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Building a Methodology to Connect Course Design with Student Outcomes: A Framework for Engineering Education

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Introduction

This full-length methods study presents a systematic framework for examining how instructional design features in engineering courses relate to student learning, engagement, and academic progression, within the broader shift toward online and blended learning in higher education. Over the past two decades, online and blended modalities have expanded rapidly from niche alternatives to central modes of pedagogical delivery [1]. This shift accelerated sharply during the COVID-19 pandemic, compelling institutions worldwide to convert face-to-face instruction into emergency remote teaching and, subsequently, to design more intentional online learning environments [2]. In engineering education, this expansion has heightened the need to move beyond technological adoption toward systematic evaluation of learner experience, instructional quality, and measurable outcomes [3].

Central to the success of online engineering courses are learner engagement and satisfaction, both of which are strongly associated with academic persistence and achievement [3, 4]. Effective pedagogical strategies such as active learning, authentic assessment, and structured interaction are essential for sustaining engagement, preventing isolation, and supporting deeper learning [5, 6]. Self-regulatory behavior further predicts success in online environments [7]. Yet engagement and persistence do not emerge by chance: they are products of deliberate instructional design decisions embedded in course structure, feedback mechanisms, and accessible resources [8, 9]. As online learning matures within colleges of engineering, there remains a persistent need to evaluate its effectiveness systematically by examining how specific design configurations relate to what students actually do and how they ultimately perform.

To address this need, an instructional support unit at a large public R1 engineering institution developed an internal course review tool to assess the quality of online courses. Originally created as a checklist informed by instructional designer expertise, the tool evolved into a rubric adapted from the OSCQR framework developed by the State University of New York [10]. The rubric integrates established research on online course quality with faculty feedback to ensure relevance to engineering education. This study leverages the rubric alongside learning management system (LMS) behavioral data to examine relationships between course design features and student outcomes, with the goal of advancing a replicable, transparent framework for evaluating online course design across institutional contexts. Specifically, we ask: 1) How can existing course review artifacts be operationalized into theoretically grounded design indices, and 2) how do these indices relate to course-level patterns in LMS behavior and student performance in online engineering courses?

Literature Review

Research on online and blended learning has consistently demonstrated that instructional design shapes student learning experiences and outcomes. Prior studies have examined how decisions related to learning objectives, assessment structures, interaction opportunities, and course organization influence engagement, satisfaction, and achievement [8, 11, 12]. Meta-analyses further indicate that well-designed online courses can produce learning outcomes comparable to or exceeding those of traditional instruction when alignment, feedback, and interaction are intentionally structured [5, 7]. Despite this empirical base, prior work has been less successful in establishing systematic, replicable approaches for connecting instructional design artifacts to student outcomes in a theoretically grounded and analytically transparent manner [8, 13].

Instructional Design as a Dimension of Course Quality

A substantial body of research has formalized principles of effective online course design through instructional design frameworks and course quality rubrics. These frameworks emphasize alignment among learning objectives, activities, and assessments; clear course structure; appropriate workload and pacing; meaningful interaction; and accessibility for diverse learners [8, 9]. In engineering education, such frameworks have been widely adopted to support faculty development, ensure baseline quality across online offerings, and guide course review at scale, particularly following COVID-19 [2, 3]. Empirical studies using course quality rubrics typically focus on documenting design practices, examining faculty perceptions, or evaluating changes following redesign initiatives [14, 15]. While this work has established shared design standards, instructional design is often treated as an evaluative outcome rather than an analytic construct [8, 16]. Rubric scores are frequently aggregated into overall quality ratings, limiting insight into how distinct design dimensions function in relation to student engagement and learning. As a result, instructional design frameworks have been underutilized as data sources for empirical analysis of student outcomes.

