Adaptive Assessment Feedback in Competency Based Learning Ecosystems

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ABSTRACT

Agile feedback frameworks utilized in competency-based learning (CBL) environments and adaptive instructional systems (AIS) are crucial to support next generation training and learning ecosystems for the military, warfighters and future workforce. Current adaptive systems utilizing learner analytics often elicit copious performance data without considering holistic, personal characteristics essential to learning. This includes prior knowledge, differentiated learning constructs, learner preferences, and scaffolding learning progress through continuous, agile feedback. Without the direct correlation to immediate, actionable feedback and progress measurement within an assessment, learners are ill-equipped for operational readiness within the learning ecosystem.

This paper provides an overview of current CBL evaluation approaches and contemporary issues encompassing universal designs within digital transformations to inform the conceptual development of a Competency-Based Learning Environment Assessment Feedback Framework matrix (CB-LEAFF). Grounded in theories of distributed learning and cognition, CB-LEAFF intends to provide an adaptive, assessment feedback architecture for capturing interactions between training and learning assessment artifacts by leveraging parallel streams of data and information. Finally, the paper identifies barriers impacting future readiness and concludes with a discussion of future CB-LEAFF development and research.

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INTRODUCTION

Competency-based learning (CBL) is not a new paradigm. According to Stafford (2019), competency-based learning is a logical derivation from explicit innovations, including the scaffolding of skills and knowledge; development of outcome-based levels of mastery; assessments to demonstrate mastery; and converging notions of outputs (learner rather than instructor) and inputs (curriculum and time invested). Recent advancements in digitalization and automation across industry, government, and military sectors have led to sustainability challenges. These challenges have compounding effects in training and education (Simic & Nedelko, 2019). According to Smith, Hernandez, and Gordon (2018), an assessment of the Future Operational Environment conducted by the U.S. Army Training and Doctrine Command (TRADOC G-2) underscores rapid training, societal, and cultural changes driven by advances in science and technology which will impact the art of warfare through 2050 (p.1). Globally, this equates to a need for highly qualified, skilled personnel who can respond to change, demonstrate enhanced problem-solving skills, and easily adapt to complex needs (Andrews and Higson, 2008; Boahin and Hofman, 2013). The implication for future readiness requires not only technical skills but additionally employability skills allowing personnel to develop, adapt, and transform existing skills to new contexts (NCTVET, 2006; Gibbs, 2004; Boahin and Hofman, 2013). This underscores the importance of the human component as the cornerstone of successful plans to implement technological advancements using competency-based learning frameworks. This paper explains the urgent need for an innovative framework using mobile learning technologies and describes some efforts that move in this direction. based on adaptive instructional systems, mobile learning frameworks, and theoretical paradigms.

Challenges of Competency-Based Evaluation Frameworks

Hattie (2012) named two elements as "essential to learning": 1) a challenge for the learner; and 2) feedback. If either is insufficient, neural connections are neither strengthened nor altered and performance is therefore unaltered. To meet the needs of diverse learners, key methodologies in teaching and training must be utilized which emphasize the development of not only employable skills, but relatable and authentic feedback experiences within CBL. This includes frameworks and theories that utilize educational technology, such as mobile devices, to afford users and learners greater access to relevant information, reduce cognitive load, and increase access to competencies and systems (Koole, 2009). The demand driven and outcomes-based frameworks of CBL paired with technology assessment frameworks can bridge the gap for urgently needed skills to support current work and future innovation. Yet, gaps in research attest to the lack of universality in competency-based evaluation frameworks, especially those utilizing mobile technology. Assessment must be viewed as a continuum from the earliest stages of professional training through continued learning in practice (Bashook, 2005). Skill acquisition within CBL frameworks is affected by assessment and feedback, which have been recognized as the most crucial aspects to enhance skill sets.

The struggle for a large portion of trainees and learners in competency evaluation is not the assessment itself, but rather underlying issues of access to relevant information, extension/review materials, peers/cohorts, agile technologies with sound theoretical underpinnings, and most importantly real-time feedback (Woods & Hollnagel, 2006). Learning content as a hierarchical structure has reflected shifts in paradigms revealing the need for personalized learning paths incorporating learner preferences and cognitive styles. However, these personalized approaches have yet to transfer to assessment feedback frameworks which further obstructs learning outcomes (Abbott, 2019). Data is not being recorded and utilized in a way that is truly meaningful to provide the adequate information regarding the actual learner's distinct knowledge, skills, and attributes (Gervais, 2016). As a result, this wasteful lack of efficiency further compounds content iterations and resources for nontraditional education and training practices, such as competency-based training and assessments (Dreyfus & Dreyfus, 1980; Gervais, 2016; Woods & Hollnagel, 2006). Often stakeholders are operating under outdated models of assessment, typically with data focused on summative evaluations or decontextualized snapshots of a learner's performance without authentic feedback (Smith, Hernandez, & Gordon, 2018).

