to encourage independent learning and provide direct feedback on students' readiness, which is used to maximise the benefits of experimentation (Jacobson, Said, and Rehman 2006; Vial et al. 2015). However, students may not necessarily perceive such benefits (Van De Heyde and Siebrits 2019).

The focus of studies in relation to pre-lab assessment has not been on the assessment itself but rather on the type of pre-lab activity being undertaken. For example, a study by Abdulwahed and Nagy (2014) suggested that the type of pre-lab activity impacted student performance in the pre-lab assessment.

4.6.1. Assessment integrity

The implementation and risk/reward of the assessment is key to determining the risk. For example, if the quiz is conducted at the start of the laboratory in a supervised and secure environment, security will be strong. However, if the assessment can be undertaken anywhere and anytime before the scheduled laboratory, a friend or contract cheater may be engaged. GenAI can be highly successful for text-based questions, with short-term security raised by incorporating specific contexts, images and tables – but these options will be short lived (Nikolic et al. 2024a).

4.7. Laboratory exam (practical and non-practical)

In a practical laboratory exam, students apply the skills they have developed through experimentation in a formal exam setting. If designed correctly, practical tests can assess a wide range of cognitive, psychomotor and affective skills but have limitations (Nikolic et al. 2015). When designing a practical laboratory exam, logistical factors must be considered, such as configuring and resetting experimental setups. Additionally, much thought needs to be placed on the design of the questions or learning extraction approach to measure holistic (multi-domain) learning. To help overcome such issues, Chen et al. (2018) outlined a framework for designing practical exams. Meanwhile, Pereira, Leonardi, and Melo (2003) outlined a paired approach to save time.

The non-practical laboratory exam focuses on the learning achieved and the theory associated with experimentation (Campbell et al. 2002). The students answer questions on paper or electronically. They also may not necessarily be integrated into the laboratory component itself. For example, Gamo (2019) included questions related to the laboratory component within the ordinary final exam. One problem with final exams is that they generally might not provide students with proper feedback (Gratchev, Howell, and Stegen 2024).

Some studies have explored the differences between practical and non-practical tests. For example, in a coding environment, Jevinger and Von Hausswolff (2016) did not find that one type was more comprehensive than the other. Each had different strengths and weaknesses. Non-practical assessments were better at assessing the understanding of different concepts, while practical assessments were better at assessing authentic competencies.

4.7.1. Assessment integrity

Integrity is very high if the practical exam can be completed in one sitting. However, it can drop when logistics plays a factor, such as when large student numbers require multiple sittings of the practical exam. With limited laboratory equipment, multiple repeat tests are needed to cover the entire cohort, resulting in time, expense and, most importantly, content-leaking issues (Nikolic et al. 2015). GenAI security risks can become negligible in a supervised and secure laboratory setting. A secure test may be one based on observation, a pen and paper test or in a computer lab in a locked-down environment (Nikolic et al. 2024a). For the non-practical laboratory test, the risk is determined by the implementation. Integrity risk is high for non-supervised and non-secure tests.

4.8. Demonstration and interview

Demonstration and interview assessments are, in some ways, complementary. The demonstration requires students to show a working end product, while an interview is focused on the student answering questions. It is not uncommon for a demonstration and interview to be used complimentary. For example, Laverty et al. (2012) used a 10 min interview to confirm originality and ensure students understood the solution to their project work. The demonstrator asked several questions from a prepared question bank. Then, they asked to see a demonstration of the mini-project in operation and explain a particular piece of their source code. The real risk for such assessments is within the grades' reliability. This is because there is a level of subjectivity to how a specific response or demonstration correlates to a specific mark. As the evidence may not be recorded, it may not be possible to quality assure or guarantee that the mark given reflects the competency demonstrated.

Strong links to why and how demonstrations and interviews are used are limited in the literature. For example, the implementation described by Tejado and Pérez (2020) outlined the demonstration of practical skills during all lessons against a rubric, but no detailed information was provided. Likewise, Rodgers et al. (2020) outlined using an interview, but no substantial details were provided.

However, contrary to the lack of detail in most studies, the work of Seery et al. (2017) positioned the use of demonstration within formative assessment, outlining an innovative approach. In the lab, students demonstrated techniques to peers, who verified each step using an observation sheet. Demonstrations were recorded on mobile phones, allowing for review and potential reshoots based on feedback. Once satisfied with the demonstration, both peers and demonstrators signed off on the form. Videos showing competency earned the student a digital badge in the respective technique.

4.8.1. Assessment integrity

This assessment type is secure because it allows the teaching staff to interact and modify the questions or required observed actions in real-time, creating uniqueness. However, for very large cohorts, there may only be a limited amount of observable events or questions to ask, resulting in content-leaking issues, allowing students to practice. Interestingly, the consequence of extra practice may result in students learning more, a positive outcome. GenAI could also be used to help students practice by prompting for the most likely questions to be asked (Nikolic et al. 2024a).

4.9. Group presentation

As outlined in 4.1, through laboratory reports, written communication is a dominant competency measured. However, oral communication skills are just as important as written ones. A group presentation provides a time-efficient approach to overseeing group cohesion and observing oral communication skills (Jacobson, Said, and Rehman 2006). The singular equivalent would be the demonstration or interview assessment. While group presentations are common in the literature, they are rare when placed in a laboratory setting. While pedagogical details of implementation are limited, numerous studies outline the oral communication and teamwork implementation of such an assessment (Jamshidi and Milanovic 2022; Samah et al. 2014).

4.9.1. Assessment integrity

The risk is determined by the learning objective. If the objective is to determine what students learned from an activity, team members or GenAI can help provide scripts or other resources that would enable a student to pass the presentation (Nikolic et al. 2024a). Additional questions at the end of the presentation can be beneficial to combat that. However, if the learning objective is to improve presentation skills, then the help of team members or GenAI can aid such learning.

4.10. Instructor observation

Instructor observation is closely aligned with demonstration. While demonstration focuses on the end product, observation focuses on showing competency across a range of laboratory skills. In laboratory settings with a low student-to-teacher ratio, assessment can be conducted through instructor observations complemented with a performance mark (Vial et al. 2015).

In a chemistry setting, Zhang and Wink (2021) outline the use of a checklist to document that students are doing specific procedural steps. This process is intended to show direct evidence of psychomotor competency. Within an engineering setting, Aishah (2015) created a rubric to assess a student's manipulation and observation competencies based on instructor observation. The study found that it could be difficult to match the observed individual student's behaviour to the suitable descriptor if experimentation was group-based. This is because each student did a different activity in a group setting to contribute to successful experimentation. This process enabled assessing competencies not available through traditional means but highly constrained by setup and teacher-to-student ratio.

4.10.1. Assessment integrity

Integrity is high because the assessment is fully supervised. Through observation, a holistic set of learning objectives can be monitored, such as the ability of students to manipulate equipment or work with others, providing reach into psychomotor and affective-based learning objectives. However, just like the other non-written assessments, observation can be limited in regard to the subjective nature of marking. As the evidence may not be recorded, it may not be possible to quality assure or guarantee that the mark given reflects the competency demonstrated.

5. Material and methods

Highlighted throughout the literature review was that, as a community, the evidence that connects learning objectives with assessment is rather limited. Hence, the need for this study to answer the research question, '*Which assessment types are best considered appropriate to verify laboratory learning objectives?*' To accomplish this, in 2021, academics from around the world were invited to participate in an online survey. Participants were invited through targeted invitations through the extensive academic networks of the research team and formal organisations, such as the Australasian Association of Engineering Education.

To be included in the study, participants were required to have experience in coordinating subjects that included laboratory components, ensuring that they had subject design experience. They then had to list the assessment tasks they used in their subjects. Participants were then given a matrix that connected the assessment tasks to laboratory learning objectives via the LLOM instrument, introduced in section 2.

The LLOM instrument was selected due to its template-based structure, providing academics from any engineering discipline, regardless of the laboratory implementation type, the ability to consider the objectives in their specific context. To do this, keywords (shown in italics) in the template are interchanged with words directly related to the implementation. Changing the keywords provides flexibility to use it in any discipline or in any lab setup, even new innovative ones. The design of the instrument is based on the synthesis of the thirteen laboratory objectives (Feisel and Rosa 2005) discussed in Section 2 with Bloom's Taxonomy (Anderson et al. 2001) discussed in Section 3. This is an instrument used as a foundation for multiple papers (Nikolic et al. 2021b, 2023b, 2024b) and has undergone a range of testing, including Cronbach's alpha and factor analysis (Kaiser rule, parallel analysis, optimal coordinates and acceleration factor) as outlined in Nikolic et al. (2021b).

Within the survey matrix, participants needed to reflect on their own assessment implementations and express if the assessment and a particular learning objective had an explicit, implicit, or no connection. To clarify, using definitions from the Oxford's English dictionary:

- **Explicit Connection:** the connection between the assessment and objective are stated clearly and in detail, leaving no room for confusion or doubt.
- **Implicit Connection:** the connection between the assessment and objective are suggested though not directly expressed.

For example, an explicit connection could be where a laboratory report is used to measure if a student can write a conclusion to summarise their findings from experimental work. There is a clear (explicit) connection between writing and the written report. An implicit example could be where a laboratory report is used to measure if a student can interpret sounds, temperature, smells and visual cues. It may be expected that it is highly unlikely that the student could complete the experiment error free, and therefore have implicitly demonstrated this competency by completing the experiment in order to present the results in the report.

There were 219 survey commencements and 134 completed all components of the survey. Of this 96 were from Australasia, 19 from Europe, 10 from Asia, 8 from North America, and 1 from South America. This high dropout rate was expected because this task was time-consuming and placed a high cognitive load on participants. Of those who completed, 18% had less than five years of teaching experience, 22% had between five and ten years of experience, and 60% had ten or more years of teaching experience. The skew towards more experienced staff was expected, as the cognitive load and time hurdle to complete the survey would probably have fallen on those with experience and passion towards laboratory learning. In terms of discipline, the distribution was 2 Aeronautical, 6 Biomedical, 11 Chemical, 11 Civil, 15 Computer, 20 Electrical, 16 Electronics, 2 Industrial/Process, 8 Materials, 21 Mechanical, 8 Mechatronics, 1 Mining, 2 Other, 5 Software and 6 Telecommunications engineering.