Linking Course Design Features to Student Outcomes

Active learning, authentic tasks, structured feedback, and interaction are associated with improved engagement and learning in engineering contexts [5, 6, 17]. Research on persistence further emphasizes clear expectations, coherent organization, and instructor presence for learners requiring greater self-regulation [11, 12]. However, most of this work operationalizes design at a granular level, isolated components such as discussion frequency or assessment type, rather than as an integrated system [18, 19]. This fragmentation limits cumulative comparison and weakens understanding of how combinations of design decisions shape outcomes across contexts.

Learning Analytics and the Absence of Design Artifacts

Learning analytics has introduced powerful methods for modeling student engagement, performance, and persistence from LMS trace data [13, 19]. In engineering education, these approaches have been used to identify behavioral patterns, predict course success, and flag students at risk of attrition [13, 20]. Despite their analytic sophistication, such studies typically treat course design as an implicit background condition rather than an explicit object of analysis [20]. LMS behaviors are shaped by instructional intent, assessment structures, and interaction requirements, yet these design elements are rarely incorporated into analytic models. As a result, learning analytics findings often lack interpretive grounding in instructional design and are difficult to translate into concrete improvement decisions [19, 20]. This disconnect between design artifacts and outcome modeling has been identified as a key barrier to actionable analytics and design-informed intervention [13, 21]. Prior research establishes that course design matters but reveals a persistent methodological gap: design frameworks remain largely descriptive, learning analytics models omit instructional context, and studies linking design to outcomes focus on isolated features rather than integrated systems. This gap is particularly consequential in high-stakes online engineering courses, where design decisions compound across a full semester of student experience. The present study addresses this gap by demonstrating a systematic methodology that treats instructional design artifacts as analyzable data, operationalizes design constructs transparently, and links them directly to student-level outcomes to produce a pipeline that is replicable, adaptable, and grounded in both theory and practice.

Theoretical Framework

This study views online course design as a key mechanism through which engineering programs shape student learning, engagement, and progression. Four theoretical strands anchor the framework and map directly onto the Scorecard's domains.

Constructive alignment [22] holds that objectives, activities, and assessments must cohere so that every course element supports intended learning. The Scorecard captures this through measurable objectives, milestone-structured assignments, calibrated formative and summative assessments, and transparent grading policies [8, 9].

Scaffolding and pacing involve sequencing tasks and gradually releasing support to build learner competence [7]. The Scorecard operationalizes this through content chunking, balanced workload distribution, clear orientations and schedules, and documentation of instructional time — features particularly consequential in engineering courses where technical content density is high.

Engagement and interaction must be deliberately designed in online engineering environments [6]. The Scorecard addresses instructor presence, substantive feedback, higher-order activities, and structured peer collaboration — factors linked to persistence, deeper learning, and professional identity formation [3, 12].

Accessibility and inclusive design are treated as core dimensions of quality rather than compliance add-ons [3]. Accessible formats, assistive technology compatibility, and color-independent visuals reduce participation barriers and support equitable engagement across diverse student populations.

Collectively, the Scorecard's domains are synthesized into four analytic constructs: alignment quality, scaffolding and pacing, engagement and interaction, and accessibility and inclusion. The framework posits that measurable variation in these constructs corresponds to meaningful variation in student outcomes [20, 22], and the study's contribution lies in demonstrating a replicable pipeline for examining these relationships using existing course artifacts, one that any institution with an LMS and a course review process can adapt.