Joint Cognitive System Models for Assessment Feedback

Emerging technologies are transforming how training and education enhance learner outcomes causing radical shifts in antiquated paradigms of instructional delivery and assessment. This includes deviations in instructional theories on meeting needs of diverse learners through design, delivery, and coordination of learning processes. Optimizing learner mastery within CBL frameworks requires a joint cognitive system framework incorporating human-computer interactions, learning environments, and learning artifacts to redefine and reimagine successful learning interventions. Current advancements in data analytics, learning science and cognitive science create innovative opportunities to scaffold learning through feedback enhancing self-regulatory behaviors and self-efficacy strategies. For instance, some such models which engage learners in deeply metacognitive instances integrate interdisciplinary frameworks of distributed cognition and learning, feedback models, feedback loop frameworks, neural networks, and machine learning models of feedback. These holistic frameworks provide necessary instances to propel learning outcomes.

According to Smith, Hernandez, & Gordon (2018), an effective CBL framework envisions the learners and the environments they interact within as a joint cognitive system. This joint cognitive system includes the interfaces between peers, supervisors, systems and components that represent the tasks, skill sets, standards, and other system components that enhance learning activities (Woods & Hollnagel, 2006). Namely, the joint cognitive system equates to the perspectives of distributed cognition and adaptive instructional systems: a learner using one or more cognitive artifacts (or tools) which constitutes as a functional system for learning. According to Anderman (2008) distributed cognition is the cognitive system where an individual learner achieves new knowledge or skill through the interactions within their environment, a new tool or artifact, through peers, or feedback. As a symbol processing entity, distributed cognition is similar to the cognitive revolution that led to information processing psychology and artificial intelligence, cognition is "…computation accomplished through the propagation of representational states across representational media, which may be internal or external to the individual" (Anderman, 2008).

Distributed cognition models offer powerful tools for conceptualizing the complex roles and interactions of tools within CBL environments (Martin, 2012). In particular distributed cognition frameworks articulate four pedagogical functions often performed by technology in cognitive systems where learning is meant to occur: connection, translation, off-loading, and monitoring (Martin, 2012). These functions, often researched within the field of educational technology, have yet to be applied to research utilizing CBL assessments and feedback (Shutkin, 2019). Hattie and Timperley's (2007) Model of Feedback, see Figure 1, addresses conditions of effective feedback and encompasses differentiated components for diverse learners. These conditions include clarifying expectations and standards, formative feedback, feedback for self-regulation, and feedforward (Brooks et al., 2019). Impactful components of Hattie and Timperley's (2007) model posit notions of visible learning and the

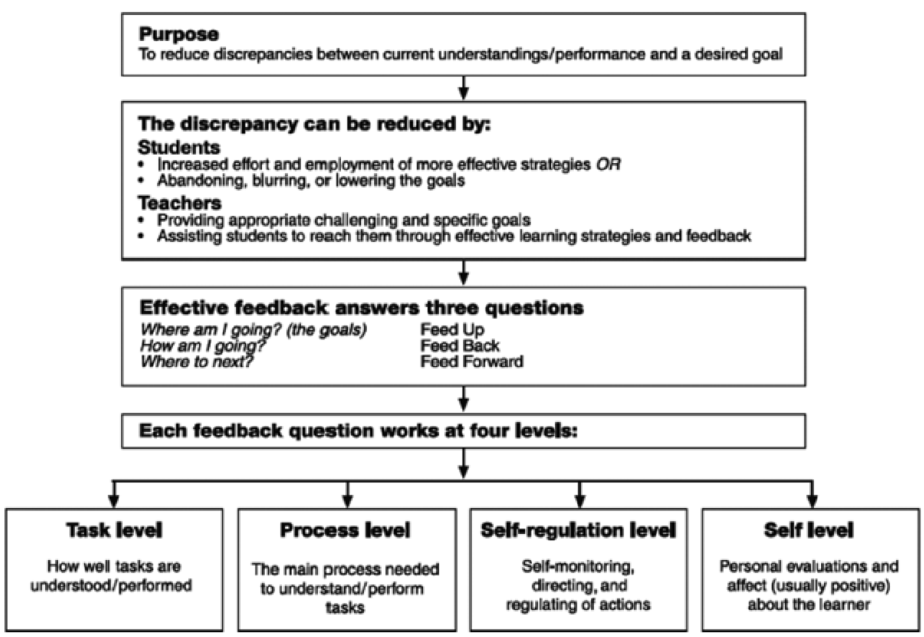

Figure 1. Model of Feedback (Hattie and Timperley, 2007)

interaction of learner and instructor (Brooks et al., 2019). Visible learning includes clarification components of learning intent, establishing learning goals, and criteria for success to instill active-learning processes (Brooks et al., 2019). This model exemplifies the purpose of formative assessment to provide cyclical evidence to instructors, learners, and others through informed feedback structures. According to Brooks et al. (2019) the model of feedback facilitates early constructs of adaptive instructional systems of feedback through targeting specific, differentiated feedback to an individual learner dependent on specific needs. Integral to this model are opportunities for improvement-based feedback through formative assessments. Targeted, specific, and dynamic feedback received during the current learning phase is more dominant than feedback collected at summative assessments (Brooks et al., 2019; Boud & Molloy, 2012; Hattie & Timperley, 2007; Hounsell et al., 2008).