5.1. Statistical analysis

In this study, we seek to understand the likelihood of different assessment tasks being used to verify a particular learning objective has been mastered. To achieve this, we analyse how strongly engineering academics agree that such verification is implicit, explicit or combined (either implicit or explicit). The strength is given by the size of the proportion. Noting that these proportions are based on perception. They have just been identified as such by the respondents as being used in their own practice in such a way. To consider uncertainty in these proportion estimates, we calculated the confidence intervals (CI) at the 95% level. Calculating a confidence interval around the observed proportion can provide additional insight into the strength and reliability of the relationship. A narrow confidence interval around a high proportion suggests a strong and precise estimate of strength.

The next step in the analysis is to compartmentalise the probability ranges, using both words and coloured heatmaps. To do this, a defining set of Words of Estimative Probability (WEP) is established because it is a common and preferred method of communicating probabilistic information to the general public (Lenhardt et al. 2020). The overarching goal of the study is to provide an easy-to-follow snapshot of verification likelihood for any academic in the fields of engineering or science. By using WEP and corresponding heatmaps, any academic, with or without statistical knowledge, will be able to quickly gauge which assessment tasks are possibly best suited to a particular learning objective.

The downside of compartmentalising using WEP instead of simply relying directly on the numbers is that words create greater ambiguity and that words can mean different things to different people (Lenhardt et al. 2020; Wintle et al. 2019). Additionally, WEP classifications have spawned from the field of intelligence, using words to convey the likelihood of a future event occurring (Kent 1964).

Without any discipline-specific standard to work against that the authors could find, it is important that the ambiguity in the word definition is explicitly defined (Friedman and Zeckhauser 2015).

Table 1. Words of estimative probability (WEP) classification definitions.

WEP Classification	Definition
Almost Certain (dark green)	The average value is above 90%, and the lower bound CI value is above 85%
Highly Likely (light green)	The average value is above 80%, and the lower bound CI value is above 70%
Likely (dark yellow)	The average value is above 65%, and the lower bound CI value is above 55%
Better than even (light yellow)	The average value is above 55%, and the lower bound CI value is above 50%
Chances about even (pink)	The average value is above 50%, and the lower bound CI value is above 40%
Probably Not (light red)	The average value is above 30%, and the lower bound CI value is above 20%
Almost No Chance (red)	Any proportion that does not fit into the categories above

Note. The colours represent the visual coding of the traffic light-style heatmap.

For this reason, a definition of WEP as used by the authors is presented. The definition is not as strict as that defined by Kent (1964), rather it represents a synthesis of the field, sample and literature (Fagen-Ulmschneider 2019; Friedman and Zeckhauser 2015; Kent 1964; Lenhardt et al. 2020; Wintle et al. 2019). Ultimately, the numbers speak for themselves and are the most accurate form of interpretation (Wintle et al. 2019), should the WEP definitions used be found ambiguous.

The WEP classification used to compartmentalise the data is shown in Table 1.

The WEP classifications have been assigned different colours to produce a heatmap representative of a traffic light system. Heatmaps provide a compelling and effective way to summarise and communicate data (Bojko 2009), supporting the overarching goal of providing an easy-to-follow snapshot for the academic community. To interpret the WEP, consider the colour coding of a traffic light. Green is used to represent strong relationships between objectives and assessments and the red colours to represent weak relationships. The yellow colours suggest more research is needed.

The data collected will provide insights into which assessments can be used with a level of confidence to verify a particular learning objective. From this, the range of available assessment types can be determined with the security profile of each assessment considered. This can then be used to answer the second research question, '*How can we improve assessment integrity in the teaching laboratory?*'.

5.2. Limitations

The sample size is low, but as mentioned above, expected due to the deep reflective nature of completing the online survey. Therefore, it is assumed that the survey was mostly completed by academics passionate about laboratory learning. Therefore, the perceptions obtained, or the assessment diversity recorded may differ for a more general audience. However, it is believed that this may be advantageous due to the possible development of more experienced reflections, leading to more accurate perceptions of the learning objectives and assessment tasks. However, these are just assumptions, and no evidence is provided to support this. Additionally, a further limitation is that the survey instrument did not collect the context of the assessment type used. The survey responses are based on how the respondent used the assessment type in their own teaching environments, so each implementation may be slightly different in structure or focus, leading to different use cases. In particular, this may impact if the relationship between the variables is implicit or explicit.

Table 2. The reported usage of assessment types by the 134 respondents (highest usage at the top).

Assessment type	Usage	Usage %
Lab Report (Individual)	86	14.7%
In-class Activity or Questions	67	11.5%
Project (Group)	53	9.1%
Project (Individual)	47	8.1%
Lab Report (Group)	46	7.9%
Demonstration	41	7.0%
Instructor Observation	38	6.5%
Group Presentation	37	6.3%
Prelab	34	5.8%
Lab Notebook Entry	28	4.8%
Lab Exam (Practical)	28	4.8%
Online Lab Report	27	4.6%
Weekly Mini-Assignment or Report	24	4.1%
Interview	17	2.9%
Lab Exam (Non-practical)	11	1.9%
Total:	**584**	**100%**

6. Results

The 134 respondents completing the survey collectively used a total of 584 assessment types, or on average, each respondent used four different assessment types. Table 2 shows that the laboratory report is the most commonly used assessment type. If we consider the online, individual and group laboratory report, 27.2% of laboratory learning is assessed in this way. This confirms the work by Parkinson (2017) that the laboratory report remains the most prevalent assessment type for engineering students. When considering both individual and group project-based assessments, 17.1% of learning is assessed through projects. This is followed by in-class quizzes with 11.5%. The top five most used assessment types (without grouping similar types) make up 51.3%.

Tables 3–5 provide insights into the confidence relationships between the assessment types and the LLOM objectives for when the verification is either implicit or explicit. The tables represent how the respondents, if applicable, use the different assessment types to verify the various LLOM objectives. Table 3 focuses on cognitive-based objectives, Table 4 focuses on psychomotor-based objectives, and Table 5 focuses on affective-based objectives. It is important to note that almost all objectives overlap multiple domains, with a detailed explanation of this separation and the limitations of this approach available in Sasha Nikolic et al. (2024b). The data provides insights into the likelihood of an assessment being used either explicitly or implicitly to verify a LLOM objective. The definitions and methodology behind this were outlined in Section 5. Educators can use this information to consider the alignment of laboratory assessments with cognitive, psychomotor, and affective learning objectives. This helps identify which assessment types most effectively verify specific learning objectives and which need further investigation.

Appendices 1–3 provide the same data based on whether the verification is implicit, while Appendices 4–6 consider if it is explicit. What is striking is that these relationships are not strong. This either suggests the community is unsure or that educators are simply using the verification differently. Further research is needed to explain this.

While a detailed analysis of these results is outlined in the discussion, some striking observations include:

1. The concentration of green in Table 3 shows that the community is more confident in the verification relationships for cognitive learning objectives compared to the psychomotor (Table 4) and affective (Table 5) objectives, which are almost completely void of green. While all three tables share substantial yellow shading, indicating a somewhat likely relationship exists, this finding confirms the conclusions from the literature review that the research gap in laboratory education literature is on psychomotor and affective learning and needs to be closed to help combat the upcoming GenAI risks.

2. The laboratory report is the most commonly used assessment type, one that educators are most confident in using for verification purposes. The problem is that it is a high-risk assessment type, posing a high risk to validity. The data shows that some of these risks can be mitigated by considering other assessments, such as projects, demonstrations, and presentations.
3. The verification relationships were expected to be stronger for several less-used assessment types like laboratory exams, interviews and observation, mainly due to the lower-bound confidence interval. Due to their low usage, further research and training may be needed to change perceptions. These more secure assessment types will need greater attention to tackle GenAI risks.

The following provides an explanation of all the abbreviations used in the tables:

ForLabRep = Formal Laboratory Report (see Section 4.1)
OnLabRep = Online Laboratory Report (see Section 4.1)
LabRepGRP = Group-based Laboratory Report (see Section 4.1)
LabNotEnt = Laboratory Note Entries (see Section 4.4)
WkAssRep = Weekly Mini-Assignment or Report (see Section 4.2)
InclassQs = In-class Activity/Questions (see Section 4.3)
ProjINDV = Project-based Assessment – Individual (see Section 4.5)
ProjGRP = Project-based Assessment – Group-based (see Section 4.5)
Prelab = Pre-Lab Quiz or Assessment (see Section 4.6)
LabExamP = Laboratory Exam – Practical (see Section 4.7)
LabExamNP = Laboratory Exam – Non-Practical (see Section 4.7)
GrpPreso = Group Presentation (see Section 4.9)
Demo = Demonstration (see Section 4.8)
Inter = Interview (see Section 4.8)
Observ = Observation (see Section 4.10)

Table 3. The likelihood of laboratory assessments being used to verify cognitive-based learning objectives (either implicitly or explicitly), including confidence intervals (CI) at the 95% level and a Words of Estimative Probability heatmap.