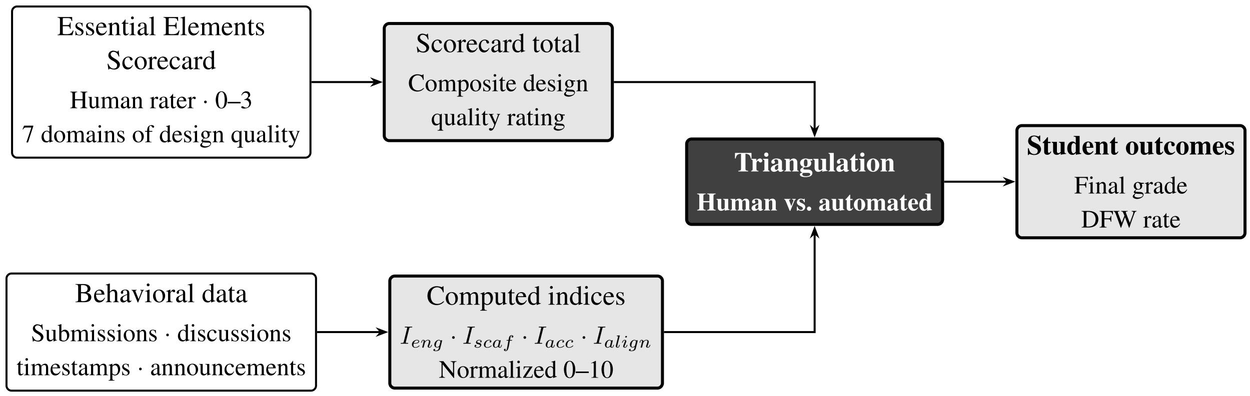

FIGURE 1. Design–outcome triangulation framework. The Essential Elements Scorecard (human rater assessment) and behavioral data extracted from the LMS operate as independent streams. Scorecard totals and computed indices converge at triangulation, which is validated against student outcomes.

Methodology

This study adopts a multi-course descriptive case study design to develop and demonstrate a systematic method for (a) quantifying online course design features using an established scorecard, (b) aggregating them into theoretically grounded constructs, and (c) linking these constructs to student outcomes. Conducted at a large public R1 engineering institution, the pilot includes 11 randomly selected fully online undergraduate engineering courses. The primary contribution lies in the methodological framework and its demonstration, rather than in making definitive causal claims about specific design features.

Context and Course Sample

The sampling frame comprised fully online undergraduate engineering courses offered within the institution's LMS during a single academic year. Eligible courses were (a) fully or primarily online, (b) enrolled undergraduate engineering students, (c) contained complete instructional materials and assessments, and (d) were taught by a primary instructor of record. Eleven courses were selected through simple random sampling to ensure methodological applicability across a diverse set of offerings rather than only exemplary or recently redesigned ones. It is worth noting that some courses in the sample, particularly capstone and small seminar sections, involve pedagogical activity outside the LMS. This is addressed as a boundary condition in the Results.

Instrument: Essential Elements Scorecard for Online Courses

Course design was measured using the Essential Elements Scorecard for Online Courses, adapted from the OSCQR framework developed by the State University of New York [10]. The Scorecard covers seven domains representing widely recognized best practices in online learning:

- *Structure:* objectives, policies, overviews, schedules, navigation
- *Content and layout:* organization, chunking, workload balance, instructions
- *Media quality:* video focus, lighting, audio consistency and pacing
- *Engagement:* interactive resources, higher-order activities

- *Accessibility:* accessible formats, assistive technology, alt text, color
- *Interaction:* instructor presence, feedback timeliness, peer collaboration
- *Assessment:* grading policies, formative and summative methods, rubrics, alignment

Each element is scored on a four-point scale: 3 (present and meets good practice), 2 (somewhat present; $\sim$30 min of revision), 1 (needs major improvement; $\geq$1 hr of revision), and 0 (absent). These anchors are calibrated around revision effort as a practical proxy for design presence and quality—a convention consistent with prior rubric-based research [8, 14]. While the anchors are ordinal in origin, analyses rely on continuous scores to preserve variability in course design quality, which is standard practice in rubric-based learning analytics research. The Scorecard also includes a Documentation of Instructional Time Planning Table that catalogs faculty instruction and student academic activities, supporting estimates of workload distribution.

Data Pipeline and Extraction

To complement scorecard evaluations with behavioral data, raw student interaction logs were extracted from the institutional LMS data warehouse using SQL-based queries. The extraction workflow joined course, assignment, and submission tables to reconstruct the temporal flow of each course. These logs were aggregated into normalized indices on a 0–10 scale to enable direct comparison across varied courses (Fig. 1). All data handling procedures complied with the institutional IRB protocols for secondary use of educational records.