Wang et al. (2021) utilized the conceptual Model of Feedback of Hattie & Timperley to construct a feedback loop implementation model utilizing a competency-based online course. According to Brooks et al. (2019), feedback loops equate to hierarchies such as process, task, self-regulation, and the self-level. Wang et al. (2021) posits feedback at the self-level is ineffective as most learning tasks are unrelated, while regulation level feedback provides opportunities for honing self-evaluation skills within learners. Prompting the learner to play an integral role within a feedback loop, as opposed to unidimensional feedback from an instructor, affects self-efficacy and processes integrating higher-level content. Within their framework, Wang et al. (2021) established feedback texts within the online platform to provide individualized feedback for mastery. Implications of this study provide a glimpse into feedback matrix structures for distributed learning. Over eleven types of feedback supported learners within the study, which include: diagnostic feedback, feedback for justification, feedback for improvement, feedback as complimentary teaching, motivational, feedback as praise, time management, connective feedback, encourage additional feedback, foster help-seeking, and emotional feedback (Wang et al., 2021). The effectiveness-related features of the feedback structure facilitated closing achievement gaps within learners. Limitations of the Wang et al. (2021) feedback text model necessitates the need for additional frameworks to implement regulative and emotional feedback within customizable platforms.

Improving human performance requires extensive experiential and real-time feedback generation, as highlighted in previous sections. With recent advances in machine learning, deep neural networks, intelligent tutoring systems, and simulation-based training (SBT) these resources expound on the challenges of feedback generation and curation systems. Namely barriers include feedback to be produced and delivered in a short span of time (less than 1 second), must be aligned to actionable competencies, and feedback constructs concise (Ma et al., 2017). Often, these feedback generation methods are not directly transferrable to non-cognitive SBT and SBL scenarios (Ma et al., 2017; Wijewickrema et al., 2016; Chen et al., 2015) A novel neural network-based feedback (NNFB) generation study conducted by Ma et al. (2017) aimed at exploring challenges of SBT through an adversarial technique. The model utilized an automatic feedback generation method that could be deployed using SBT through supervised learning, shown in Figure 2. Intriguing properties of the NNFB includes the opportunity for dynamic inputs altered through maximizing prediction error within training scenarios (Ma et al., 2017). In real-time, suggested action through feedback aims to guide learners from novice CBL content and performance tasks to actionable expert skills. Automated feedback has predominately utilized within intelligent tutoring systems that rely on a user's performance on fixed learning task sequences (Lee et al., 2021). Capturing feedback within complex assessment and skill performance within natural language processing, neural networks, and log data streams are relatively recent (Lee et al., 2021; Martin and Sherin, 2013). Machine learning algorithms can represent important roles in evaluating CBL and assessment performances however, most have been limited to student-generated texts (Lee et al., 2021).

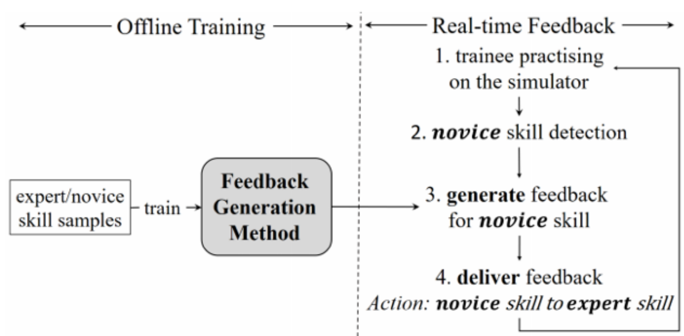

Figure 2. The Real-Time Feedback Process in SBT (Ma et al., 2017).

Deploying rapidly agile platforms to target and assess learner outcomes includes additional risks, or novelty effects, that some learning technologies mask within their user interface designs. Undervalued learner outcomes might indicate issues with feedback implementation: the task may not be fully understood, terminology or instructional task may be flawed, the learner may have ineffectively mastered the tacit knowledge, or the learner may have inaccurately consolidated or applied the feedback for learning to transfer to long-term memory (Smith, Hernandez, & Gordon, 2018). Walcutt (2019) posits the more a specific activity requires higher-order cognitive and social-emotional competence to successfully transfer tacit to explicit knowledge, the more difficult the task is to define and assess. Without the direct correlation to immediate feedback and progress measurement within an assessment to guide growth, the individual learner is ill-equipped for operational readiness regardless.