Obj	LLOM Objective	ForLabRep	OnLabRep	LabRepGRP	LabNotEnt	WkAssRep	InclassQs	ProjINDV	ProjGRP	Prelab	LabExamP	LabExamNP	GrpPreso	Demo	Inter	Observ
C1	Understand the operation of equipment/software used within the laboratory	0.919 (0.841,0.960)	0.926 (0.766,0.979)	**0.957 (0.855,0.988)**	0.893 (0.728,0.963)	0.917 (0.742,0.977)	0.910 (0.818,0.958)	0.936 (0.828,0.978)	**0.962 (0.872,0.990)**	0.912 (0.770,0.970)	0.893 (0.728,0.963)	1.000 (0.741,1.000)	**1.000 (0.906,1.000)**	0.878 (0.745,0.947)	0.824 (0.590,0.938)	0.895 (0.759,0.958)
C2	Design experiments/models (physical or simulation) to verify course concepts	0.919 (0.841,0.960)	0.889 (0.719,0.961)	**0.957 (0.855,0.988)**	0.893 (0.728,0.963)	0.958 (0.798,0.993)	0.851 (0.747,0.917)	**0.957 (0.858,0.988)**	0.943 (0.846,0.981)	0.794 (0.632,0.897)	0.786 (0.605,0.898)	1.000 (0.741,1.000)	**0.973 (0.862,0.995)**	0.902 (0.775,0.961)	0.824 (0.590,0.938)	0.789 (0.637,0.889)
C3	Use engineering tools (e.g. [name of hardware/software used]) to solve problems	**0.930 (0.856,0.968)**	0.889 (0.719,0.961)	0.935 (0.825,0.978)	0.857 (0.685,0.943)	0.958 (0.798,0.993)	0.836 (0.729,0.906)	0.915 (0.801,0.966)	0.906 (0.797,0.959)	0.853 (0.699,0.936)	0.857 (0.685,0.943)	0.909 (0.623,0.984)	**0.973 (0.862,0.995)**	0.927 (0.806,0.975)	0.882 (0.657,0.967)	0.816 (0.666,0.908)
C4	Read and understand datasheets/circuit-diagrams/ procedures/user-manuals/ help-menus	0.907 (0.827,0.952)	0.889 (0.719,0.961)	0.913 (0.797,0.966)	0.893 (0.728,0.963)	0.917 (0.742,0.977)	0.851 (0.747,0.917)	0.936 (0.828,0.978)	0.906 (0.797,0.959)	0.853 (0.699,0.936)	0.857 (0.685,0.943)	1.000 (0.741,1.000)	**0.973 (0.862,0.995)**	0.902 (0.775,0.961)	0.824 (0.590,0.938)	0.763 (0.608,0.870)
C5	Draw & interpret relevant charts, graphs, tables & signals	0.907 (0.827,0.952)	0.852 (0.675,0.941)	0.870 (0.743,0.939)	0.929 (0.774,0.980)	0.833 (0.641,0.933)	0.791 (0.679,0.871)	0.872 (0.748,0.940)	0.377 (0.259,0.512)	0.853 (0.699,0.936)	0.786 (0.605,0.898)	0.909 (0.623,0.984)	0.946 (0.823,0.985)	0.756 (0.607,0.862)	0.882 (0.657,0.967)	0.711 (0.552,0.830)
C6	Recognise safety issues associated with laboratory experimentation	0.837 (0.745,0.900)	0.704 (0.515,0.841)	0.826 (0.693,0.909)	0.786 (0.605,0.898)	0.875 (0.690,0.957)	0.746 (0.631,0.835)	0.809 (0.675,0.896)	0.358 (0.243,0.493)	0.735 (0.569,0.854)	0.821 (0.644,0.921)	0.818 (0.523,0.949)	0.892 (0.753,0.957)	0.805 (0.660,0.898)	0.824 (0.590,0.938)	0.789 (0.637,0.889)
C7	Analyse the results from an experiment	0.895 (0.813,0.944)	0.852 (0.675,0.941)	0.870 (0.743,0.939)	0.821 (0.644,0.921)	0.833 (0.641,0.933)	0.791 (0.679,0.871)	0.894 (0.774,0.954)	0.377 (0.259,0.512)	0.706 (0.538,0.832)	0.786 (0.605,0.898)	0.909 (0.623,0.984)	0.919 (0.787,0.972)	0.732 (0.581,0.843)	0.941 (0.730,0.990)	0.684 (0.525,0.809)
C8	Write a conclusion summarising your findings from an experiment	0.895 (0.813,0.944)	0.889 (0.719,0.961)	0.804 (0.668,0.893)	0.714 (0.529,0.847)	0.833 (0.641,0.933)	0.672 (0.553,0.772)	0.851 (0.723,0.926)	0.358 (0.243,0.493)	0.647 (0.479,0.785)	0.750 (0.566,0.873)	0.818 (0.523,0.949)	0.946 (0.823,0.985)	0.659 (0.505,0.784)	0.765 (0.527,0.904)	0.579 (0.422,0.721)
C9	Write a laboratory report/entry into a logbook in a professional manner	0.844 (0.743,0.825)	0.815 (0.633,0.918)	0.761 (0.621,0.861)	0.821 (0.644,0.921)	0.792 (0.595,0.908)	0.672 (0.553,0.772)	0.723 (0.582,0.831)	0.321 (0.211,0.455)	0.559 (0.395,0.711)	0.714 (0.529,0.847)	0.727 (0.434,0.903)	0.811 (0.658,0.905)	0.707 (0.555,0.824)	0.588 (0.360,0.784)	0.553 (0.397,0.699)

Note. The colours represent the visual coding of the traffic light-style heatmap.

Table 4. The likelihood of laboratory assessments being used to verify psychomotor-based learning objectives (either implicitly or explicitly), including confidence intervals (CI) at the 95% level and a Words of Estimative Probability heatmap.

Obj	LLOM Objective	ForLabRep	OnLabRep	LabRepGRP	LabNotEnt	WkAssRep	InclassQs	ProjINDV	ProjGRP	Prelab	LabExamP	LabExamNP	GrpPreso	Demo	Inter	Observ
P1	Correctly conduct an experiment on [course equipment/ software name- e.g. power systems]	0.814 (0.719,0.882)	0.815 (0.633,0.918)	0.804 (0.668,0.893)	0.786 (0.605,0.898)	0.708 (0.508,0.851)	0.776 (0.663,0.859)	0.702 (0.560,0.813)	0.736 (0.604,0.836)	0.647 (0.479,0.785)	0.893 (0.728,0.963)	0.909 (0.623,0.984)	0.811 (0.658,0.905)	0.732 (0.581,0.843)	0.824 (0.590,0.938)	0.684 (0.525,0.809)
P2H	Select and use appropriate instruments for the input, output and measurement of your circuit/system	0.767 (0.668,0.844)	0.704 (0.515,0.841)	0.761 (0.621,0.861)	0.750 (0.566,0.873)	0.708 (0.508,0.851)	0.627 (0.507,0.733)	0.723 (0.582,0.831)	0.774 (0.645,0.865)	0.559 (0.395,0.711)	0.786 (0.605,0.898)	0.636 (0.354,0.848)	0.757 (0.599,0.866)	0.756 (0.607,0.862)	0.765 (0.527,0.904)	0.579 (0.422,0.721)
P2S	Select appropriate commands and navigate interface to simulate/program a model	0.698 (0.594,0.785)	0.778 (0.592,0.894)	0.674 (0.530,0.791)	0.679 (0.493,0.821)	0.708 (0.508,0.851)	0.642 (0.522,0.746)	0.681 (0.538,0.796)	0.717 (0.584,0.820)	0.588 (0.422,0.736)	0.714 (0.529,0.847)	0.636 (0.354,0.848)	0.757 (0.599,0.866)	0.732 (0.581,0.843)	0.765 (0.527,0.904)	0.579 (0.422,0.721)
P3	Plan and execute experimental work related to this course	0.779 (0.681,0.854)	0.741 (0.553,0.868)	0.804 (0.668,0.893)	0.786 (0.605,0.898)	0.750 (0.551,0.880)	0.627 (0.507,0.733)	0.787 (0.651,0.880)	0.849 (0.729,0.921)	0.706 (0.538,0.832)	0.821 (0.644,0.921)	0.818 (0.523,0.949)	0.811 (0.658,0.905)	0.683 (0.530,0.804)	0.765 (0.527,0.904)	0.526 (0.373,0.675)
P4	Construct/code a working circuit/simulation/program	0.698 (0.594,0.785)	0.667 (0.478,0.814)	0.717 (0.575,0.827)	0.679 (0.493,0.821)	0.708 (0.508,0.851)	0.612 (0.492,0.720)	0.745 (0.605,0.847)	0.774 (0.645,0.865)	0.559 (0.395,0.711)	0.786 (0.605,0.898)	0.727 (0.434,0.903)	0.730 (0.570,0.846)	0.756 (0.607,0.862)	0.647 (0.413,0.827)	0.553 (0.397,0.699)
P5	Interpret sounds, temperature, smells and visual cues and use tools to diagnose faults/errors	0.663 (0.558,0.754)	0.741 (0.553,0.868)	0.652 (0.508,0.773)	0.643 (0.458,0.793)	0.708 (0.508,0.851)	0.687 (0.568,0.785)	0.681 (0.538,0.796)	0.679 (0.545,0.789)	0.529 (0.367,0.685)	0.750 (0.566,0.873)	0.818 (0.523,0.949)	0.757 (0.599,0.866)	0.732 (0.581,0.843)	0.824 (0.590,0.938)	0.579 (0.422,0.721)
P6H	Operate instruments (e.g. [equipment name]) required for experimentation	0.756 (0.655,0.834)	0.778 (0.592,0.894)	0.783 (0.644,0.877)	0.750 (0.566,0.873)	0.750 (0.551,0.880)	0.731 (0.615,0.823)	0.745 (0.605,0.847)	0.774 (0.645,0.865)	0.647 (0.479,0.785)	0.857 (0.685,0.943)	0.727 (0.434,0.903)	0.838 (0.689,0.923)	0.829 (0.687,0.915)	0.824 (0.590,0.938)	0.684 (0.525,0.809)
P6S	Operate software packages (e.g. [software name]) required for coding/simulation	0.721 (0.618,0.805)	0.815 (0.633,0.918)	0.761 (0.621,0.861)	0.679 (0.493,0.821)	0.708 (0.508,0.851)	0.642 (0.522,0.746)	0.766 (0.628,0.864)	0.774 (0.645,0.865)	0.618 (0.450,0.761)	0.821 (0.644,0.921)	0.818 (0.523,0.949)	0.730 (0.570,0.846)	0.829 (0.687,0.915)	0.765 (0.527,0.904)	0.632 (0.473,0.766)
P7	Take the reading of the output from circuits/ instruments/sensors	0.767 (0.668,0.844)	0.852 (0.675,0.941)	0.761 (0.621,0.861)	0.786 (0.605,0.898)	0.708 (0.508,0.851)	0.701 (0.583,0.798)	0.766 (0.628,0.864)	0.774 (0.645,0.865)	0.647 (0.479,0.785)	0.786 (0.605,0.898)	0.909 (0.623,0.984)	0.811 (0.658,0.905)	0.829 (0.687,0.915)	0.824 (0.590,0.938)	0.658 (0.499,0.788)

Note. The colours represent the visual coding of the traffic light-style heatmap.

Table 5. The likelihood of laboratory assessments being used to verify affective-based learning objectives(either implicitly or explicitly), including confidence intervals (CI) at the 95% level and a Words of Estimative Probability heatmap.