Operationalization of Design Constructs

Item-level scorecard scores were aggregated into four subscale indices instantiating the theoretical constructs. The aggregation approach is transparent and adaptable: institutions may adjust item assignments to match their own scorecard structure.

- *Alignment quality index (I_{align}):* Items addressing coherence among objectives, activities, and assessments, including measurable objectives, milestone-structured assignments, appropriate formative and summative assessments, and consistent grading policies. Due to the semantic complexity of alignment judgment, I_{align} was evaluated through structured human assessment using a standardized rubric rather than automated extraction.
- *Scaffolding and pacing index (I_{scaf}):* Content chunking, workload balance, course and module-level overviews, navigation clarity, and documentation within the instructional time planning table.
- *Engagement index (I_{eng}):* Interactive resources, higher-order and real-world activities, instructor presence and feedback, structured peer interaction, and participation expectations.
- *Accessibility index (I_{acc}):* Accessible content formats, assistive technology compatibility, text equivalents for media, and color usage.

For the quantitative demonstration, constructs were operationalized as normalized indices on a 0–10 scale using the formulations in Table 1. Equal weighting across index components was adopted as a neutral baseline pending empirical validation of differential weights in engineering course contexts.

TABLE 1. Calculated Indices for Analysis

Index	Formula / Description
Engagement (I_{eng})	$I_{eng} = \frac{10}{3}\left[\frac{P_{disc}}{100} + \frac{N_{rep}}{\max(N_{rep})} + \frac{N_{ann}}{\max(N_{ann})}\right]$ P_{disc}: % of distinct students posting at least once N_{rep}: instructor reply count N_{ann}: announcement count
Scaffolding (I_{scaf})	$I_{scaf} = \frac{10}{3}\left[\delta_{orient} + \left(1 - \frac{D_{first} - \min(D)}{\max(D) - \min(D)}\right) + (1 - P_{late})\right]$ δ_{orient}: 1 if orientation/welcome module exists, else 0 D_{first}: median days to first student submission P_{late}: proportion of late submissions
Accessibility (I_{acc})	$I_{acc} = \frac{\text{Accessibility Score}}{10}$ Derived from Anthology Ally institutional reporting; rescaled to 0–10.
Alignment Quality (I_{align})	Due to the semantic complexity of aligning course learning outcomes with assignment and quiz content, alignment quality was evaluated through structured human assessment using a standardized rubric examining coherence among learning objectives, instructional activities, and assessments.

Data Collection and Analysis

Scorecard review. Each course was independently reviewed in the LMS by at least two trained raters, assigning scores from 0 to 3 per element. Raters recorded qualitative notes to support score-level discussion.

Rater training and calibration. Prior to scoring, raters completed a calibration session using practice courses not included in the main sample, developing shared interpretations of each score level.

Interrater reliability. All 11 courses were double-coded. Reliability was assessed at item level using Cohen's kappa and at subscale level using intraclass correlation coefficients. Substantial disagreements were resolved through consensus discussion.

Outcome data extraction. Student-level data were extracted under IRB-approved protocols. Identifiers were removed or replaced with pseudonyms; course identifiers were coded to prevent instructor or student identification. Outcome variables were merged with course-level design indices using course IDs.

Analysis. Descriptive statistics were computed for item-level and subscale scores. Distributions across domains were examined to identify design strengths and weaknesses. The Scorecard's interpretive thresholds (excellent, good, average, undesirable) contextualized aggregate quality while preserving domain-level nuance. Exploratory correlations between course-level indices and aggregated outcomes (mean final grade, DFW rate, LMS engagement) illustrated potential design–outcome linkages, consistent with the study's focus on methodological demonstration rather than causal inference.

Results

Aggregate Analysis: Design-Behavior Hierarchy

Courses were clustered into three implementation tiers—High, Mixed, and Low Structure—based on the distribution of I_{scaf} scores across the sample. Table 2 presents the full set of indices and outcomes by course. The clusters reveal a broad pattern: courses in the High Structure tier tend toward lower DFW rates, while courses in the Low Structure tier show higher attrition, with notable exceptions addressed in the Boundary Conditions section. This pattern supports treating course design as a measurable, differentiated construct rather than an abstract notion of quality.