A NEW FRAMEWORK FOR COMPETENCY-BASED LEARNING ASSESSMENT FEEDBACK

While technological platforms have offered more substantial opportunities for learning in recent years, there is a significant deficit in research focusing on authentic assessment feedback within mobile platforms. Disparate emphasis has been placed on adaptive and personalized instructional content in recent years, neglecting a total learning architecture approach encompassing sustainable feedback loops between the instructor(s) and learner(s). Based on a review of current literature, there are critical issues found in implementing mobile learning frameworks for feedback including challenges of wide-scale adoption, underlying pedagogical theories, and overall instructor lack of confidence using mobile platforms (Bikanga, 2018). Opportunities to utilize assessment feedback as performance support, reminders, notifications, formative, and summative information can help guide learners and trainees towards a formalized mobile learning framework for competency feedback. Feedback is a powerful affective learning tool to support competency development, however learners are not always satisfied with the feedback received (Radloff, 2010; Mulliner & Tucker, 2017; Hattie & Timerley, 2007; Hattie & Gan, 2011). Extensive research has been conducted highlighting student learning outcomes within higher education, yet formative gaps exist within government system's training incorporating CBL (Morley et al., 2019). High quality feedback within repetitive practice modules enhances competency development and increases interactions between the learner and instructors (Eppich et al., 2015).These frameworks designed in previous studies have utilized overarching themes of the personalized learner, context, content, time, and interoperability within online and simulated environments however none have addressed assessment feedback within mobile platforms (Crook et al., 2012; Kearney et al., 2012; Koole, 2009; Laurillard, 2007; Motiwalla, 2007; Ozdamli, 2012; Park, 2011; Parsons et al., 2007).

Advanced Technological Learning Frameworks of Mobile Learning

Based on evidence-informed research and neuroscience principles, contemporary learning theories indicate learning is optimized when personal responsibility is at the forefront (Koole, Buck, Anderson, & Laj, 2018). Mastery is the desired outcome within competency-based learning. The most effective CBL frameworks directly link preparations to operations, while providing differentiated processes for 21st century learners. Traditional models of education practices and learning theories were characterized as a one-size-fits-all approach to teaching and evaluating outcomes (Ada, 2018). However, current shifts in formats incorporating multidimensional learner aspects and distributed learning platforms warrant deviations from antiquated learning theories crosscutting boundaries of context, delivery modalities, and devices (Bannan, Dabbagh, & Walcutt, 2019). Although innovations in networked technologies have advanced opportunities for lifelong learning, CBL instructional strategies and assessments have yet to match the pace (Ada, 2018; Bannan, Dabbagh, & Walcutt, 2019). Mobile learning frameworks encompassing a variety of feedback interactions are necessary to support the warfighter and future workforce.

Past barriers to mobile learning included multiple deployments to different platforms, shifting standards, security issues, economics, and data requirements impacting speed (Meister & Willyerd, 2020). Previous research has provided evidence that mobile learning can extend, enhance, and enrich concepts of learning through didactic, discursive, pedagogically sound, and individualized learning (Traxler, 2010; Traxler, 2011). The most pressing implications of mobile learning frameworks are theoretical paradigms guiding effective instructional design and evaluation of training programs utilizing mobile learning that can support feedback loops. For instance, Sharples et al. (2005) posit learning is mediated by technology as instruments for effective inquiry through dynamic shifts in knowledge. This mediation model for analyzing mobile learning, as shown below in Figure 3, promotes an interaction of perspectives including human-computer interactions, physical context, digital communication, social conventions, community influences, and conversations (Sharples et al., 2005). This framework emphasizes the joint cognitive network pivotal to holistic training.

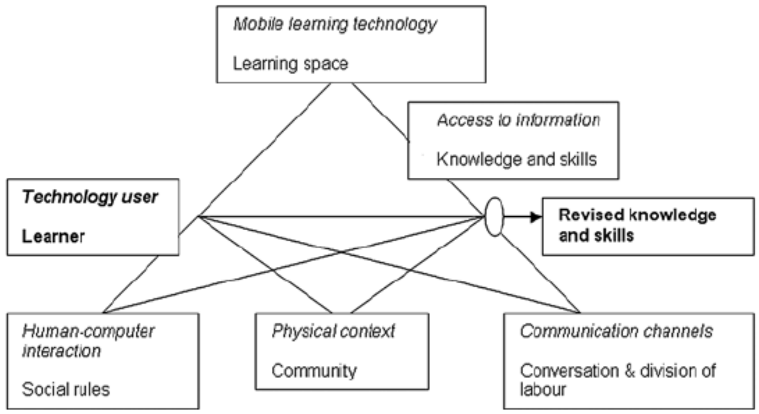

Figure 3. Framework for Analyzing Mobile Learning (Sharples et al., 2005)

Often feedback has been construed as an "extra workload", targeting an instructor's inability to provide personal and individualized assessment feedback within typical learning environments (Crook et al., 2012; Belshaw, 2010). Mobile and portable devices provide viable solutions for increasing access to assessment feedback (Bikanga, 2018). Mobile learning frameworks deployed to portable devices create opportunities to support the personal agency of a learner/trainee instrumental within just-in-time learning formats and on-demand learning (Khaddage et al., 2016).