Obj	LLOM Objective	ForLabRep	OnLabRep	LabRepGRP	LabNotEnt	WkAssRep	InclassQs	ProjINDV	ProjGRP	Prelab	LabExamP	LabExamNP	GrpPreso	Demo	Inter	Observ
A1	Work in a team to conduct experiments, diagnose problems and analyse results	0.733 (0.631,0.815)	0.778 (0.592,0.894)	0.826 (0.693,0.909)	0.643 (0.458,0.793)	0.750 (0.551,0.880)	0.701 (0.583,0.798)	0.660 (0.517,0.778)	0.792 (0.665,0.880)	0.559 (0.395,0.711)	0.679 (0.493,0.821)	0.727 (0.434,0.903)	0.865 (0.720,0.941)	0.683 (0.530,0.804)	0.882 (0.657,0.967)	0.605 (0.447,0.744)
A2	Communicate laboratory setup, fault diagnosis, readings and findings with others	0.791 (0.693,0.863)	0.815 (0.633,0.918)	0.848 (0.718,0.924)	0.679 (0.493,0.821)	0.750 (0.551,0.880)	0.657 (0.537,0.759)	0.660 (0.517,0.778)	0.774 (0.645,0.865)	0.559 (0.395,0.711)	0.714 (0.529,0.847)	0.727 (0.434,0.903)	0.838 (0.689,0.923)	0.732 (0.581,0.843)	0.882 (0.657,0.967)	0.526 (0.373,0.675)
A3	Work independently to conduct experiments, diagnose problems and analyse results	0.733 (0.631,0.815)	0.778 (0.592,0.894)	0.739 (0.597,0.844)	0.750 (0.566,0.873)	0.708 (0.508,0.851)	0.701 (0.583,0.798)	0.766 (0.628,0.864)	0.642 (0.507,0.757)	0.647 (0.479,0.785)	0.821 (0.644,0.921)	0.727 (0.434,0.903)	0.757 (0.599,0.866)	0.683 (0.530,0.804)	0.706 (0.469,0.867)	0.500 (0.348,0.652)
A4	Consider ethical issues in laboratory experimentation and communication of discoveries	0.733 (0.631,0.815)	0.778 (0.592,0.894)	0.717 (0.575,0.827)	0.643 (0.458,0.793)	0.708 (0.508,0.851)	0.597 (0.477,0.706)	0.702 (0.560,0.813)	0.717 (0.584,0.820)	0.588 (0.422,0.736)	0.643 (0.458,0.793)	0.818 (0.523,0.949)	0.784 (0.628,0.886)	0.683 (0.530,0.804)	0.824 (0.590,0.938)	0.553 (0.397,0.699)
A5	Creatively use software/hardware to design or modify an experiment to solve a problem	0.709 (0.606,0.795)	0.778 (0.592,0.894)	0.739 (0.597,0.844)	0.607 (0.424,0.764)	0.667 (0.467,0.820)	0.627 (0.507,0.733)	0.787 (0.651,0.880)	0.774 (0.645,0.865)	0.529 (0.367,0.685)	0.679 (0.493,0.821)	0.818 (0.523,0.949)	0.784 (0.628,0.886)	0.732 (0.581,0.843)	0.824 (0.590,0.938)	0.658 (0.499,0.788)
A6	Learn from failure (when experiment/simulation/code fails or results are unexpected)	0.779 (0.681,0.854)	0.852 (0.675,0.941)	0.761 (0.621,0.861)	0.750 (0.566,0.873)	0.792 (0.595,0.908)	0.701 (0.583,0.798)	0.723 (0.582,0.831)	0.774 (0.645,0.865)	0.618 (0.450,0.761)	0.750 (0.566,0.873)	0.818 (0.523,0.949)	0.811 (0.658,0.905)	0.683 (0.530,0.804)	0.824 (0.590,0.938)	0.605 (0.447,0.744)
A7	Motivate yourself to complete experiments and learn from the laboratory activities	0.744 (0.643,0.825)	0.852 (0.675,0.941)	0.739 (0.597,0.844)	0.643 (0.458,0.793)	0.750 (0.551,0.880)	0.746 (0.631,0.835)	0.745 (0.605,0.847)	0.774 (0.645,0.865)	0.647 (0.479,0.785)	0.714 (0.529,0.847)	0.818 (0.523,0.949)	0.757 (0.599,0.866)	0.634 (0.481,0.764)	0.706 (0.469,0.867)	0.579 (0.422,0.721)

Note. The colours represent the visual coding of the traffic light-style heatmap.

7. Discussion

7.1. Cognitive objectives

Table 3 provides insights into the perceived likelihood of different assessment tasks being used to verify a particular learning objective in the cognitive domain. The standout in the dataset is that the laboratory report is the only assessment type that has been perceived capable as either 'highly likely' or 'almost certain' to verify either implicitly or explicitly every one of the cognitive-based objectives. While there is a lack of agreement on whether that verification is specifically explicit or implicit for many of the objectives (see Appendix 1 and 4), the perceptions are strongest compared to all other assessment types. Possibly, this could be correlated to the extensive research conducted on the laboratory report (e.g. (Chen et al. 2018; Parkinson 2017; Ranawake and Wilson 2016)), providing confidence in its capability and application. This may explain why the laboratory report is the most used assessment type, as evidenced in Table 2. However, as discovered in the work of Nikolic et al. (2023a) and Nikolic et al. (2024a) the laboratory report is a GenAI academic integrity risk and its use should be substantially reduced. This is because the writing components can be easily generated by GenAI or, at the minimum, simplify the paraphrasing of another student's report. Therefore, it is important to consider replacing the laboratory report with other assessment types identified through this process. Any replacement needs to consider the cost-effectiveness of laboratory reports. Marking budgets at many institutions are limited, so any changes must consider possible budgetary implications.

The data suggests that there is an underused alternative, the group presentation, with 6.3% use. While a 'highly likely' or 'almost certain' likelihood was not achieved for all objectives (only C9 was lower), four of the nine objectives were given an almost certain verification, more than any other assessment type. While GenAI can provide students with a script, or a team member can provide another student with a script (Nikolic et al., 2023a), learning that script does at least engage the cognitive skill of remembering, and does develop a range of competencies associated with presenting. Furthermore, asking the presenter some questions at the end of the presentation can improve assessment integrity.

While the group presentation is suitable for team-based experimentation, interestingly, an individual alternative, the interview, was not perceived in the same light. From the lack of literature on using an individual presentation, observation or interview is primarily used instead. While the average likelihood for the interview to verify many of the objectives was in the 80's, the lower bound confidence interval was generally low. This suggests that the perceptions regarding verification were not uniform. This is not helped by the fact that only 2.9% of the respondents used this assessment type. With the interview-based format having strong assessment integrity (Nikolic et al., 2023a), it may be time for greater research and awareness of the benefits of using interviews more frequently in the assessment mix. Research suggests that oral assessments via individual or group means bring different benefits and motivations to student learning (Chou 2011).

Identified as another holistic assessment for cognitive objectives is the individual project. The likelihood that it can be used to verify most of the cognitive objectives was high. Being used by 8% of the respondents (fourth highest on the list) suggests that it is a popular type. The group project was used slightly more (9.1%) but had less verification impact, with confidence that it could verify only four of the nine cognitive objectives. This can be acceptable due to the scaffolding and assessment mix (Laverty et al. 2012). What is important about project work is that it can be associated with high assessment security in terms of GenAI use (Nikolic et al. 2024a).

Across the nine cognitive-based objectives, there are multiple assessment options for verification. Objectives C1–C4 all had over ten possible assessment types, suggesting that the dominance of the laboratory report is unnecessary and assessment variety can be encouraged, increasing assessment security. This also opens up the opportunity of allowing students to 'choose their assessment', possibly allowing students to take some control of their learning, leading to the concept of an 'inclusive approach to learning' (O'Neill 2011). Only two objectives lacked diversification, with objectives C6 (two assessments) and C9 (one assessment). Collectively, the data shows much confidence in verifying all the cognitive-based objectives. Many assessment types can verify most objectives. However, there tends to be a lack of consensus on whether verification is being achieved explicitly or implicitly, which warrants further investigation.

7.2. Psychomotor objectives

While in section 7.1, it was shown that the academic community has much confidence in how assessments can be used to verify cognitive-based learning objectives, Table 4 paints a different picture of psychomotor-based learning objectives. There were no assessment tasks found to be 'almost certain' of being able to verify any of the psychomotor objectives. This reiterates the calls for the need to develop a more holistic understanding (May, Alves, et al. 2023). Only objectives P1 (two assessment types) and P3 (one assessment type) had a likelihood of 'highly-likely'. The concentration was predominately at the 'likely' level, suggesting that many psychomotor learning objectives can be verified by the different assessment types, however the confidence across all the respondents for each particular assessment type was not uniformly high. This finding is not surprising because the preference for cognitive assessment is documented (Sabri et al. 2013), and so much research-backed assessment focus has targeted cognitive learning (Nikolic et al. 2021a). Compounding the confidence is that for almost every relationship, there is no clear understanding of whether verification is explicit or implicit (see Appendix 2 and 5), with almost all items labelled as 'probably not', or 'almost no chance'. This is not saying that verification does not take place, it is simply saying that there is little confidence that such a verification relationship exists.

Interestingly, the instructor observation assessment type had some of the lowest verification probabilities. Using checklists and rubrics (Aishah 2015; Zhang and Wink 2021), one could easily consider observation an easy way to verify if students can apply psychomotor skills. It is possible to observe the students using laboratory equipment, fault-finding, and executing work, but instead, the results show greater confidence in using observation for cognitive-based objectives. Even the practical laboratory exam did not produce the verification confidence levels that the authors would have expected. This provides further evidence that perceptions might not translate into reality and that further research and training on assessment practices can change mindsets and approaches (Reimann 2018).

Meeting expectations of a low probability of verification relationships, the pre-lab assessment showed limited effectiveness in verifying psychomotor learning objectives. For all but one objective, the likelihood of verification was classified as 'Chances about even' or lower. Pre-lab assessments, typically designed as written or online quizzes, aim to evaluate students' foundational knowledge prior to engaging in practical activities. While cognitive objectives are the targeted measure, using a pre-lab assessment can help students gain more from their practical learning experience (Abdulwahed and Nagy 2014; Costello, Logue, and Dunne 2022; George-Williams et al. 2022).