TABLE 2. Course Design Indices and Student Performance Outcomes

Course	I_{eng}	I_{scaf}	I_{acc}	**Avg Grade** ($\bar{M}$)	**DFW (%)**
High Structure					
Course 01	10.00	9.58	9.1	78.7	15.3
Course 02	7.97	9.40	9.5	94.6	0.3
Course 03	3.83	9.27	9.9	92.9	27.5
Course 04	3.48	9.64	8.9	91.7	4.2
Mixed Structure					
Course 05	0.89	8.80	8.5	94.8	0.7
Course 06	0.27	7.06	9.9	97.4	0.0
Course 07	0.81	6.37	9.3	87.9	12.5
Low Structure					
Course 08	0.11	5.87	9.9	96.4	0.0
Course 09	0.05	4.01	5.8	78.5	35.2
Course 10	0.00	2.87	9.7	87.1	27.3
Course 11	1.04	2.54	9.8	88.6	20.2

Note. All indices normalized 0–10. DFW = D, F, or Withdrawal rate. Shaded rows indicate courses discussed in the boundary condition analysis.

Methodological Validation: Automated vs. Human Assessment

A critical methodological question is whether automated LMS signals align with the qualitative realities observed by human reviewers. To examine this, we conducted a comparative case analysis between Course 02 (High Structure) and Course 09 (Low Structure), the two courses with the greatest divergence in I_{scaf}. Table 3 presents the triangulation of automated indices, scorecard audit findings, rater comments, behavioral results, and student outcomes. Across all three automated indices, the quantitative signals showed convergence with the human rater's qualitative assessment: Course 02 was rated as meeting good practice with high instructor presence, while Course 09 was flagged for an inactive office hours link and absent course introduction video. The correspondence between a 0.3% and 35.2% DFW rate across these two courses further suggests that design intent, as captured by the indices, is reflected in observed student outcomes.

TABLE 3. Triangulation of Automated Signals and Human Design Review

Comparison Point	**Course 02 (High)**	**Course 09 (Low)**
Engagement (I_{eng})	7.97 — high engagement	0.05 — low engagement
Scaffolding (I_{scaf})	9.40 — high structure	4.01 — low structure
Accessibility (I_{acc})	9.5 — high access	5.8 — low access
Scorecard audit	Meets good practice	Needs improvement
Rater comments	"High level of instructor presence observed."	"Office hours button not active; no course intro video."
Behavioral result	27 instructor replies	0 instructor replies
Student outcome	0.3% DFW rate	35.2% DFW rate

Boundary Conditions of the Framework

The methodology highlights the importance of contextualizing design indices with course metadata. Three boundary conditions emerged that clarify the limits of LMS-based indices.

Class size effect. Course 06 achieved a 0.0% DFW rate despite low engagement ($I_{eng} = 0.27$). Its very small enrollment ($N = 5$) enabled high-touch instruction occurring outside the LMS.

Assessment type effect. Course 07 showed modest scaffolding ($I_{scaf} = 6.37$) but a contained DFW rate (12.5%), reflecting an exam-heavy structure where pacing is driven by high-stakes assessments rather than LMS-mediated scaffolding.

Capstone effect. Course 08 recorded very low engagement ($I_{eng} = 0.11$) and moderate scaffolding ($I_{scaf} = 5.87$) yet a 0.0% DFW rate. As a project-based capstone for graduating seniors, substantive work occurred offline, limiting the interpretive value of LMS engagement indicators.

Collectively, these patterns suggest that LMS-based design indices become more analytically powerful as courses scale in enrollment and rely more heavily on structured digital interaction. Small, capstone, or seminar-style courses may require adjusted or reweighted indices that reflect their distinct pedagogical models.