Moreover, the universality of mobile learning provides increased inclusivity for populations with prior limited access to course engagement. According to Koole (2009), mobile learning technologies offer a learner greater access to relevant information, reduced cognitive load, and enhanced access to macro-level systems. This ubiquitous nature of mobile learning is an attractive option, supported by evidence that frameworks can enhance, extend, and enrich learning concepts (Traxler, 2011).

Competency-Based Learning Environment Assessment Feedback Frameworks (CB-LEAFFs)

Both Hattie and Timperley's (2007) feedback model and Sharples et al. (2005) mobile learning conceptual frameworks guides the initial development of a Competency-Based Learning Environment Assessment Feedback Frameworks (CB-LEAFFs) for mobile learning platforms. CB-LEAFFs hierarchical structure aims at utilizing machine learning to enable an intelligent, agile feedback system which analyzes CBL skill assessments, task complexity, and learner outcomes to enable the quantity, quality, and delivery of adaptive feedback to learners. Grounded in theoretical paradigms including cognitive science, educational psychology, and network science assessment feedback will foster learner outcomes such as: enhanced motivation, interaction loops, clarification, extension of learning, closing achievement gaps, content and performance skill transfer, and self-regulation (Smith, Hernandez, & Gordon, 2018; Walcutt, 2019; Ada, 2018; Koole, 2009). This subsection will provide an overview of the CB-LEAFFs model attributes integrating mobile learning frameworks.

CB-LEAFFs Conceptual Model

The CB-LEAFFs Conceptual Model (see Figure 4) intends to utilize functions of joint cognitive and adaptive instructional system within three constructs: learning as acquisition, learning as participation, and learning as knowledge creation, as seen in the schemata proposed by Wang et al. (2021). Specifically, the CB-LEAFFs model employs an adaptive, cyclic loop between content, assessment, and feedback derived from learning artifacts within CBL modules. These attributes equate to competency-based learning strategies of harnessing outcomes at the *micro* and *macro* levels of a holistic learning ecosystem. This specifically targets the components and environments that support the individual learner through simulated feedback.

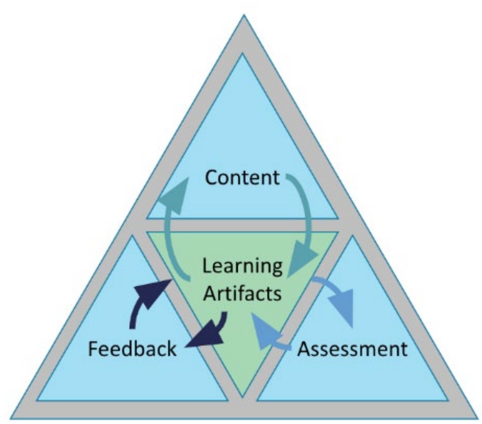

Figure 4. CB-LEAFFs Conceptual Model

This socio-constructivist perspective of the pedagogical architecture indicates the mobile learning environments' pivotal emphasis on distributed cognition and mobile learning frameworks in order to support new knowledge and skill processes based on collectively seeking, sieving, and synthesizing feedback. Within the model, feedback is placed within learners, between instructors, and the tools or artifacts individuals derive. This feedback matrix enables dynamic interactions between the joint cognitive system, learner, and instructor. These components of CB-LEAFFs provides opportunities and prompts for iterative feedback throughout the learning processes.

CB-LEAFFs Framework

Based on theories and models of distributed learning, distributed cognition, cognitive/learning science, data science, and mobile learning some key abstractions found within the CB-LEAFFs Conceptual Framework (shown in Figure 5) are derived within five categories: learning content, assessment, CB-LEAFFs Feedback Matrix, learner artifacts, and learner outcomes. These constructs directly impact learning effectiveness within the CB-LEAFFs framework. The learner and instructor both play an integral role coordinating capabilities, course content, feedback and the overall interaction on the mobile platform. Feedback is most crucial for applied learner outcomes when it moves cyclically between instructor and the learner (Brooks et al., 2019; Hattie, 2012). Situated as formal assessments, CB-LEAFFs feedback framework provides learner artifact evidence for the instructor to consider impacts based on instruction, content delivery, and assessment formats. These aspects drive the need for adjustments within instruction, future processes for feedback, and potential enhanced metacognitive monitoring for the learner. As simulated feedback is generated, attributes of feedback levels provide additional information to both the learner and instructor.