When considering the evolution of assessments in a GenAI world, a key recommendation is that we need to improve focus on assessments that can't be done by machines (Bearman, Nieminen, and Ajjawi 2023), and psychomotor activities are a strong starting point. Therefore, this finding provides the case that we need research to understand psychomotor assessment better and then disseminate that knowledge to the wider community. For example, looking at the average and upper confidence interval, it is clear many academics see the psychomotor relationships with assessments such as the practical laboratory exam, interview and demonstration; however, the lower confidence interval showcases that such confidence is not uniform. To improve assessment integrity, the community needs to be prepared to adapt, and confidence in verification is needed to select the best and most appropriately secure assessment for the given learning objective. Headway may come from new innovative assessment approaches that enable marking efficiency. Some examples include the autonomous marking prototype for digital hardware content (Dunne and Nikolic 2021) or the growing use of virtual reality technology within the medical sciences (Efendi et al. 2023).

7.3. Affective objectives

Table 5 provides insights into the perceived likelihood of different assessment tasks being used to verify a particular learning objective in the affective domain. Per the psychomotor objectives, there is limited confidence in how the different assessment types can verify the various learning objectives. This includes the explicit and implicit relationships (see Appendix 3 and 6). Interestingly, across both the psychomotor and affective-based objectives, the laboratory report, the most used assessment type, is not associated with high confidence as it was for all cognitive-based objectives. This provides further evidence for the recommendations of Sasha Nikolic et al. (2021a) that it's time to accept that we are confident in the cognitive-based learning advantages of the laboratory and start concentrating our efforts on better understanding the psychomotor and affective advantages.

The two most highly ranked affective learning objectives, A1 (teamwork) and A2 (communication) (Nikolic et al., 2024b) did both at least have one assessment type linked with a strong verifying relationship, the group presentation and group laboratory report, respectively. Teamwork and communication skill development are essential for engineers as this is what they spend much of their professional careers undertaking (Trevelyan 2014). Helping students develop such skills can improve their transition to industry (Nikolic et al. 2016; Vuoriainen et al. 2024). The other affective objectives had no such strong relationship identified.

As per the psychomotor results, instructor observation was not seen as a strength. Together with interviews and presentations, one might assume that they can help assessors understand a student's feelings and attitudes towards a subject. One possible reason for the low confidence levels could be that the current set of assessment tasks might not be fit for purpose. Reflective journals, portfolios and self – and peer-assessment may be suited to providing insights into emotional growth or to evaluate their own and others' development in areas such as teamwork, empathy, and ethical understanding. For such assessment formats, the greatest hurdle will be the academic integrity factor due to GenAI capability (Nikolic et al. 2024a).

In the author's experiences, they have not seen evidence of any attempts within engineering to even consider emotional growth within a rubric in an engineering laboratory. As discovered in Sasha Nikolic et al. (2024b), such objectives are considered at the bottom of all other objectives and are not seen as being of any major importance. The question becomes, is this an implementation gap, or within engineering evidence of such growth not needed? The work by Jobel, Ziminski, and Li (2024) suggests that emotional regulation is an important skill to help students overcome failures in a laboratory setting, especially underrepresented students.

The lack of confidence in verifying ethical competency is also a concern. We need students to show that they have developed the competencies that lead them to question their actions regarding right and wrong, regarding what should or should not be done (Clancy and Zhu 2024). Such questioning can help students consider the consequences of applying correct laboratory data recording even when results are not as expected (Nikolic et al. 2024b). This is because data manipulation can lead to substantial reputational and career damage (Kaiser 2023). Such ethical guidance is linked to a range of GenAI challenges that include academic integrity risks, and more effort is needed within engineering education (Quince et al. 2024).

Again, considering the assessment guidance of Bearman, Nieminen, and Ajjawi (2023), affective-based objectives are something that contract cheaters or GenAI can't do. Much of the work conducted by engineers is founded on strong written and oral communication skills and professional competencies (Trevelyan 2021) in which affective objectives are vital.

7.4. Moving forward

The education of engineering professionals commenced with a heavy learning-by-doing approach that shifted to a heavy theoretical concentration over time (Feisel and Rosa 2005). If GenAI transforms cognitive aspects of engineering education, the community will need to learn to work with it, including within the laboratory, and discover how to use it as a tool, helping students move to more complex systems. It will become important to move into areas that GenAI can't do (Bearman, Nieminen, and Ajjawi 2023), at least temporarily, where learning by doing via the laboratory may substantially increase in importance. It is through practice that higher education can continue to provide value for students. For this to occur, the demands on academic staff will increase, and the importance of engineering education will be vital to prepare future graduates for the new skills they face (Dart et al. 2023). The immediate roadblock is the lack of training and policy on GenAI, which is needed to provide educators with the confidence and roadmap to move forward (Nikolic, Wentworth, et al. 2024c). These issues are also recognised by students (Margetts, Cunningham, and Boles 2024). In terms of assessment, the laboratory report is heavily used because of its marking efficiency, but as the community shifts focus, new assessment innovations will be needed (Dunne and Nikolic 2021).

8. Conclusion

This study commenced by providing a literature-based overview of assessments used within the teaching laboratory. This provided a guide to the assessment options and academic integrity risks. Highlighted was the concentration of research related to the laboratory report and the prominent knowledge gaps across the diverse range of other assessment tasks. In particular, no empirical evidence could be found on which learning objectives the different assessment tasks could verify, either explicitly or implicitly. Therefore, this study addresses two critical research questions identified as a major research gap: (1) '*Which assessment types are best considered appropriate to verify laboratory learning objectives?*' and (2) '*How can we improve assessment integrity in the teaching laboratory?*' Through an innovative mapping of assessment types against cognitive, psychomotor, and affective learning objectives, this research offered educators a comprehensive framework to improve both the validity and integrity of laboratory assessments, particularly in the context of challenges posed by Generative Artificial Intelligence (GenAI).

Key findings highlighted the preference for the laboratory report as an assessment mechanism capable of assessing all cognitive learning objectives. However, for psychomotor and affective-based objectives, this confidence was lower. Furthermore, the relationships between learning objectives and all assessment types were strongest in the cognitive domain. Holistically, this work has shown that there are some validity and integrity gaps, especially due to GenAI, that need addressing. To overcome these limitations, the study presents a pathway for adapting and transforming laboratory assessment practices.

Firstly, this study highlights **the importance of aligning assessment types with learning objectives**. By using the 'Words of Estimative Probability' heatmap presented, educators can identify which assessment types most effectively verify specific learning objectives and which need further investigation. This can include the need for extra training, as some expected relationships, such as those between a laboratory exam and psychomotor, were not as strong as expected. Through alignment, assessments are validated, as they directly measure the intended competencies, reducing the risk of a disconnect between objectives and evaluation.

Secondly, this study suggests that **assessment validity can be improved through diversity**. The study advocates for a departure from over-reliance on laboratory reports, highlighting alternatives like interviews, instructor observations, and group presentations. Such diversity is generally found in project-based assessments. These assessment types can be used to verify a broader spectrum of skills and knowledge while addressing the limitations of single-format assessments. This enables data triangulation, where multiple methods converge to validate learning outcomes, thereby enhancing the overall reliability and validity of the evaluation process.

Thirdly, this study addresses the **importance of assessment selection in ensuring assessment integrity, especially against GenAI risks**. Assessment types such as supervised practical exams, live demonstrations, and interviews help combat the risks posed by GenAI. Their dynamic and interactive nature ensures that students authentically demonstrate their understanding and capabilities in real time. Additionally, by considering the diversity of options, educators can integrate scaffolding techniques, such as combining assessments, so that educators can monitor student progress and reduce opportunities for academic dishonesty.

Finally, this study has highlighted **the importance of reflective practice**, encouraging educators to continually evaluate and improve their assessments in response to evolving challenges. Such practice can help educators refine their methods to enhance validity and reliability.

It is important to note that these correlations are based on academic perceptions, and these relationships may not hold. A future study will look to confirm if these perceptions hold. Further research is also needed to determine if confidence can be increased to verify relationships for assessments linked to psychomotor or affective-based objectives. Furthermore, new innovative assessment types could be developed.

By addressing the research questions, this study has underscored the critical need for laboratory assessments that not only measure intended learning outcomes but also maintain integrity and adaptability in a changing academic landscape. The findings equip educators with the knowledge and tools to design assessments that are not only valid but also secure, ensuring that laboratory education remains a cornerstone of authentic and effective learning in science, technology, engineering, and mathematics (STEM) disciplines.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT-4 with SciSpace GPT and Grammarly in order to help identify relevant literature and for proofreading purposes. After using this tool/service, the authors reviewed and edited the content as needed and takes full responsibility for the content of the publication.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Appendices

Appendix 1. The likelihood of laboratory assessments being used to verify cognitive-based learning objectives implicitly, *including confidence intervals (CI) at the 95% level and a Words of Estimative Probability heatmap*

Obj	LLOM Objective	ForLabRep	OnLabRep	LabRepGRP	LabNotEnt	WkAssRep	InclassQs	ProjINDV	ProjGRP	Prelab	LabExamP	LabExamNP	GrpPreso	Demo	Inter	Observ
C1	Understand the operation of equipment/software used within the laboratory	0.360 (0.267,0.466)	0.296 (0.159,0.485)	0.370 (0.245,0.514)	0.357 (0.207,0.542)	0.542 (0.351,0.721)	0.328 (0.228,0.447)	0.468 (0.333,0.608)	0.528 (0.397,0.656)	0.265 (0.146,0.431)	0.250 (0.127,0.434)	0.273 (0.097,0.566)	0.595 (0.435,0.737)	0.293 (0.176,0.445)	0.471 (0.262,0.690)	0.474 (0.325,0.627)
C2	Design experiments/models (physical or simulation) to verify course concepts	0.291 (0.205,0.394)	0.296 (0.159,0.485)	0.348 (0.227,0.492)	0.500 (0.326,0.674)	0.458 (0.279,0.649)	0.463 (0.349,0.581)	0.234 (0.136,0.372)	0.377 (0.259,0.512)	0.294 (0.168,0.462)	0.214 (0.102,0.395)	0.364 (0.152,0.646)	0.432 (0.287,0.591)	0.317 (0.196,0.470)	0.412 (0.216,0.640)	0.474 (0.325,0.627)
C3	Use engineering tools (e.g. [name of hardware/software used]) to solve problems	0.326 (0.236,0.430)	0.333 (0.186,0.522)	0.370 (0.245,0.514)	0.536 (0.358,0.705)	0.292 (0.149,0.492)	0.299 (0.202,0.417)	0.404 (0.276,0.547)	0.434 (0.310,0.567)	0.294 (0.168,0.462)	0.357 (0.207,0.542)	0.273 (0.097,0.566)	0.649 (0.488,0.782)	0.268 (0.157,0.419)	0.529 (0.310,0.738)	0.421 (0.279,0.578)
C4	Read and understand datasheets/circuit-diagrams/ procedures/user-manuals/ help-menus	0.465 (0.363,0.570)	0.370 (0.215,0.558)	0.543 (0.402,0.678)	0.393 (0.236,0.576)	0.417 (0.245,0.612)	0.493 (0.377,0.609)	0.574 (0.433,0.705)	0.679 (0.545,0.789)	0.412 (0.264,0.578)	0.357 (0.207,0.542)	0.455 (0.213,0.720)	0.703 (0.542,0.825)	0.561 (0.410,0.701)	0.353 (0.173,0.587)	0.474 (0.325,0.627)
C5	Draw & interpret relevant charts, graphs, tables & signals	0.186 (0.118,0.281)	0.370 (0.215,0.558)	0.217 (0.123,0.356)	0.214 (0.102,0.395)	0.333 (0.180,0.533)	0.343 (0.241,0.463)	0.340 (0.222,0.483)	0.132 (0.065,0.248)	0.382 (0.239,0.550)	0.286 (0.153,0.471)	0.091 (0.016,0.377)	0.514 (0.359,0.666)	0.415 (0.278,0.566)	0.647 (0.413,0.827)	0.553 (0.397,0.699)
C6	Recognise safety issues associated with laboratory experimentation	0.581 (0.476,0.680)	0.370 (0.215,0.558)	0.630 (0.486,0.755)	0.429 (0.265,0.609)	0.667 (0.467,0.820)	0.403 (0.294,0.523)	0.532 (0.392,0.667)	0.226 (0.135,0.355)	0.265 (0.146,0.431)	0.571 (0.391,0.735)	0.455 (0.213,0.720)	0.568 (0.409,0.713)	0.488 (0.343,0.635)	0.412 (0.216,0.640)	0.421 (0.279,0.578)
C7	Analyse the results from an experiment	0.058 (0.025,0.129)	0.148 (0.059,0.325)	0.152 (0.076,0.282)	0.286 (0.153,0.471)	0.208 (0.092,0.405)	0.284 (0.190,0.401)	0.213 (0.120,0.349)	0.113 (0.053,0.226)	0.353 (0.215,0.521)	0.143 (0.057,0.315)	0.091 (0.016,0.377)	0.270 (0.154,0.430)	0.341 (0.216,0.495)	0.353 (0.173,0.587)	0.395 (0.256,0.553)
C8	Write a conclusion summarising your findings from an experiment	0.105 (0.056,0.187)	0.111 (0.039,0.281)	0.130 (0.061,0.257)	0.357 (0.207,0.542)	0.292 (0.149,0.492)	0.418 (0.307,0.537)	0.298 (0.187,0.440)	0.132 (0.065,0.248)	0.441 (0.289,0.605)	0.464 (0.295,0.642)	0.273 (0.097,0.566)	0.270 (0.154,0.430)	0.439 (0.299,0.590)	0.471 (0.262,0.690)	0.368 (0.234,0.527)
C9	Write a laboratory report/entry into a logbook in a professional manner	0.209 (0.137,0.307)	0.259 (0.132,0.447)	0.348 (0.227,0.492)	0.286 (0.153,0.471)	0.458 (0.279,0.649)	0.448 (0.335,0.566)	0.447 (0.314,0.588)	0.132 (0.065,0.248)	0.412 (0.264,0.578)	0.393 (0.236,0.576)	0.455 (0.213,0.720)	0.595 (0.435,0.737)	0.390 (0.257,0.543)	0.294 (0.133,0.531)	0.342 (0.212,0.501)

Note. The colours represent the visual coding of the traffic light-style heatmap.

Appendix 2. The likelihood of laboratory assessments being used to verify psychomotor-based learning objectives implicitly, *including confidence intervals (CI) at the 95% level and a Words of Estimative Probability heatmap*

Obj	LLOM Objective	ForLabRep	OnLabRep	LabRepGRP	LabNotEnt	WkAssRep	InclassQs	ProjINDV	ProjGRP	Prelab	LabExamP	LabExamNP	GrpPreso	Demo	Inter	Observ
P1	Correctly conduct an experiment on [course equipment/ software name- e.g. power systems]	0.233 (0.156,0.332)	0.259 (0.132,0.447)	0.304 (0.191,0.448)	0.357 (0.207,0.542)	0.208 (0.092,0.405)	0.269 (0.177,0.385)	0.213 (0.120,0.349)	0.283 (0.180,0.416)	0.441 (0.289,0.605)	0.214 (0.102,0.395)	0.273 (0.097,0.566)	0.432 (0.287,0.591)	0.244 (0.138,0.393)	0.412 (0.216,0.640)	0.395 (0.256,0.553)
P2H	Select and use appropriate instruments for the input, output and measurement of your circuit/system	0.326 (0.236,0.430)	0.222 (0.106,0.408)	0.413 (0.283,0.557)	0.429 (0.265,0.609)	0.208 (0.092,0.405)	0.224 (0.141,0.337)	0.319 (0.204,0.462)	0.434 (0.310,0.567)	0.294 (0.168,0.462)	0.250 (0.127,0.434)	0.182 (0.051,0.477)	0.405 (0.263,0.565)	0.268 (0.157,0.419)	0.235 (0.096,0.473)	0.316 (0.191,0.475)
P2S	Select appropriate commands and navigate interface to simulate/program a model	0.419 (0.320,0.524)	0.481 (0.307,0.660)	0.391 (0.264,0.535)	0.393 (0.236,0.576)	0.292 (0.149,0.492)	0.284 (0.190,0.401)	0.383 (0.258,0.526)	0.377 (0.259,0.512)	0.471 (0.315,0.633)	0.357 (0.207,0.542)	0.364 (0.152,0.646)	0.459 (0.310,0.616)	0.293 (0.176,0.445)	0.471 (0.262,0.690)	0.342 (0.212,0.501)
P3	Plan and execute experimental work related to this course	0.233 (0.156,0.332)	0.333 (0.186,0.522)	0.283 (0.173,0.425)	0.357 (0.207,0.542)	0.208 (0.092,0.405)	0.269 (0.177,0.385)	0.234 (0.136,0.372)	0.321 (0.211,0.455)	0.471 (0.315,0.633)	0.250 (0.127,0.434)	0.273 (0.097,0.566)	0.351 (0.218,0.512)	0.244 (0.138,0.393)	0.235 (0.096,0.473)	0.316 (0.191,0.475)
P4	Construct/code a working circuit/simulation/program	0.291 (0.205,0.394)	0.333 (0.186,0.522)	0.326 (0.209,0.470)	0.393 (0.236,0.576)	0.208 (0.092,0.405)	0.224 (0.141,0.337)	0.298 (0.187,0.440)	0.321 (0.211,0.455)	0.353 (0.215,0.521)	0.214 (0.102,0.395)	0.000 (0.000,0.259)	0.459 (0.310,0.616)	0.195 (0.102,0.340)	0.294 (0.133,0.531)	0.316 (0.191,0.475)
P5	Interpret sounds, temperature, smells and visual cues and use tools to diagnose faults/errors	0.419 (0.320,0.524)	0.519 (0.340,0.693)	0.413 (0.283,0.557)	0.321 (0.179,0.507)	0.458 (0.279,0.649)	0.433 (0.321,0.552)	0.574 (0.433,0.705)	0.472 (0.344,0.603)	0.471 (0.315,0.633)	0.357 (0.207,0.542)	0.364 (0.152,0.646)	0.541 (0.384,0.690)	0.512 (0.365,0.657)	0.647 (0.413,0.827)	0.421 (0.279,0.578)
P6H	Operate instruments (e.g. [equipment name]) required for experimentation	0.407 (0.309,0.513)	0.481 (0.307,0.660)	0.435 (0.302,0.578)	0.429 (0.265,0.609)	0.417 (0.245,0.612)	0.224 (0.141,0.337)	0.404 (0.276,0.547)	0.434 (0.310,0.567)	0.324 (0.191,0.492)	0.393 (0.236,0.576)	0.455 (0.213,0.720)	0.486 (0.334,0.641)	0.415 (0.278,0.566)	0.412 (0.216,0.640)	0.368 (0.234,0.527)
P6S	Operate software packages (e.g. [software name]) required for coding/simulation	0.442 (0.342,0.547)	0.593 (0.407,0.755)	0.478 (0.341,0.619)	0.464 (0.295,0.642)	0.417 (0.245,0.612)	0.239 (0.153,0.353)	0.319 (0.204,0.462)	0.415 (0.293,0.549)	0.294 (0.168,0.462)	0.357 (0.207,0.542)	0.273 (0.097,0.566)	0.405 (0.263,0.565)	0.317 (0.196,0.470)	0.353 (0.173,0.587)	0.368 (0.234,0.527)
P7	Take the reading of the output from circuits/ instruments/sensors	0.221 (0.146,0.319)	0.333 (0.186,0.522)	0.413 (0.283,0.557)	0.429 (0.265,0.609)	0.292 (0.149,0.492)	0.299 (0.202,0.417)	0.340 (0.222,0.483)	0.434 (0.310,0.567)	0.382 (0.239,0.550)	0.250 (0.127,0.434)	0.091 (0.016,0.377)	0.514 (0.359,0.666)	0.268 (0.157,0.419)	0.471 (0.262,0.690)	0.421 (0.279,0.578)

Note. The colours represent the visual coding of the traffic light-style heatmap.

Appendix 3. The likelihood of laboratory assessments being used to verify affective-based learning objectives **implicitly**, *including confidence intervals (CI) at the 95% level and a Words of Estimative Probability heatmap*

Obj	LLOM Objective	ForLabRep	OnLabRep	LabRepGRP	LabNotEnt	WkAssRep	InclassQs	ProjINDV	ProjGRP	Prelab	LabExamP	LabExamNP	GrpPreso	Demo	Inter	Observ
A1	Work in a team to conduct experiments, diagnose problems and analyse results	0.349 (0.257,0.454)	0.259 (0.132,0.447)	0.239 (0.139,0.379)	0.357 (0.207,0.542)	0.292 (0.149,0.492)	0.343 (0.241,0.463)	0.383 (0.258,0.526)	0.264 (0.164,0.396)	0.412 (0.264,0.578)	0.357 (0.207,0.542)	0.455 (0.213,0.720)	0.243 (0.134,0.401)	0.415 (0.278,0.566)	0.529 (0.310,0.738)	0.474 (0.325,0.627)
A2	Communicate laboratory setup, fault diagnosis, readings and findings with others	0.442 (0.342,0.547)	0.333 (0.186,0.522)	0.370 (0.245,0.514)	0.464 (0.295,0.642)	0.417 (0.245,0.612)	0.343 (0.241,0.463)	0.383 (0.258,0.526)	0.396 (0.276,0.531)	0.441 (0.289,0.605)	0.357 (0.207,0.542)	0.364 (0.152,0.646)	0.351 (0.218,0.512)	0.317 (0.196,0.470)	0.529 (0.310,0.738)	0.316 (0.191,0.475)
A3	Work independently to conduct experiments, diagnose problems and analyse results	0.337 (0.246,0.442)	0.407 (0.245,0.593)	0.500 (0.361,0.639)	0.464 (0.295,0.642)	0.250 (0.120,0.449)	0.328 (0.228,0.447)	0.106 (0.046,0.226)	0.453 (0.327,0.585)	0.412 (0.264,0.578)	0.393 (0.236,0.576)	0.273 (0.097,0.566)	0.405 (0.263,0.565)	0.390 (0.257,0.543)	0.353 (0.173,0.587)	0.342 (0.212,0.501)
A4	Consider ethical issues in laboratory experimentation and communication of discoveries	0.488 (0.386,0.592)	0.593 (0.407,0.755)	0.543 (0.402,0.678)	0.536 (0.358,0.705)	0.583 (0.388,0.755)	0.478 (0.363,0.595)	0.532 (0.392,0.667)	0.585 (0.451,0.707)	0.471 (0.315,0.633)	0.429 (0.265,0.609)	0.455 (0.213,0.720)	0.595 (0.435,0.737)	0.439 (0.299,0.590)	0.471 (0.262,0.690)	0.421 (0.279,0.578)
A5	Creatively use software/hardware to design or modify an experiment to solve a problem	0.349 (0.257,0.454)	0.444 (0.276,0.627)	0.370 (0.245,0.514)	0.464 (0.295,0.642)	0.417 (0.245,0.612)	0.373 (0.267,0.493)	0.426 (0.295,0.567)	0.358 (0.243,0.493)	0.441 (0.289,0.605)	0.357 (0.207,0.542)	0.364 (0.152,0.646)	0.432 (0.287,0.591)	0.293 (0.176,0.445)	0.294 (0.133,0.531)	0.500 (0.348,0.652)
A6	Learn from failure (when experiment/simulation/code fails or results are unexpected)	0.465 (0.363,0.570)	0.370 (0.215,0.558)	0.478 (0.341,0.619)	0.357 (0.207,0.542)	0.375 (0.212,0.573)	0.388 (0.280,0.508)	0.511 (0.372,0.647)	0.509 (0.379,0.639)	0.529 (0.367,0.685)	0.393 (0.236,0.576)	0.364 (0.152,0.646)	0.514 (0.359,0.666)	0.268 (0.157,0.419)	0.412 (0.216,0.640)	0.368 (0.234,0.527)
A7	Motivate yourself to complete experiments and learn from the laboratory activities	0.535 (0.430,0.637)	0.444 (0.276,0.627)	0.522 (0.381,0.659)	0.464 (0.295,0.642)	0.417 (0.245,0.612)	0.493 (0.377,0.609)	0.468 (0.333,0.608)	0.528 (0.397,0.656)	0.500 (0.341,0.659)	0.429 (0.265,0.609)	0.455 (0.213,0.720)	0.459 (0.310,0.616)	0.366 (0.236,0.519)	0.353 (0.173,0.587)	0.447 (0.301,0.603)

Note. The colours represent the visual coding of the traffic light-style heatmap.

Appendix 4. The likelihood of laboratory assessments being used to verify cognitive-based learning objectives **explicitly**, *including confidence intervals (CI) at the 95% level and a Words of Estimative Probability heatmap*

Obj	LLOM Objective	ForLabRep	OnLabRep	LabRepGRP	LabNotEnt	WkAssRep	InclassQs	ProjINDV	ProjGRP	Prelab	LabExamP	LabExamNP	GrpPreso	Demo	Inter	Observ
C1	Understand the operation of equipment/software used within the laboratory	0.558 (0.453,0.658)	0.630 (0.442,0.785)	0.587 (0.443,0.717)	0.536 (0.358,0.705)	0.375 (0.212,0.573)	0.582 (0.463,0.693)	0.468 (0.333,0.608)	0.434 (0.310,0.567)	0.647 (0.479,0.785)	0.643 (0.458,0.793)	0.727 (0.434,0.903)	0.405 (0.263,0.565)	0.585 (0.434,0.722)	0.353 (0.173,0.587)	0.421 (0.279,0.578)
C2	Design experiments/models (physical or simulation) to verify course concepts	0.628 (0.522,0.723)	0.593 (0.407,0.755)	0.609 (0.465,0.736)	0.393 (0.236,0.576)	0.500 (0.314,0.686)	0.388 (0.280,0.508)	0.723 (0.582,0.831)	0.566 (0.433,0.690)	0.500 (0.341,0.659)	0.571 (0.391,0.735)	0.636 (0.354,0.848)	0.541 (0.384,0.690)	0.585 (0.434,0.722)	0.412 (0.216,0.640)	0.316 (0.191,0.475)
C3	Use engineering tools (e.g. [name of hardware/software used]) to solve problems	0.605 (0.499,0.701)	0.556 (0.373,0.724)	0.565 (0.422,0.698)	0.321 (0.179,0.507)	0.667 (0.467,0.820)	0.537 (0.419,0.651)	0.511 (0.372,0.647)	0.472 (0.344,0.603)	0.559 (0.395,0.711)	0.500 (0.326,0.674)	0.636 (0.354,0.848)	0.324 (0.196,0.485)	0.659 (0.505,0.784)	0.353 (0.173,0.587)	0.395 (0.256,0.553)
C4	Read and understand datasheets/circuit-diagrams/ procedures/user-manuals/ help-menus	0.442 (0.342,0.547)	0.519 (0.340,0.693)	0.370 (0.245,0.514)	0.500 (0.326,0.674)	0.500 (0.314,0.686)	0.358 (0.254,0.478)	0.362 (0.240,0.505)	0.226 (0.135,0.355)	0.441 (0.289,0.605)	0.500 (0.326,0.674)	0.545 (0.280,0.787)	0.270 (0.154,0.430)	0.341 (0.216,0.495)	0.471 (0.262,0.690)	0.289 (0.170,0.448)
C5	Draw & interpret relevant charts, graphs, tables & signals	0.721 (0.618,0.805)	0.481 (0.307,0.660)	0.652 (0.508,0.773)	0.714 (0.529,0.847)	0.500 (0.314,0.686)	0.448 (0.335,0.566)	0.532 (0.392,0.667)	0.245 (0.149,0.376)	0.471 (0.315,0.633)	0.500 (0.326,0.674)	0.818 (0.523,0.949)	0.432 (0.287,0.591)	0.341 (0.216,0.495)	0.235 (0.096,0.473)	0.158 (0.074,0.304)
C6	Recognise safety issues associated with laboratory experimentation	0.256 (0.175,0.357)	0.333 (0.186,0.522)	0.196 (0.107,0.332)	0.357 (0.207,0.542)	0.208 (0.092,0.405)	0.343 (0.241,0.463)	0.277 (0.169,0.418)	0.132 (0.065,0.248)	0.471 (0.315,0.633)	0.250 (0.127,0.434)	0.364 (0.152,0.646)	0.324 (0.196,0.485)	0.317 (0.196,0.470)	0.412 (0.216,0.640)	0.368 (0.234,0.527)
C7	Analyse the results from an experiment	0.837 (0.745,0.900)	0.704 (0.515,0.841)	0.717 (0.575,0.827)	0.536 (0.358,0.705)	0.625 (0.427,0.788)	0.507 (0.391,0.623)	0.681 (0.538,0.796)	0.264 (0.164,0.396)	0.353 (0.215,0.521)	0.643 (0.458,0.793)	0.818 (0.523,0.949)	0.649 (0.488,0.782)	0.390 (0.257,0.543)	0.588 (0.360,0.784)	0.289 (0.170,0.448)
C8	Write a conclusion summarising your findings from an experiment	0.791 (0.693,0.863)	0.778 (0.592,0.894)	0.674 (0.530,0.791)	0.357 (0.207,0.542)	0.542 (0.351,0.721)	0.254 (0.165,0.369)	0.553 (0.412,0.686)	0.226 (0.135,0.355)	0.206 (0.103,0.368)	0.286 (0.153,0.471)	0.545 (0.280,0.787)	0.676 (0.515,0.804)	0.220 (0.120,0.367)	0.294 (0.133,0.531)	0.211 (0.111,0.363)
C9	Write a laboratory report/entry into a logbook in a professional manner	0.535 (0.430,0.637)	0.556 (0.373,0.724)	0.413 (0.283,0.557)	0.536 (0.358,0.705)	0.333 (0.180,0.533)	0.224 (0.141,0.337)	0.277 (0.169,0.418)	0.189 (0.106,0.314)	0.147 (0.064,0.301)	0.321 (0.179,0.507)	0.273 (0.097,0.566)	0.216 (0.114,0.372)	0.317 (0.196,0.470)	0.294 (0.133,0.531)	0.211 (0.111,0.363)

Note. The colours represent the visual coding of the traffic light-style heatmap.