Discussion

The results demonstrate that composite course design indices show preliminary alignment with student success patterns. The distinction among high-, mixed-, and low-structure courses supports a foundational premise: design is not an abstract notion of quality but a measurable, differentiated configuration of deliberate instructional choices. This suggests a reframing of what learning analytics can do in engineering education. Rather than asking only *how students behave*, the framework asks *why* and finds the answer, in part, in the course itself.

The convergence between automated LMS indices and human scorecard ratings is a practically meaningful observation in this study. Constructive alignment theory holds that coherent course design shapes the conditions for learning [22]; the triangulation in Table 3 shows this is not merely theoretical. When a course lacks an orientation module, provides no instructor replies, and leaves an office hours button inactive, the LMS detects the absence. When a course is intentionally structured with visible milestones, timely feedback, and clear interaction expectations, the indices reflect that too. Design intent is legible in behavioral data and that legibility is what makes this framework actionable.

The boundary conditions identified earlier are equally instructive. Small enrollment courses, capstone sections, and exam-heavy designs each expose a limit of LMS-centric indices. Not because the framework fails, but because these course types route meaningful pedagogical activity outside the platform. This aligns with Gašević et al.'s argument that learning analytics must account for instructional conditions rather than treating them as fixed background [20].

Implications for Practice

For instructional support/design units, the framework offers a scalable diagnostic pipeline. Rubric-based scorecard reviews already exist at many institutions; what has been missing is a systematic method for connecting those reviews to behavioral and outcome data. Instructional units can use the four indices to prioritize redesign efforts, targeting courses where scaffolding is low, DFW rates are high, or engagement diverges from alignment quality. Faculty development can shift from generic best-practice workshops toward data-informed conversations grounded in a specific course's design profile.

For engineering education programs, the framework surfaces design as a lever for equity. DFW rates are not randomly distributed. They concentrate in courses where structure is low, feedback is absent, and accessibility is inadequate. The methodology makes this visible at a high-level program scale and such visibility is the precondition for change.

Implications for Research

The methodology advances learning analytics by treating instructional design artifacts as analyzable data rather than background conditions [13, 19]. This supports cumulative, comparative research across courses, institutions, and modalities. Future work should expand the sample to support inferential analysis, validate index weights against outcome data across disciplines, and examine whether the framework generalizes beyond engineering to other STEM fields with similarly high-stakes online offerings.

A particularly promising direction is the automation of I_{align} through large language model (LLM) evaluation. Alignment quality currently requires human raters because coherence between learning objectives and assessment content demands semantic judgment. LLMs fine-tuned on rubric anchors could automate this step by ingesting course learning outcomes and assignment prompts and returning alignment scores at scale. This would close a manual bottleneck in the pipeline, enabling institution-wide deployment without proportional increases in rater labor. Validation against expert coders would be an essential prerequisite before deployment.

Limitations

Generalizability is constrained by the small course sample, which was selected to demonstrate methodological feasibility rather than support statistical inference. LMS data, for online courses, omit activity in external tools, office hours, and informal channels, potentially underestimating engagement in courses that route instruction outside the platform. Index weights were set as equal-weighted baselines; differential weighting validated against outcome data may improve predictive utility. Member checking with instructors familiar with these courses would help verify whether the indices capture meaningful variation in course quality [8]. Finally, in this study, I_{align} relies on human assessment, limiting scalability until automated scoring is validated.

Conclusion

Online courses leave a trail. Every submission timestamp, every instructor reply, every accessibility score is a trace of deliberate design decisions or the absence of them. This study introduced a replicable methodology for connecting online course design to student outcomes in engineering education. By operationalizing the Essential Elements Scorecard into four theoretically grounded indices (engagement, scaffolding, accessibility, and alignment) and linking those indices to LMS behavioral data and student performance, the framework demonstrates that instructional design artifacts can function as analyzable data rather than background conditions. The triangulation of automated signals against human scorecard ratings provides a validation mechanism, and the boundary condition analysis clarifies where LMS-based indices are most and least interpretable. Together, these contributions offer a transparent, adaptable pipeline that instructional support units and researchers can deploy across institutional contexts.