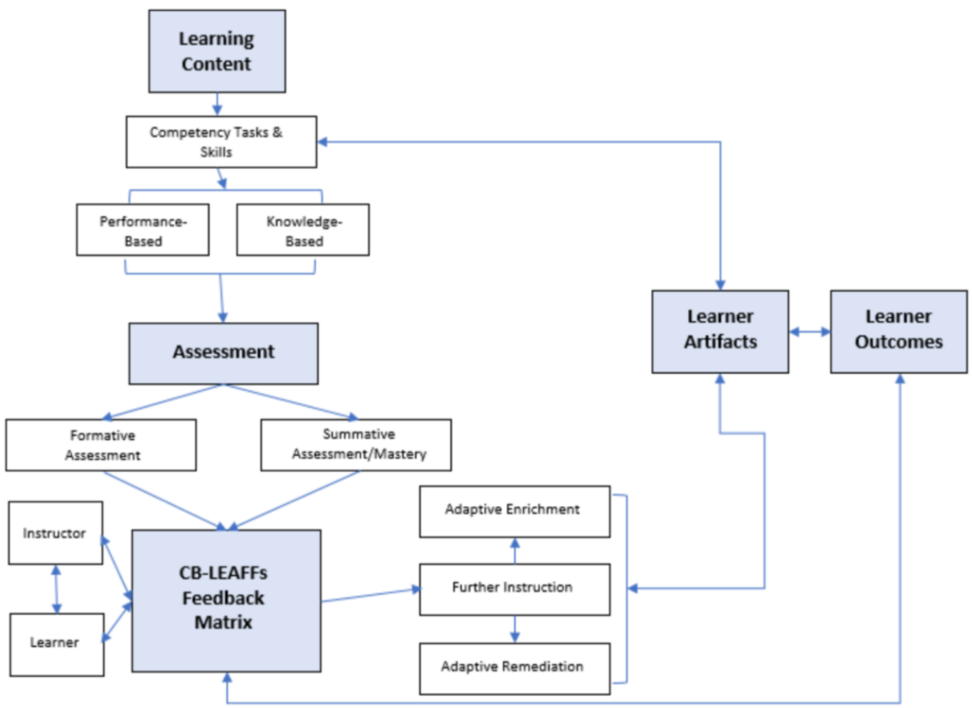

Figure 5. CB-LEAFFs Conceptual Framework

Based on Hattie & Timperley's Model of Feedback (2007), CB-LEAFFs four feedback levels inform the transfer of learning: task level, process level, self-regulatory level, and self-level. Learner artifacts from assessments generate information to both learner and the instructor through an analysis of one or more of the feedback levels, shown in Table 1 below. Feedback level data informs how the learning is going (*feed back*) and next steps for CBL instruction *(feed forward)*.

Table 1. CB-LEAFFs Feedback Level

Feedback Level	Description
Task Level	Pertains to feedback specific to competency-based learning tasks. Known as confirmatory feedback (Hattie, 2012), this level of feedback permits learners to build foundational learning knowledge based on content and tasks.

Process Level	Refers to feedback distinctive to the competency-based learning processes, strategies, and/or skills to master a task. This level of feedback requires augmentation of deeper learning and extension of tasks (Brooks et al., 2019; Hattie, 2012).
Self-Regulatory Level	Defined as feedback that cues self-regulatory and monitoring progress towards desired competency-based outcomes. This level of feedback requires the learner to plan, monitor, and problem solve discrepancies in their learning and assessment outcomes.
Self-Level	Specifies learner self-evaluations and affect within the learner. Alters learner habituations.

CB-LEAFFs Feedback Matrix

Within the CB-LEAFFs model and framework agile structure, CBL outcome tasks are facilitated through performance-based or knowledge-based assessments to commence a cyclical feedback loop. The Wang et al. (2021) study deployed coded feedback within an online course substantiated attributes of formative and summative feedback from instructors that facilitate CBL growth. Outcomes indicated instructor facilitation of diverse feedback supported learning within an online course module to mitigate learner perceived feedback experience dissatisfaction (Wang et al., 2021). The current conceptual model proposes an alignment of facilitative feedback within the Wang et al. (2021) study to include additional components of feedback and shift the learning environment to mobile platforms. Future case comparisons would highlight the feedback needed within mobile learning environments.

Within the current framework learning outcomes within the CBL assessment will generate the novel CB-LEAFFs Conceptual Feedback Matrix (shown in Table 2, below) to expedite simulated feedback components, prompting both the learner and instructor to collaborate in addition to recommending further instruction. Learning artifacts are then mapped back to mobile learning content with the CBL module, collecting data produced by CBL content, tasks, feedback generation, and assessments. As a conceptual construct, CB-LEAFFs Conceptual Feedback Matrix consists of fifteen feedback types to support the facilitation of learner growth within CB-LEAFFs Feedback Levels. The CB-LEAFFs Conceptual Feedback Matrix, although specifically designed to provide additional information for the learner and prompts cyclical lines of communication between the instructors and learners.