Appendix 5. The likelihood of laboratory assessments being used to verify psychomotor-based learning objectives explicitly*, including confidence intervals (CI) at the 95% level and a Words of Estimative Probability heatmap*

Obj	LLOM Objective	ForLabRep	OnLabRep	LabRepGRP	LabNotEnt	WkAssRep	InclassQs	ProjINDV	ProjGRP	Prelab	LabExamP	LabExamNP	GrpPreso	Demo	Inter	Observ
P1	Correctly conduct an experiment on [course equipment/ software name- e.g. power systems]	0.581 (0.476,0.680)	0.556 (0.373,0.724)	0.500 (0.361,0.639)	0.429 (0.265,0.609)	0.500 (0.314,0.686)	0.507 (0.391,0.623)	0.489 (0.353,0.628)	0.453 (0.327,0.585)	0.206 (0.103,0.368)	0.679 (0.493,0.821)	0.636 (0.354,0.848)	0.378 (0.241,0.539)	0.488 (0.343,0.635)	0.412 (0.216,0.640)	0.289 (0.170,0.448)
P2H	Select and use appropriate instruments for the input, output and measurement of your circuit/system	0.442 (0.342,0.547)	0.481 (0.307,0.660)	0.348 (0.227,0.492)	0.321 (0.179,0.507)	0.500 (0.314,0.686)	0.403 (0.294,0.523)	0.404 (0.276,0.547)	0.340 (0.227,0.474)	0.265 (0.146,0.431)	0.536 (0.358,0.705)	0.455 (0.213,0.720)	0.351 (0.218,0.512)	0.488 (0.343,0.635)	0.529 (0.310,0.738)	0.263 (0.150,0.420)
P2S	Select appropriate commands and navigate interface to simulate/program a model	0.279 (0.195,0.382)	0.296 (0.159,0.485)	0.283 (0.173,0.425)	0.286 (0.153,0.471)	0.417 (0.245,0.612)	0.358 (0.254,0.478)	0.298 (0.187,0.440)	0.340 (0.227,0.474)	0.118 (0.047,0.266)	0.357 (0.207,0.542)	0.273 (0.097,0.566)	0.297 (0.175,0.458)	0.439 (0.299,0.590)	0.294 (0.133,0.531)	0.237 (0.130,0.392)
P3	Plan and execute experimental work related to this course	0.547 (0.442,0.647)	0.407 (0.245,0.593)	0.522 (0.381,0.659)	0.429 (0.265,0.609)	0.542 (0.351,0.721)	0.358 (0.254,0.478)	0.553 (0.412,0.686)	0.528 (0.397,0.656)	0.235 (0.124,0.400)	0.571 (0.391,0.735)	0.545 (0.280,0.787)	0.459 (0.310,0.616)	0.439 (0.299,0.590)	0.529 (0.310,0.738)	0.211 (0.111,0.363)
P4	Construct/code a working circuit/simulation/program	0.407 (0.309,0.513)	0.333 (0.186,0.522)	0.391 (0.264,0.535)	0.286 (0.153,0.471)	0.500 (0.314,0.686)	0.388 (0.280,0.508)	0.447 (0.314,0.588)	0.453 (0.327,0.585)	0.206 (0.103,0.368)	0.571 (0.391,0.735)	0.727 (0.434,0.903)	0.270 (0.154,0.430)	0.561 (0.410,0.701)	0.353 (0.173,0.587)	0.237 (0.130,0.392)
P5	Interpret sounds, temperature, smells and visual cues and use tools to diagnose faults/errors	0.244 (0.166,0.345)	0.222 (0.106,0.408)	0.239 (0.139,0.379)	0.321 (0.179,0.507)	0.250 (0.120,0.449)	0.254 (0.165,0.369)	0.106 (0.046,0.226)	0.208 (0.120,0.335)	0.059 (0.016,0.191)	0.393 (0.236,0.576)	0.455 (0.213,0.720)	0.216 (0.114,0.372)	0.220 (0.120,0.367)	0.176 (0.062,0.410)	0.158 (0.074,0.304)
P6H	Operate instruments (e.g. [equipment name]) required for experimentation	0.349 (0.257,0.454)	0.296 (0.159,0.485)	0.348 (0.227,0.492)	0.321 (0.179,0.507)	0.333 (0.180,0.533)	0.507 (0.391,0.623)	0.340 (0.222,0.483)	0.340 (0.227,0.474)	0.324 (0.191,0.492)	0.464 (0.295,0.642)	0.273 (0.097,0.566)	0.351 (0.218,0.512)	0.415 (0.278,0.566)	0.412 (0.216,0.640)	0.316 (0.191,0.475)
P6S	Operate software packages (e.g. [software name]) required for coding/simulation	0.279 (0.195,0.382)	0.222 (0.106,0.408)	0.283 (0.173,0.425)	0.214 (0.102,0.395)	0.292 (0.149,0.492)	0.403 (0.294,0.523)	0.447 (0.314,0.588)	0.358 (0.243,0.493)	0.324 (0.191,0.492)	0.464 (0.295,0.642)	0.545 (0.280,0.787)	0.324 (0.196,0.485)	0.512 (0.365,0.657)	0.412 (0.216,0.640)	0.263 (0.150,0.420)
P7	Take the reading of the output from circuits/ instruments/sensors	0.547 (0.442,0.647)	0.519 (0.340,0.693)	0.348 (0.227,0.492)	0.357 (0.207,0.542)	0.417 (0.245,0.612)	0.403 (0.294,0.523)	0.426 (0.295,0.567)	0.340 (0.227,0.474)	0.265 (0.146,0.431)	0.536 (0.358,0.705)	0.818 (0.523,0.949)	0.297 (0.175,0.458)	0.561 (0.410,0.701)	0.353 (0.173,0.587)	0.237 (0.130,0.392)

Note. The colours represent the visual coding of the traffic light-style heatmap.

Appendix 6. The likelihood of laboratory assessments being used to verify affective-based learning objectives explicitly*, including confidence intervals (CI) at the 95% level and a Words of Estimative Probability heatmap*

Obj	LLOM Objective	ForLabRep	OnLabRep	LabRepGRP	LabNotEnt	WkAssRep	InclassQs	ProjINDV	ProjGRP	Prelab	LabExamP	LabExamNP	GrpPreso	Demo	Inter	Observ
A1	Work in a team to conduct experiments, diagnose problems and analyse results	0.384 (0.288,0.489)	0.519 (0.340,0.693)	0.587 (0.443,0.717)	0.286 (0.153,0.471)	0.458 (0.279,0.649)	0.358 (0.254,0.478)	0.277 (0.169,0.418)	0.528 (0.397,0.656)	0.147 (0.064,0.301)	0.321 (0.179,0.507)	0.273 (0.097,0.566)	0.622 (0.461,0.759)	0.268 (0.157,0.419)	0.353 (0.173,0.587)	0.132 (0.058,0.273)
A2	Communicate laboratory setup, fault diagnosis, readings and findings with others	0.349 (0.257,0.454)	0.481 (0.307,0.660)	0.478 (0.341,0.619)	0.214 (0.102,0.395)	0.333 (0.180,0.533)	0.313 (0.215,0.432)	0.277 (0.169,0.418)	0.377 (0.259,0.512)	0.118 (0.047,0.266)	0.357 (0.207,0.542)	0.364 (0.152,0.646)	0.486 (0.334,0.641)	0.415 (0.278,0.566)	0.353 (0.173,0.587)	0.211 (0.111,0.363)
A3	Work independently to conduct experiments, diagnose problems and analyse results	0.395 (0.299,0.501)	0.370 (0.215,0.558)	0.239 (0.139,0.379)	0.286 (0.153,0.471)	0.458 (0.279,0.649)	0.373 (0.267,0.493)	0.660 (0.517,0.778)	0.189 (0.106,0.314)	0.235 (0.124,0.400)	0.429 (0.265,0.609)	0.455 (0.213,0.720)	0.351 (0.218,0.512)	0.293 (0.176,0.445)	0.353 (0.173,0.587)	0.158 (0.074,0.304)
A4	Consider ethical issues in laboratory experimentation and communication of discoveries	0.244 (0.166,0.345)	0.185 (0.082,0.367)	0.174 (0.091,0.307)	0.107 (0.037,0.272)	0.125 (0.043,0.310)	0.119 (0.062,0.218)	0.170 (0.089,0.301)	0.132 (0.065,0.248)	0.118 (0.047,0.266)	0.214 (0.102,0.395)	0.364 (0.152,0.646)	0.189 (0.095,0.342)	0.244 (0.138,0.393)	0.353 (0.173,0.587)	0.132 (0.058,0.273)
A5	Creatively use software/hardware to design or modify an experiment to solve a problem	0.360 (0.267,0.466)	0.333 (0.186,0.522)	0.370 (0.245,0.514)	0.143 (0.057,0.315)	0.250 (0.120,0.449)	0.254 (0.165,0.369)	0.362 (0.240,0.505)	0.415 (0.293,0.549)	0.088 (0.030,0.230)	0.321 (0.179,0.507)	0.455 (0.213,0.720)	0.351 (0.218,0.512)	0.439 (0.299,0.590)	0.529 (0.310,0.738)	0.158 (0.074,0.304)
A6	Learn from failure (when experiment/simulation/code fails or results are unexpected)	0.314 (0.226,0.418)	0.481 (0.307,0.660)	0.283 (0.173,0.425)	0.393 (0.236,0.576)	0.417 (0.245,0.612)	0.313 (0.215,0.432)	0.213 (0.120,0.349)	0.264 (0.164,0.396)	0.088 (0.030,0.230)	0.357 (0.207,0.542)	0.455 (0.213,0.720)	0.297 (0.175,0.458)	0.415 (0.278,0.566)	0.412 (0.216,0.640)	0.237 (0.130,0.392)
A7	Motivate yourself to complete experiments and learn from the laboratory activities	0.209 (0.137,0.307)	0.407 (0.245,0.593)	0.217 (0.123,0.356)	0.179 (0.079,0.356)	0.333 (0.180,0.533)	0.254 (0.165,0.369)	0.277 (0.169,0.418)	0.245 (0.149,0.376)	0.147 (0.064,0.301)	0.286 (0.153,0.471)	0.364 (0.152,0.646)	0.297 (0.175,0.458)	0.268 (0.157,0.419)	0.353 (0.173,0.587)	0.132 (0.058,0.273)

Note. The colours represent the visual coding of the traffic light-style heatmap.