The framework does not replace expert judgment. It directs it, surfacing which courses most urgently need attention and making the logic of design visible at program scale. When alignment quality can be evaluated computationally at scale, the pipeline becomes institutional infrastructure, supporting proactive course review before student outcomes are affected.

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Appendix A: Essential Elements Scorecard for Online Courses

The following instrument was adapted from the OSCQR Online Course Quality Review Rubric developed by the State University of New York and the Online Learning Consortium [10]. It was used as the primary course review instrument in this study. Elements shaded in grey are optional ("good to have") items. Scoring anchors: 3 = present and meets good practice; 2 = somewhat present (∼30 min of revision); 1 = needs major improvement (≥1 hr of revision); 0 = absent.

Element	3	2	1	0
Structure				
Course includes Welcome, contact information for instructor and department, and Getting Started content, with links to campus policies on plagiarism, ADA, and student support.				
Course objectives/outcomes are clearly defined, measurable, and aligned to learning activities and assessments.				
An orientation or overview is provided for the course overall and in each module. A clear schedule is provided with due dates and times for all activities. Navigation is clearly set up for learners.				
Course provides access to learner success resources including a printable and accessible syllabus, technical help, orientation, and tutoring. Requisite technology skills are clearly stated.				
Content and Layout				
A logical, consistent, and uncluttered layout is established. The course is easy to navigate with consistent color scheme, icon layout, and self-evident titles.				
Course content is chunked appropriately into manageable sections. Workload is balanced across the course period.				
Instructions are provided and well written.				
Course is free of grammatical and spelling errors. *(optional)*				
Text is formatted with titles, headings, and styles to enhance readability. *(optional)*				

Continued on next page.

Appendix A continued.

Element	3	2	1	0
Slides and documents follow a consistent layout with good practices in text density. *(optional)*				
Media Quality (if used)				
Video quality: effective focus, angles, framing, lighting, motion, and background that enhance learning.				
Audio quality: consistent volume, equalization, enunciation, pacing, and clean sound.				
Engagement				
Course offers access to a variety of engaging resources that facilitate communication, collaboration, content delivery, and learning.				
Course provides activities for learners to develop higher-order thinking and problem-solving skills, including critical reflection and analysis.				
Course provides activities that emulate real-world applications such as experiential learning, case studies, and problem-based activities. *(optional)*				
Accessibility				
Text content is available in an easily accessed format, preferably HTML. All text is readable by assistive technology, including PDFs and text in images.				
A text equivalent for every non-text element is provided (alt tags, captions, transcripts, etc.).				
Text, graphics, and images are understandable when viewed without color.				
Interaction				
There is a plan to establish and maintain instructor presence and instructor–student interaction. Expectations for timely and regular feedback are clearly outlined. One hour or more of interaction per week is included as appropriate for class size.				

Continued on next page.

Appendix A continued.

Element	**3**	**2**	**1**	**0**
Course offers opportunities for learner-to-learner interaction and constructive collaboration with activities intended to build community.				
Expectations for interaction are clearly stated (netiquette, grade weighting, models/examples, timing, and frequency of contributions).				
Assessment				
Course grading policies are clearly outlined in the syllabus and repeated in all assessment elements.				
Course includes frequent and appropriate formative and summative methods to assess learners' mastery of content.				
Criteria for graded assignments are clearly articulated through rubrics or exemplary work.				
Learners have opportunities to review their performance and assess their own learning throughout the course (pre-tests, self-tests, reflective assignments).				
Major assignments are clearly aligned to course learning objectives and have intermediate steps built in to show progress.				
Scoring thresholds (fundamental elements): Score $\geq$60 = Excellent; Score $\geq$54 = Good; Score $\geq$44 = Average; Score $\leq$40 = Undesirable.				

Note. Adapted from the OSCQR Online Course Quality Review Rubric [10]. Grey rows indicate optional elements not included in fundamental scoring.