Table 2. CB-LEAFFs Conceptual Feedback Matrix

Feedback Type	Descriptions/Examples	Aligned CB-LEAFFs Feedback Levels
Diagnostic Feedback (FM1)	Specifies CBL learning criterion achieved to provide assessment results and/or define gaps in performance.	Task Level; Process Level
Dialogic Feedback (FM2)	Creates interpretational meaning of content and assessment data through prompted dialogue cycles amongst learner and instructor.	Task Level; Process Level; Self-Level
Feedback for Justification (FM3)	Utilized to expand on instructor's explanation of CBL task requirements, assessment performance, and interactions.	Self-Regulatory Level
Feedback for Improvement (FM4)	Guides learners on goals and objectives to improve performance and cueing, clarification of assessments.	Task Level; Process Level; Self-Regulatory; Self-Level
Feedback for Content Review (FM5)	Advise learner and instructor on clarification of CBL content and/or modules to review for future mastery.	Task Level; Process Level
Feedback as Complementary Instruction (FM6)	Prompts learner on applying specific skills to enhance assessment outcomes.	Task Level; Process Level; Self-Regulatory
Culturally Responsive Feedback (FM7)	Affirm learner's capacities for mastery through validation of diversity, equity, and culturally inclusive practices to guide a cyclical, learning partnership rapport.	Task Level; Process Level; Self-Regulatory; Self-Level

Motivational Feedback (FM8)	Directly and indirectly encouraging learner progress, module check points, assessment results. Highlights incremental progress and execution of goals.	Task Level; Process Level; Self-Regulatory; Self-Level
Feedback as Praise (FM9)	Provides learning process praise specific to CBL tasks, rather than individual praise for performance.	Task Level; Process Level
Feedback for Time Management (FM10)	Guides the submission of assessments and/or assignments to assist with time management CBL skills.	Self-Regulatory; Self-Level
Connective Feedback (FM11)	Connecting diverse learning tasks and assessments to module instructions, skills previously mastered, real-world applications, and future application of CBL skill transfer.	Task Level; Process Level; Self-Regulatory
Feedback for Extension of Learning/Enrichment (FM12)	Prompts learner on content and resources to enhance achieved mastery.	Task Level; Process Level; Self-Regulatory; Self-Level
Feedback Cycle Encouragement (FM13)	Encourages continuous communication between instructor and learner, even though mastery of content may have been achieved.	Self-Regulatory
Feedback to Foster Help-Seeking (FM14)	Creates reflective opportunities for the learner and instructor to actively express questions and/or concerns.	Self-Regulatory; Self-Level
Affective Feedback (FM15)	Provides opportunities between learner and instructor to express appreciation, sympathy, emotional efforts, and mitigate apprehension	Self-Regulatory; Self-Level

CB-LEAFFs Machine Learning Components

To prevent excessive workloads for instructors, assessment of student work must be at least partially automated using machine learning algorithms. Specific features regarding how the learner interacts with the material will be captured along with the traditional responses to assessment. Unsupervised learning techniques such as hierarchical clustering will be used to identify groups of students with similar learning approaches. Based on these groups, coded feedback will be provided, and the efficacy of that feedback will be assessed. Neural networks can be implemented to allow the system to learn to optimize learning by providing the optimal feedback type at each feedback level. Another approach would be to use a probabilistic graphical model, incorporating the feedback as causal nodes, and allowing for the use of counterfactual reasoning to determine the optimal feedback. In this approach, the coded feedback types would be modeled as probabilistic nodes that are triggered in response to learner behavior.

DISCUSSION AND FUTURE WORK

The concept of competency-based learning is meant to provide current and future warfighters, personnel, and employees the knowledge and skills required to perform their jobs at their own pace. Future readiness is dependent on learners who are supported by peers and management based on CBL assessment feedback. Migrating future learning ecosystems to mobile learning platforms, which embrace competency-based learning assessments, to augment performance will not enhance learning unless it's applied with purpose. Current systems that utilize learner analytics often elicit a profusion of learner performance data without considering holistic factors essential to learning (Abbott, 2019 p. 203). Despite the affordance that technologies could provide in terms of competency-based learning assessment feedback, research in this area is scarce (Bikanga, 2018). It is important to note that not all learning artifacts a learner produces will be equivalent in value to learning goals, competency/program objectives, or learner outcomes. Therefore, prioritizing not only the design and delivery of effective assessments is important but also the application of evaluative feedback within the system is pivotal.

Common challenges within the implementation of CBL evaluation frameworks within current times includes the poorly managed migration of legacy technology, lack of learner engagement and motivation, insufficient summative and formative feedback loops, and learner analytics to drive modifications of feedback. Legacy training methods historically have been difficult to assess as progress and metrics typically involve a highly manual process which creates barriers to innovative feedback loops between instructors and learners (Bikanga, 2018; Koole, 2009). Learning analytics offers powerful tools for conceptualizing the complex roles and interactions of tools within CBL environments (Martin, 2012). In particular learning analytics and mobile learning frameworks articulate four pedagogical functions often performed by technology in cognitive systems where skill attainment is meant to occur: connection, translation, off-loading, and monitoring (Martin, 2012). These functions have yet to be applied to research utilizing summative and formative assessments and feedback loops in mobile platforms (Shutkin, 2019; Ligorio, Cesareni, & Schwartz, 2014). Presentation, complexity, and type of feedback from instructors can directly influence learner engagement. Within a mobile, multimodal feedback requires purposeful feedback types within differentiated feedback levels. Barriers to implementation emphasize real-time interactions that are non-linear pertaining to the clarification of content, sharing of success criteria, utilization of strategies and goals, and peer and self-assessments (Brooks et al., 2019). This illustrates the challenge within an agile system to represent feedback dependent on learner proficiency, individual characteristics and task-based skillets to prompt from surface learning to deeper learning levels.

The present CB-LEAFFs conceptual model intends to further examine the barriers posed within competency-based learning approaches through an agile, authentic simulated feedback generated by assessment artifacts. Next steps comprise of further development within the CB-LEAFFs learning architecture. This includes an analysis of the model, framework, and matrix using a machine learning component structure within an applied CBL training module.

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REFERENCES

Abbot, D. (2019). Assessment and feedback. Walcutt & Schatz (Eds) In *Modernizing Learning: Building the Future Learning Ecosystem*. Washington DC: Government Publishing Office.

Aboko, A., & Obeng, F. K. (2015). Students' perspective on the competency-based training. Programme in Tamale Polytechnic, Ghana. *International Journal of Economics, Commerce and Management United Kingdom, 3*(3), 1.

Anane, C. A. (2013). Competency based training: quality delivery for technical and vocational education and training (TVET) institutions. *Educational Research International, 2*(2), 117–127. Anderman, E. M. (2008). *Psychology of classroom learning: An encyclopedia*. Detroit: Macmillan.

Andrews, J., & Higson, H. (2008). Graduate employability,'soft skills' versus 'hard' business knowledge: a European study. *Higher Education in Europe, 33*(4), 411–422.

Azevedo, A., Hurst, D., & Dwyer, R. (2015). Competency-based training program for international students. *International Business Research, 8*(3), 11.

Balash, F., Yong, Z., & Bin Abu, B. (2011). Lecturers and educational technology: factors affecting educational technology adoption in teaching. In *2nd International Conference on Education and Management Technology IPCSIT* (Vol. 13).

Bikanga, A. (2018). Using design-based research to develop a mobile learning framework for assessment feedback. *Research and Practice in Technology Enhanced Learning, 13*(3).

Boahin, P., & Hofman, A. (2013). A disciplinary perspective of competency-based training on the acquisition of employability skills. *Journal of Vocational Education & Training, 65*(3), 385–401.

Boud, D., & Molloy, E. (2013). Rethinking models of feedback for learning: The challenge of design. *Assessment & Evaluation in Higher Education. 38*(6), 698-712.

Brooks, C., Carroll, A., Gillies, R. M., & Hattie, J. (2019). A matric of feedback for learning. *Australian Journal of Teacher Education, 44*(4).

Burnette, D. M. (2016). The renewal of competency-based education: a review of the literature. *The Journal of Continuing Higher Education, 64*(2), 84–93.

Cebrian, G., Junyent, M., & Mula, I. (2020). Competencies in education for sustainable development: Emerging teaching and research developments. *Sustainability, 12* (579).

Chen, C., Seff, A., Kornhauser, A., Xiao, J. (2015). Deepdriving: Learning affordance for direct perception in autonomous driving. In *ICCV*, 2722-2730.

Cunningham, J., Key, E., & Capron, R. (2016). An evaluation of competency-based education programs: a study of the development process of competency-based programs. *The Journal of Competency-Based Education, 1*(3), 130–139.
Haddouchane, Z. A., Bakkali, S., Ajana, S., & Gassemi, K. (2017). *The application of the competency-based approach to assess the training and employment adequacy problem. International Journal of Education, 5*(1):1-18.
Hattie, J.A., & Gan, M. (2011). Instruction based on feedback. In R. Mayer & P. Alexander (Eds), *Handbook of Research on Learning and Instruction*. New York: Routledge, pp. 249- 271.
Hattie, J. (2012). *Visible learning for teachers: Maximizing impact on learning*. Routledge.
Hattie, J., & Temperley, H. (2007). The power of feedback. *Review of Educational Research, 77*(1), 81-112.
Hounsell, D., McCune, V., Hounsell, J., & Litjens, J. (2008). The quality of guidance and feedback to students. *Higher Education Research & Development, 27*(1), 55-67.
Jarvis, P. (2009). In K. Illeris (Ed.), *Learning to be an expert: competence development and expertise. International perspectives on competence development, developing skills and capabilities* (pp. 99–110). London and New York: Routledge.
Lee, H. S., