Beyond guesstimating: Calculating student workload in fully online micro-credentials

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Estimating the volume of student learning in courses is more of an art than a science. Yet, mismatches between advertised workload and actual student effort can lead to high student dropout rates. To investigate the factors affecting student workload and whether they can be quantified, we undertook a mixed methods study aimed at refining and testing a student workload calculator specifically tailored for online micro-credentials. Utilising a case study methodology, we blended a literature review with our experiential knowledge as learning designers to refine existing workload calculators into a cohesive reflective tool to interrogate assumptions about learner effort and time on task. We then employed quantitative methods to test the calculator against advertised workloads in a sample of online micro-credentials from one platform. Findings suggest a potential discrepancy between provider-advertised workloads and calculator-based workload estimates, indicating that commonly used advertising practices may rely on materially different assumptions about student effort than those of conservative, research-informed modelling approaches. While this study did not measure actual student time on task, the consistency and magnitude of this discrepancy warrant closer scrutiny of how workloads are estimated and communicated to learners, as misalignment could contribute to student disengagement, lower completion rates and reduced trust in online learning.

Implications for practice:

- Course designers should take extra care when estimating workloads for online micro-credentials.
- Education providers could balance transparency and appeal by offering both typical and maximum workload estimates.
- Activity time estimates should be framed as flexible guides to support student planning.
- Educators should use workload calculators as reflective tools rather than fixed measures.

Keywords: student workload, online learning, micro-credentials, workload calculator, course design

Introduction

Online learning offers the compelling promise of flexible “anytime, anywhere” education, yet it also suffers from high dropout rates compared to traditional classroom environments (Herbert, 2006; Heyman, 2010; Smith, 2010). This phenomenon is partially caused by learners balancing their studies against other life commitments (Pollard & Vincent, 2022), with workload issues being a leading cause of student dropout in online courses (Bawa, 2016; Benda et al., 2012; Whitelock et al., 2015; Xavier & Meneses, 2021). As such, a critical factor influencing dropout rates is the accurate estimation of student learning volume (Whitelock et al., 2015). Incorrectly estimating the volume of student learning in an online course may negatively impact policy compliance, student retention and student achievement. These impacts may be even more pronounced in the case of micro-credentials, wherein the smaller scale of duration means that relatively small inaccuracies in estimation may result in significant gaps between estimates and reality. Therefore, particularly in the case of micro-credentials, ensuring success requires reliable methods for estimating student time on task.

Workload calculators present a potential method for reliably estimating time on task, yet currently available calculators do not accommodate the specific needs of the micro-credential context (Beer, 2019; Bowyer, 2012). Thus, it can be argued that there exists a need for the development of micro-credential workload calculators. Such calculators would need to consider the diversity of learners, the varying complexities of tasks and the balance between self-directed and pre-designed learning activities. Such tools would not only support more accurate workload estimations but also enhance the collaboration between academics and third-space professionals, ensuring that micro-credentials are both manageable for students and aligned with educational standards. In this study, we sought to refine and adapt existing methods for more consistent and accurate student workload calculations in fully online micro-credentials, validating them against online courses with known workloads. Three research questions guided the methodology of this study: "What factors influence student workload in fully online micro-credentials?", "Can these factors be quantified in a workload calculator?" and "How do the calculator's estimates compare to the advertised workloads?".

Background

In this study, we defined workload in line with Bowyer's (2012, p. 240) description: "the time needed for contact and independent study, the quantity and level of difficulty of the work, the type and timing of assessments, the institutional factors such as teaching and resources, and student characteristics such as ability, motivation and effort". The Innovative Learning Institute (2016) has identified three main approaches to estimating student time on task: experiential, proxy and survey. Each of these methods offers unique insights but also has significant limitations, underscoring the need for more comprehensive and accurate workload estimation techniques.

The experiential method relies on academics or third-space professionals estimating the time required based on their own experience. While rooted in practical insights, it lacks empirical validation and is prone to bias. Professionals often underestimate the time students need to complete tasks because they overlook the additional time required for processing new information and developing skills (Bjork et al., 2013; Bromme et al., 2001; Buehler et al., 1994). Moreover, this approach fails to consider diversity in student learning preferences and speeds (Light et al., 2009). Although practical in some scenarios, the experiential method alone cannot ensure an equitable workload for all students, highlighting the need for more objective and standardised approaches.

The proxy method involves the academic or third-space professional completing a task and multiplying their time by a factor, often three or four (Innovative Learning Institute, 2016). This assumes parity between professionals and students, often resulting in inaccurate estimations (Babcock & Marks, 2011; Wittwer et al., 2008). It also overlooks the time students need for critical thinking, application and synthesis of new information.

The survey method collects self-reported data from students after they have completed tasks to inform future estimations. This method provides direct feedback from the learner's perspective, making it a valuable tool for understanding student workload. This method can also reveal important trends and patterns in student experiences, offering insights into actual workload and identifying potential areas for adjustment (Kuh et al., 2010). However, recall bias and inconsistent perceptions can reduce reliability (Brady et al., 2022). Carefully designed surveys, used alongside other methods, can help triangulate more accurate time estimates.

Workload calculators: An emerging approach

Workload calculators represent an emerging approach that draws on the logic of the survey method, utilising research-informed quantifications of times to complete tasks. While workload calculators aim to provide a more standardised measure, they are not without limitations. They strive to generalise student learning volumes but overlook the inherent complexities or nuances of individual learning experiences, such as differences between disciplines, students' prior experience and the varying complexity of learning tasks (Anderson & Krathwohl, 2001; Bowyer, 2012). For instance, generalised workload estimations may not adequately reflect the specific demands of different courses, particularly those involving high levels of interaction or practical application (Lizzio et al., 2002).

Students' prior knowledge and experience significantly influence the time they need to complete tasks and/or perform other necessary follow-up learning activities, such as reflection and application (Heard et al., 2018). Research has shown that prior knowledge helps reduce cognitive load, allowing students with more experience in a subject to engage with tasks more efficiently and effectively (Bransford et al., 2000; Myhill & Brackley, 2004). Conversely, students with less background knowledge often require more time for follow-up learning activities, such as reflection and application, to fully integrate new concepts. This ability to connect prior knowledge to new tasks is critical in shaping how students organise and engage with the learning material (Efklides, 2011). A one-size-fits-all approach may, therefore, lead to either underestimation or overestimation of workload, like the proxy method, neither of which is conducive to effective learning.

In seeking to quantify learning, workload calculators can also oversimplify the multifaceted nature of education by privileging visible, countable activities such as readings, logins or discussion posts, while underestimating the cognitive labour involved in learning (Biggs & Tang, 2011; Macfarlane & Tomlinson, 2017). This reductionist approach risks misrepresenting student effort, for example, by treating the reading of dense theoretical texts as equivalent to narrative reading through uniform word-per-minute assumptions (Love, 2012; Rayner et al., 2016). Such simplifications can result in inappropriate workload expectations that fail to reflect students' intellectual engagement and that undermine the quality of the learning experience. These limitations are further compounded by disciplinary variation: humanities courses often emphasise sustained reading and writing, while science, technology, engineering and mathematics disciplines prioritise problem-solving and laboratory work (Norton, 2008, p. 156). Empirical evidence demonstrates significant differences in workload patterns across disciplines, underscoring the inadequacy of generalised calculators and the need for discipline-sensitive approaches to workload estimation (Hora & Ferrare, 2014). In particular, courses with higher levels of active learning or practical application require more nuanced approaches to workload estimation (Kember, 2004). Therefore, workload calculators must be adaptable and sensitive to the varied backgrounds and abilities of students, as well as the complexity of learning tasks.

Despite these limitations, workload calculators provide a research-based starting point for workload estimation that supports academic and learning designer judgements. Without such calculators, any workload estimates are dependent on the judgement of individuals, which may vary depending on their own experience and knowledge of workload estimation. While not perfect, workload calculators offer a more objective and consistent foundation that, when used in partnership with the experienced judgement of academics and third-space professionals, can contribute to more accurate workload estimations.

Micro-credentials: A growing focus

Micro-credentials are increasingly popular in higher education, offering short, focused courses that provide specific skills or knowledge. Their rise can be attributed to several factors: demand for lifelong learning, the need for upskilling in rapidly changing industries and flexibility in balancing studies with work and other responsibilities (Pollard & Vincent, 2022). Micro-credentials are often designed to be stackable, allowing learners to build a portfolio of competencies that can lead to larger qualifications, such as degrees or professional certifications.

The design and development process for micro-credentials is especially collaborative, involving partnerships between academics, subject matter experts and third-space professionals (e.g., learning designers and educational technologists) (Colbert et al., 2025). This collaboration leverages the expertise of all parties to create courses that are both academically rigorous and practically relevant. However, the imbalance between self-directed and structured learning can complicate these collaborations. The lack of agreed-upon standards for estimating student workload can lead to inconsistencies in course design, with some courses potentially overwhelming students and others failing to challenge them adequately. Literature on workload estimation has focused on traditional face-to-face and blended course environments and may not adequately apply to shorter, intensive offerings like micro-credentials (Beer, 2019).

Misestimating the workload in micro-credentials can contribute to high dropout rates and undermine the credibility of the credentialling system, whereas manageable workloads contribute significantly to student retention and success (Lee & Choi, 2011; Tinto, 2012). Micro-credentials, due to their compressed formats and diverse audiences, require more precise and tailored approaches to workload estimation. The number of hours required to complete a micro-credential is often prominently expressed in the selection and sign-up process. The shorter time frames necessitate careful calibration of tasks to ensure that learning outcomes are met without overwhelming learners (Ahsan et al., 2023; Oliver, 2019). Research has highlighted the importance of using multiple methods, including direct feedback from students, to refine workload estimations and ensure they are realistic and achievable (Omona & O'dama, 2024). Additionally, accurate workload estimations are vital for credentialling, badging, recognition of prior learning and stacking equivalence of outcomes (Conrad, 2022; Lee & Tan, 2023). Credentialling systems rely on accurate assessments of learning to validate the skills and knowledge that students acquire (Piedra, 2021, Chapter 1). Yet ensuring that micro-credentials are appropriately weighted and recognised requires precise workload calculations. Inaccurate workload estimations can undermine the credibility of credentials, making it difficult to equate them with traditional academic courses or other forms of professional development. Moreover, precise workload calculations are essential for recognition of prior learning processes. Accurate workload estimation helps ensure that the learning outcomes of micro-credentials are comparable to those of other educational experiences, facilitating the stacking and accumulation of credits towards higher qualifications (Wheelahan & Moodie, 2011). Accurate time on task estimation for the micro-credential context is evidently crucial for balancing self-directed and structured learning and ensuring manageable, standards-aligned micro-credentials.

Methodology

This research used mixed methods: firstly, a case study approach to blend literature and our experience to refine an existing research-informed workload calculator; secondly, quantitative methods to test the calculator against the advertised workload in online micro-credentials.

Refining the student workload calculator

To objectively and systematically interrogate the development of the student workload calculator within our learning and teaching context and through the lens of scholarly literature, we employed a case study methodology (Yin, 2017). We utilised this approach to juxtapose the literature with our lived experience to answer research questions one and two: "What factors influence student workload in fully online micro-credentials?" and "Can the factors influencing student workload be quantified in a calculator?". This allowed us to examine our approach to a student workload calculator in a manner that makes our decisions transparent and subject to critical scholarly debate (Boyer, 1990) and our conclusions documented, reproducible and open to peer review (Flyvbjerg, 2006). The bounds of this case study were explicit to our role as learning designers, collaboratively designing courses with subject matter experts at an Australian university. In this role, we have worked across multiple higher education institutions in Australia on the end-to-end development of courses, degree programmes and micro-credentials using a collaborative approach. We critically examined student workload research in published and grey literature, filtering it through our lens of learning design and experience in the development of micro-credentials. This enabled us to discern nuances between the literature and the micro-credential context, identify gaps and refine existing workload calculators to better suit the intricacies of micro-credential design and development.

We ascertained that Beer's (2019) workload calculations were the most recent comprehensive set. Thus, we agreed that this would form the basis from which to make modifications aligning with our lens as learning designers and referencing broader literature from the field. As a research team, we determined that, in keeping with Beer (2019), the workload calculator should be grounded using the conversational framework activity types (Laurillard, 2012) and tasks (Beetham, 2007). This is a framework with which most learning designers would be familiar and would provide a practical grounding for the application of a workload calculator more broadly, promoting ease of use and likely, therefore, perceived usefulness (Davis, 1989). The activity types and tasks are also aligned with our description of workload in that they include the total time for directed and independent study within a course. In contrast to other workload models, rather than aiming to build the calculator around the ”average“ student (Bowyer, 2012), we sought to develop our estimations based on a conservative workload estimate, that is, at the upper range of expected student engagement and effort.

We use the term *conservative workload estimate* not as a formally defined statistical measure but as a conceptual design heuristic to describe how workload timings were selected. Specifically, activity timings were drawn from the upper range of values reported in the literature or commonly used in workload calculators, rather than from mean or median estimates. This approach reflects a conservative modelling choice intended to reduce the risk of systematic underestimation of student workload, particularly in self-paced online micro-credentials.

Using a conservative workload estimate approach allowed us to better accommodate the variability in student engagement and learning pace. While mean or median values might capture the central tendency, they risk under-representing the time required by students who engage thoroughly with the material, including adequate time for reflection and comprehension. This conservative estimation acts as a safeguard against underestimation, which is a factor that has been associated with increased stress and dropout rates (Bawa, 2016; Benda et al., 2012; Whitelock et al., 2015; Xavier & Meneses, 2021). Although this method may appear more demanding, it is intended to reflect a realistic upper bound of student effort, ensuring that course designs account for the diversity of student experiences and promote sustainable learning practices.

The workload calculations from Beer (2019) were reviewed in conjunction with the other workload calculators (see, for example, Barre et al., n.d.) and relevant literature about student workload and time on task. Modifications were made where there were discrepancies or gaps between the calculator and research-based studies. There were some areas, such as the production of non-text artefacts (e.g., graphics), which were not estimated in either the published literature or prior workload calculators. Where this occurred, we relied on our collective experience in learning design, teaching and comparable workload synthesis to estimate an initial workload value. The outputs of this synthesis of literature with learning design expertise are displayed in Table 1 and expanded below.

Table 1
Student workload calculations for activities and tasks

Learning activity	Task	Calculation	
Acquisition	Reading	Survey	360 WPM
		Understand	180 WPM
		Engage	90 WPM
		Complex	+ 50% to reading time
	Watching and listening	Double the duration of media	
Practice	Quiz questions	Multiple-choice	2 minutes per question
		Short answer	5 minutes
		Long answer	See Production – Written content.

Learning activity	Task	Calculation	
		Calculation	5 minutes for each main step in the calculation (approx. 1 mark)
	Interactives	Simple	15 minutes
		Complex	30 minutes
Discussion	In-depth discussion	1.5 hours for a 250-word or 2-minute video post three responses to peers, and replies to key responses on their original post	
	Response to a prompt	20 minutes	
Production	Written content	Reflective	250 WPH
		Argumentative	125 WPH
		Research	62 WPH
	Presentation or video	Reflective	2 minutes of media per hour
		Argumentative	1 minute of media per hour
		Research	30 seconds of media per hour
	Artefact	Low complexity	30 minutes
		Medium complexity	60 minutes
		High complexity	120 minutes
Investigation	Searching for and evaluating information	125 WPH of written evaluation	
	Conducting experiments or collecting data	1 hour per data set	
Collaboration	Cooperation	Double the time allocated if the task were individual	
	Collaboration	Triple the time allocated if the task were individual	
	Peer review	40 minutes per review task	
Other	Timed assessment (exam)	4 hours of preparation per 1 hour of exam time	
	Synchronous learning	1.5 times the duration of the synchronous session	

Note. WPM = words per minute. WPH = words per hour.

Acquisition (Reading)

Research demonstrates that reading rates vary considerably depending on whether students are skimming, reading for comprehension or engaging deeply with a text (Carver, 1983; Rayner et al., 2016). While simple narrative texts may be read at approximately 300 words per minute, complex materials, particularly those dense with graphics, mathematical notation or abstract concepts, can reduce reading speeds to around 65 words per minute when deep engagement is required (Parker, 1962; Rayner et al., 2016). Texts with high visual or symbolic content also impose greater cognitive load, requiring additional time for decoding and meaning-making (Hackemann et al., 2022; Rezat et al., 2022) – a challenge that is especially pronounced in science, technology, engineering and mathematics disciplines, where learners must integrate textual, mathematical and graphical information concurrently (Bennett et al., 2019). Accordingly, workload estimation based solely on word count is insufficient and must account for conceptual density and multimodal complexity (Adams, 2003; Fazio et al., 2022). Barre et al. (n.d.) offer the most comprehensive research-informed estimates of reading time, differentiating by reading purpose, depth of engagement and the introduction of new concepts. To balance rigour with usability, we adopted a simplified version of their model, proposing reading rates of 360 WPM for survey reading, 180 WPM for reading for understanding and 90 WPM for active engagement. For complex readings containing substantial non-text elements, we further assumed reading times to be at least 1.5 times longer than standard estimates.

Acquisition (Watching and listening)

Some existing workload calculators, such as that by Barre et al. (n.d), indicate that video and podcast content have the same workload for students as the duration of the media, while North Carolina State University (n.d.) and Beer (2019) have suggested doubling the duration of the media to account for additional tasks such as note-taking and reviewing. We know that students interacting with media in online courses use strategies such as self-pacing (speeding up or slowing down) and rewatching (Dinmore, 2019). When including post-video reflection time, we agree that doubling the duration of the media will provide the most reasonable estimate of student workload.

Practice (Quiz questions)

Beer (2019) has synthesised multiple quiz-timing sources, concluding that 60 seconds per multiple-choice question is appropriate, with estimates of 120 seconds for short-answer items and 10–15 minutes for essay questions. However, many of these sources (e.g., Clay, 2001) are based on exam conditions and therefore do not account for formative quiz behaviours such as reviewing feedback or revisiting course content. Gaps also remain for certain question types, including numerical or calculation-based responses, while the variability inherent in essay questions limits the usefulness of generic timing estimates.

To address these limitations, we extended standard exam-based timings to account for feedback and revision. While North Carolina State University (n.d.) has proposed 1 hour for a 10-question quiz, this approach does not differentiate between question types. Accordingly, we propose 2 minutes per multiple-choice question, 5 minutes for short-answer questions limited to one or two sentences and 5 minutes per main step in calculation-based questions (i.e., 5 minutes per mark). Timing for longer essay-style questions is addressed through the production (written content) estimates below.

Practice (Interactives)

Interactive content authored using software such as Articulate Storyline or H5P frequently appears in online courses. Yet, there is no readily available literature on which to base the time it takes a student to complete these types of activities. Given the varying nature of interactives, we believe it is necessary to split this category into two: simple interactives (e.g., hotspots, those containing multiple-choice quiz questions) and complex interactives (e.g., branching scenarios). We have extrapolated from the known timings of quizzes as a proxy, assuming that an equivalence between interactive and quiz times can be made. As such, we propose a timing of 15 minutes for a simple interactive and 30 minutes for a complex interactive.

Discussion (In-depth discussion)

Discussion forums, comment threads and social interactions on platforms such as Padlet are central to socially constructivist online learning (Galikyan et al., 2021; Kanchana & Cherukuri, 2024). Existing guidance on discussion workload is broadly consistent: Barre et al. (n.d.) have estimated 1 hour for a 250-word or 3-minute video post; North Carolina State University (n.d.) has suggested 2 hours for an original post plus peer responses; and Coventry University (2018, as cited in Beer, 2019) has estimated 300 WPH. Drawing on this convergence, we allocate 1.5 hours of student workload for a 250-word written post or a 2-minute video post, inclusive of the initial contribution, responses to three peers and follow-up replies, in line with Turner's (2005) guidance on interactive discussion engagement.

Speech-rate research has indicates that while conversational speech may reach approximately 209 WPM (Tauroza & Allison, 1990), listening comprehension declines beyond 200 WPM (Griffiths, 1990, 1992). As discussion videos typically combine scripted and spontaneous speech, a more realistic range is 140–190 WPM (Barnard, 2022), with further variability introduced by cognitive load and discourse demands (Wang & Narayanan, 2007). On this basis, a 2-minute video post broadly corresponds to 280–380 written words, though this may be lower for unscripted or cognitively demanding tasks. Additional time is incorporated to account for the cognitive and logistical demands of recording, editing and uploading video content.

Discussion (Response to a prompt)

In online micro-credentials, there are often shorter responses to prompts, such as reflections, social prompts or share-your-thought tasks. These clearly do not require as much time spent as an in-depth discussion and could be considered in line with Turner's (2005) suggestion of 30 minutes for responding to an instructor's prompt. We propose that 20 minutes for responding to a prompt seems a reasonable baseline, in line with the time that could be expected to be spent on a short-answer question (above). This workload allocation would also help account for tasks such as self-reflective prompts – after all, there is a tendency in online courses to measure only what can be observed and omit self-reflection (Gourlay, 2015).

Production (Written content)

Written content is likely to be a component of many summative assessments, yet there is little agreement on how long it takes to produce. Barre et al. (n.d.) has indicated the following production times, with minimal redrafting: reflective writing 250 WPH, argument writing 125 WPH and research writing 62.5 WPH. Interestingly, the paper they cited suggests writing rates of between 100 and 160 WPH. Comparatively, Coventry University (2018, as cited in Beer, 2019) has estimated formative assessment at 50 WPH and summative assessment at 40 WPH. The New York State Department of Education (2021) table broadly aligns with the Barre et al. estimations. As the Beer (2019) and New York State Department of Education tables lack any further references, we assume that the Barre et al. work may be a better representation and, as such, use it unedited. For these timings, we presume there is a linear relationship between the overall length of the written work and the speed of its production.

Production (Presentation or video)

Given that a relationship between the duration of media and the word count has been made earlier in the in-depth discussion post section (2 minutes of video equals 250 words of written text), this will be replicated here for want of a better system. Thus, we propose producing a reflective video of 2 minutes per hour, an argument video of 1 minute per hour and a research video of 30 seconds per hour of work.

Production (Non-text artefact)

Although limited, research and insights from related fields have informed estimates for non-text artefact creation. E-learning development time varies widely with complexity, ranging from weeks for small projects to months for multimedia-intensive curricula (Cloke, 2023; Tucker, 2019). Similarly, the four-dimensional framework for artefacts in design has demonstrated how artefacts develop across physical, temporal, social and task-related dimensions, with increasing complexity requiring extended development time (Muñoz-Cristóbal et al., 2018). For example, a graphic design artefact may evolve from a rough sketch through multiple digital iterations and collaborative refinement before finalisation.

Drawing on these insights, we categorise artefact production into three levels suitable for the micro-credential course type: low complexity (e.g., short code segments or minor table edits, 30 minutes), medium complexity (e.g., simple flowcharts or extended code segments, 60 minutes) and high complexity (e.g., standalone web pages or infographics, 120 minutes). These categories provide a structured, research-informed basis for estimating student workload and support cumulative time calculations where artefacts are developed iteratively toward a final product.

Investigation (Searching for and evaluating information)

Borlund et al. (2012) have provided the only literature-based study on the time taken to investigate topics. Students took a mean time of 14 and 17 minutes to search for information on a known and unknown topic, respectively. The maximum time taken for either was just under 30 minutes. Therefore, the suggestion is to allow 30 minutes for searching for and evaluating information and then to presume that the information needs to be shared somehow in the online course. The sharing could be expected to be half that of a discussion post, as the information needs to be presented rather than constructed. As such, we propose 1 hour for undertaking the investigation and producing a 250-word write-up.

Investigation (Conducting experiments or collecting data)

In practice, educators, particularly those experienced in laboratory-based or practical courses, often have an informed sense of how long experiments or data collection tasks are likely to take, drawing on prior course iterations, task complexity, learning outcomes and student feedback (Amolins et al., 2015; Herzog & Mawn, 2020). Nevertheless, estimating time accurately across diverse student cohorts remains challenging, as proficiency, prior knowledge, and contextual factors such as equipment access or collaboration demands can substantially affect time on task (Dong et al., 2020; Hailikari et al., 2008). Educators may refine their estimates through pilot testing, student feedback, comparison with similar courses or workload models or technology-assisted tracking within learning management systems. On this basis, and to provide a modifiable baseline suitable for varied contexts, we propose allocating 1 hour per data set.

Collaboration (Collaboration and cooperation)

Collaboration requires students to work together towards shared outcomes, introducing organisational and time management demands beyond those of individual tasks. Beer (2019) has noted that collaborative work involves additional time for coordination, negotiation, consensus-building and peer review, and therefore recommends doubling the time allocated for individual production tasks. Building on this, we distinguish between cooperative and collaborative tasks to better reflect differing workload demands. In cooperative tasks, students coordinate while producing individual outputs; to account for the associated organisational overhead, we propose doubling the time required for individual tasks. Collaborative tasks involve the joint production of a shared output and require more extensive coordination, negotiation, and collective decision-making. Given that learners in online micro-credentials are often unfamiliar with one another, additional time must also be allocated to support the social dimensions of group work. Accordingly, we propose tripling the time required for individual production tasks for collaborative activities. This distinction provides a more nuanced basis for workload estimation, to be used as an initial guideline pending further empirical validation.

Collaboration (Peer review)

Peer review is a further core component of collaborative work and is particularly difficult to quantify in workload models. Appropriate time allocation depends on several interrelated factors, including task complexity, length of the work reviewed, expectations regarding feedback depth, group size, rubric complexity and student experience. More complex or longer tasks, detailed critique requirements, larger review groups and novice reviewers all increase the time required to provide meaningful feedback. Given these variables, we propose allocating 40 minutes for a peer review task. This estimate reflects approximately triple the time typically allocated in academic workload models for expert marking and feedback and recognises that peer reviewers require additional time to interpret criteria and formulate feedback. As most micro-credentials are relatively short, peer review tasks are also unlikely to involve large or highly complex artefacts, making this a reasonable baseline estimate.

Other (Timed assessment – exam)

Some learning types are not captured within the conversational framework activity types (Laurillard, 2012) or the associated tasks (Beetham, 2007) and are therefore documented in this section separately. When timed assessments such as exams are used, workload considerations must include both the assessment itself and preparation or revision time. The New York State Department of Education (2021) has suggested that students typically require 4 hours of preparation for a 1- to 2-hour exam; for simplicity, we therefore propose 4 hours of preparation and revision per hour of exam time.

However, the calculations that follow are not incorporated into the workload calculator. Instead, they are intended to support exam design by helping course teams determine appropriate assessment length based on the volume of work students can reasonably complete within a fixed time. This distinction is important, as workload estimation accounts for total student effort across a course, whereas exam design focuses on performance within time-constrained conditions. For example, earlier quiz timings incorporated time for feedback and reflection, which is not relevant in an exam context. Accordingly, we revert to unmodified exam-based timings of 30 seconds per true–false question, 60 seconds per multiple-choice question, 120 seconds per short-answer question, 10–15 minutes per essay question and 5–10 minutes for review, as outlined by Clay (2001) and supported by related studies (Schneid et al., 2014; Vegada et al., 2016). These estimates support the design of exams that are appropriately timed without under- or overloading students.

Other (Synchronous learning)

While the focus of this study is predominantly self-paced micro-credentials, these courses do occasionally contain synchronous learning sessions. The only workload calculator to propose timings for this kind of activity is that of Beer (2019), who has suggested that sessions should comprise only the time that they are scheduled for. However, this is a relatively normative perspective on engagement and does not account for the personally focused reflective practices that are also encompassed by engagement (Gourlay, 2015). As such, we propose that the duration of the synchronous session be multiplied by 1.5 to account for the invisible practices of preparation and reflection.

Testing the student workload calculator

To compare the research-based student workload calculator outputs to the advertised workload of courses, we undertook a sampling of online micro-credentials. Micro-credentials were selected as they are often offered free and fully online. Their comparatively low workload hours enabled us to more easily test the workload calculator against a higher sample of courses. Finally, learners predominantly undertake micro-credentials for lifelong learning, often while studying, working or alongside other life commitments (Pollard & Vincent, 2022). Given that workload issues are known to result in higher dropout rates (Whitelock et al., 2015), the advertised workload of micro-credentials must be accurate.

To answer research question three "How do the workload estimations produced by the calculator compare to the advertised course workload in online micro-credentials?", we identified the inclusion and exclusion criteria for micro-credentials, displayed in Table 2. These criteria not only ensured that a wide range of courses was identified but also that the sampling was reasonably constrained. FutureLearn was selected as it is a familiar platform for which we had co-designed courses. Free courses were selected as they have high enrolments. Courses of under 20 hours were selected due to high enrolment numbers but also to keep the volume of work within this study in scope. Self-paced courses were selected as they aligned with the metrics of the calculator and the aims of this research.

Table 2
Inclusion and exclusion criteria for micro-credential courses

Inclusion	Exclusion
On the FutureLearn platform	Any other learning management system or provider
Free or free to access the content with an upgrade payment for a certificate	Paid for
Course duration of under 20 hours	Course duration over 20 hours
English	Any other language
Self-paced	Facilitated

Due to the large population of online micro-credentials, we used random sampling to identify a sample set. To ensure a representative selection from the populations of online micro-credentials, systematic random sampling was employed. A confidence level of 90% and a margin of error of 10% were deemed acceptable for this research to ensure statistical robustness while ensuring practical feasibility. As of 21 June 2024, the FutureLearn population consisted of 1,363 free online micro-credentials, and as such, a sample size of 65 courses was selected. To achieve this, every 21st course was sampled, commencing at the starting point of 13, which was randomly generated using the Microsoft Excel *randbetween()* function.

On 21 June 2024, the sample courses were identified from the population of courses that met the inclusion criteria. Search filters on the FutureLearn website were used to automatically exclude any course that did not meet the selection criteria. To ensure the requisite number of courses was selected, circular random sampling was used, which meant that when we reached the end of the population, we restarted at the beginning and continued sampling until the sample size was fulfilled. We enrolled in the courses identified in the systematic random sampling. The advertised student workload (hours per week and total hours) was recorded, and then, one of us worked through the content of the course and used the workload calculator to calculate the student learning workload (total hours, hours per week and hours per learning activity type).

We set up a Microsoft Excel spreadsheet to perform the workload calculations to ensure that we consistently and reliably recorded the data. Into this, we input the word count of any written content, the duration of any multimedia and the count of any other learning activities, for example, the number of quiz questions. Other contextual data were recorded, including the course name, provider, discipline area and the level identified by the platform (beginner, intermediate or advanced). To support consistency in applying the workload calculator, we met at the commencement of data collection to collaboratively work through a course and agree on standardised means of classifying learning activities and applying workload estimates. These conventions were then applied consistently across all sampled courses. Where ambiguities arose, we discussed and resolved them through consensus rather than individual judgement. On occasion, there were tasks in a course that were unclear, either in terms of whether they were mandatory or optional; where this occurred, we examined the task and context as a group to determine how it should be classified. Further, some courses contained tests, which are a paid feature of otherwise free FutureLearn courses that students are required to complete to gain a certificate. These tests are advertised to contain between 3 and 10 multiple-choice questions. To ensure these were included in the calculated student learning time and given that our estimates are generally based on the conservative workload estimate a student is likely to spend on a course, we assumed the quizzes would contain 10 questions and, therefore, were 20 minutes in duration.

In March 2025, due to pragmatic constraints associated with an ongoing university merger, the initial sample size of 65 courses was reduced to 34. This adjustment was necessary to maintain the feasibility of data collection and analysis while preserving the integrity of the research. As a result, the margin of error increased from 10% to 15%, reflecting a reduction in statistical precision. However, a 90% confidence level was still maintained, ensuring that the findings remain robust and generalisable within reasonable limits. The systematic random sampling method was preserved, and the revised sample continues to reflect the diversity of micro-credentials available on the platform. While a larger sample would enhance precision, the revised sample remains sufficient for identifying patterns and trends in student workload estimation across online micro-credentials. While the reduction in sample size may introduce a risk of sampling bias, particularly through the under-representation of certain disciplines, course lengths or instructional designs, the preservation of the original systematic random sampling procedure helps mitigate this risk. Nevertheless, the smaller sample increases the possibility that extreme cases may exert greater influence on our results, and findings should therefore be interpreted as indicative of patterns and trends. Once the data were collected and sorted, basic descriptive statistical analysis was then undertaken using Microsoft Excel. Statistical analysis of groups based on characteristics was conducted using paired *t* tests.

Findings

The 34 courses sampled produced a relatively varied selection of duration, level and disciplinary areas. The demographic features of the courses are displayed in Table 3.

Table 3
Demographics of sampled courses (n = 34)

Domain	Classifications	*n*	%
Level of courses	Open (accessible with broad appeal)	7	21
	Introductory (no prior knowledge required)	18	53
	Intermediate (some prior knowledge required)	8	24
Overall advertised course duration	3–7 hours	13	38
	8–10 hours	11	32

Domain	Classifications	*n*	%
	11–20 hours	10	29
Disciplinary areas	Healthcare and medicine	8	24
	Business and management	8	24
	Nature and environment	4	12
	Teaching	3	9
	Study skills	3	9
	History	2	6
	Information technology and computer science	2	6
	Language	2	6
	Politics and society	2	6

A key focus of this study was the discrepancy between the advertised course duration, as determined by the provider institution, and the actual duration calculated using our workload calculator. As shown in Figure 1, the majority of courses had calculated durations longer than advertised, many substantially so. A small portion of courses had calculated durations shorter than advertised.

Analysis showed that, when compared with provider-advertised durations, 79% of the sampled courses were at least 10% longer than advertised, with 51% exceeding the advertised duration by 70% or more, and 24% taking more than twice the stated time to complete. On average, calculator-based workload estimates exceeded advertised durations by 64%, highlighting a substantial discrepancy between the two estimation approaches. A statistical test yielded a *p* value of 1.31×10^{-6}, indicating a significant difference between the advertised and calculated durations. This pattern reflected a consistent divergence between advertised and modelled workloads rather than evidence that either estimate reflected actual student workload.

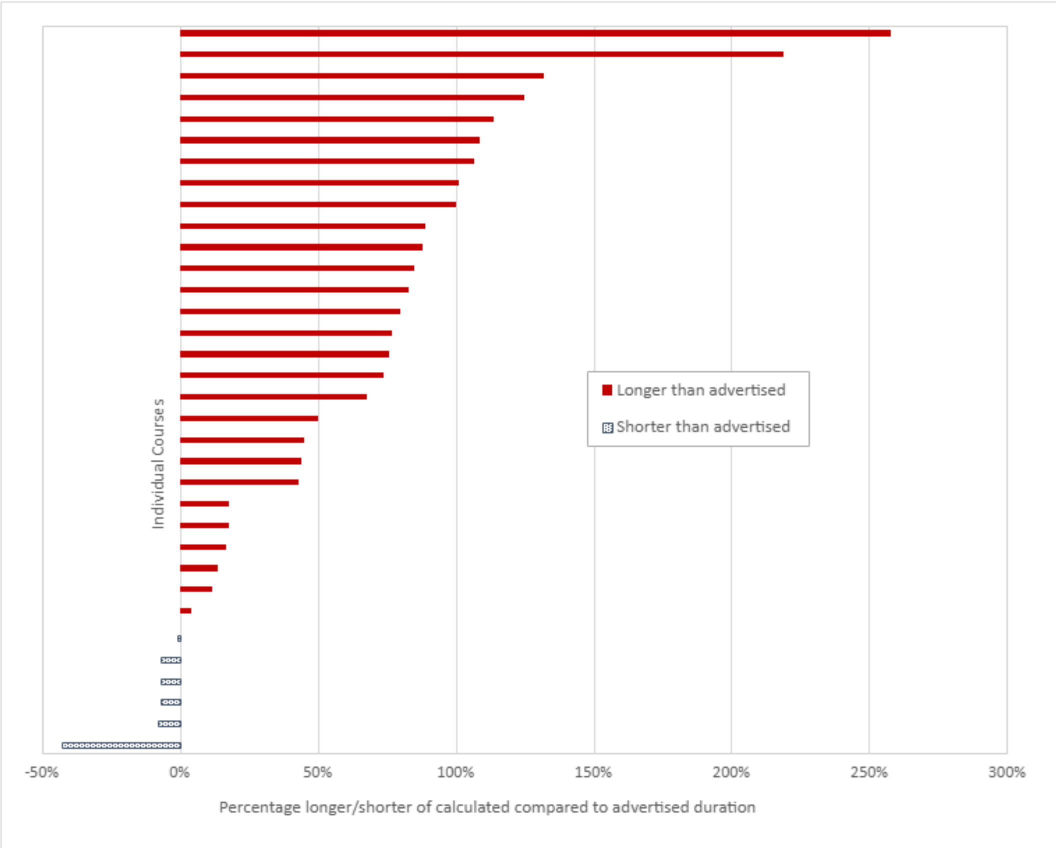

Figure 1. The percentage difference between advertised course duration and calculated course duration

While no clear pattern emerged in the discrepancy of workload estimation by discipline area or course level, a minor trend was observed in relation to course length. Specifically, courses with a shorter advertised duration (under 7 hours) were more likely to be underestimated. This trend aligned, at least anecdotally, with our experiences as learning designers, where the most significant discrepancies in estimated workload tend to occur in courses with comparatively shorter durations. There was no correlation between the misestimation of course duration and the types of activities or tasks present in the course.

Implications for practice

One of our motivations for undertaking this research was to better understand short online micro-credential courses and the associated workload, and why we felt they were comparatively more often misestimated. This study highlights a discrepancy between advertised workloads and calculator-based estimates in online micro-credentials, suggesting that commonly used advertising practices may rely on materially different assumptions about student effort than conservative, research-informed modelling approaches. While this study did not measure actual student time on task, the consistency of this discrepancy on one online platform may warrant closer scrutiny of how workloads are estimated and communicated to learners more broadly. Workload estimation is not merely a logistical concern but a fundamental issue affecting learner engagement, retention and depth of learning. When workloads are underestimated, students may struggle to balance their study commitments alongside work and personal responsibilities, leading to increased stress and a higher likelihood of disengagement. More concerningly, discrepancies in workload could push learners towards superficial skimming rather than deep engagement with course materials, undermining the quality of learning experiences (Bowyer, 2012).

A particularly notable trend emerging from our findings is that courses under 8 hours in duration exhibited the highest likelihood of workload discrepancy. One explanation for this is that shorter courses are more sensitive to minor miscalculations in individual activity durations. Unlike longer courses, where workload inaccuracies may be absorbed across multiple activities, short courses are disproportionately affected by even small variations. For example, a miscalculated reading or discussion task in a 5-hour course has a far greater impact than the same miscalculation in a 20-hour course. This aligns with our professional experience as learning designers, where shorter courses are often the most misestimated, particularly in relation to tasks that involve self-paced engagement. This suggests that providers may need to exercise greater caution when estimating the workload for short courses to ensure more accurate student expectations.

An additional consideration is the way workload is represented in advertised course durations. Many providers present a single estimate, perhaps reflecting a best-case scenario. However, our approach uses a conservative workload estimate by producing an estimate based on the higher end of what most students are likely to experience. While this ensures a more realistic workload representation, it raises questions about how best to communicate workload to students. Overly optimistic estimates may attract more students but risk higher dropout rates when they realise the course is more demanding than expected. Conversely, conservative estimates reflecting maximum workloads may deter potential learners who perceive the course as too time-intensive. Striking a balance between transparency and accessibility remains a key challenge for institutions designing online micro-credentials.

The presence of workload estimations within courses themselves also warrants discussion. Providing learners with explicit time expectations for activities can be beneficial. However, it can also have unintended consequences. If students find that their actual engagement time exceeds the suggested duration, they may experience frustration or self-doubt about their progress. The utility of workload estimates may also vary by task type and discipline. For structured activities such as multiple-choice quizzes, estimated completion times are relatively stable. In contrast, open-ended activities, such as investigative tasks or discussion contributions, can vary significantly depending on individual engagement levels. Here, estimated times may serve more as a scoping tool, helping students understand the expected depth of engagement rather than dictating an absolute duration.

Finally, while workload calculators offer a structured approach to estimating study time, it is essential to recognise that they are not objective instruments but interpretive tools. Any workload calculator is built upon underlying normative assumptions about student engagement, prior knowledge and cognitive effort – all of which are inherently variable. Rather than serving as definitive measures, these tools should be seen as prompts for critical reflection. When discrepancies arise between estimated and actual workloads, they should prompt educators to interrogate their assumptions about learning tasks: Are certain activities taking longer than expected? Are self-directed elements of learning being adequately accounted for? How do different learners experience the same workload? By using workload calculators as reflective instruments rather than rigid formulas, educators can refine course design to better support student learning and success. When used in this way, workload calculators function less as objective measurement instruments and more as reflective tools that prompt educators to interrogate assumptions about task design, learner effort and time on task.

Conclusions

This study represents a cohesive drawing together of disparate workload calculators and literature into a single combined workload calculator that can be adopted and adapted by the reader. Through the application of this calculator, we identified widespread discrepancies between advertised workloads and calculator-based estimates, raising concerns about the potential for workload underestimation in online micro-credentials. Importantly, this study did not establish which workload estimate was more accurate in relation to student experience; rather, it demonstrated that different estimation logics produced different results.

While workload calculators provided a structured approach to estimation, they should be viewed as reflective tools rather than definitive measures. Ensuring realistic workload estimates is not just a matter of accuracy but a crucial factor in supporting student engagement, retention and deep learning. Institutions must strike a balance between transparency and accessibility in workload communication, recognising that overestimation or underestimation can have unintended consequences. Moving forward, a more nuanced approach to workload estimation (one that accounts for the variability of student experience and the complexity of learning tasks) will be essential in improving the design and delivery of online micro-credentials.

Limitations

Estimating student workload is inherently complex, as it is influenced by multiple interrelated factors, including disciplinary differences, prior knowledge, variations in learning pace and the nature of learning activities (Bowyer, 2012). While workload calculators provide a systematic approach, they remain a blunt instrument for a precise task, relying on generalised assumptions that cannot fully capture the diversity of student experience. Averages obscure outliers, meaning that although the calculator offers a structured estimate, individual students may experience substantially different workloads based on their backgrounds, learning strategies, and external commitments. A further limitation is the reliance on conservative workload estimates. While this reduces the risk of underestimation, it may not reflect all learners' experiences: some students may complete tasks efficiently, while others require additional time, particularly for open-ended or cognitively demanding activities. Workload estimates also do not account for external factors such as interruptions, digital literacy or personal circumstances – all of which affect time on task. We also note that this study, and the research underpinning the calculator, predate the widespread availability of generative artificial intelligence tools; evolving technologies and study practices may therefore affect the calculator's future reliability.

Testing of the workload calculator introduces additional limitations. The sample was drawn from a single platform and limited to free, self-paced micro-credentials, constraining generalisability to paid, facilitated or differently structured offerings. Pragmatic constraints also reduced sample size, increasing the margin of error and the likelihood that some course types or disciplines are under-represented, despite the use of systematic random sampling. Finally, although workload calculations were guided by a standardised, rule-based approach and supported through team calibration and consensus, formal measures of inter-rater reliability were not calculated. These limitations reflect the exploratory, modelling-oriented nature of the study and identify clear directions for future research across platforms, course types and independent raters.

Given these complexities, workload estimation should be treated not as a definitive measure but as a critical lens through which academic staff and learning designers can reflect on course workload and structure. Rather than replacing academic judgement, workload calculators should complement it by prompting educators to interrogate assumptions and refine design decisions. A more triangulated approach – combining institutional workload reporting, calculator estimates, and student self-reported workload – would provide a richer understanding of student experience and help ensure that online micro-credentials remain both manageable and pedagogically effective.

Author contributions

Richard McInnes: Conceptualisation, Methodology, Investigation, Formal analysis, Project administration, Writing – original draft, Writing – review and editing; **Ngoc Nhu (Ruby) Nguyen:** Writing – original draft, Writing – review and editing, Methodology; **Sasikala Rathnappulige:** Writing – original draft, Writing – review and editing; **Simon Marek:** Investigation, Writing – review and editing; **Daniel J. Searson:** Investigation, Visualisation; **Ashlee Waterland:** Investigation.

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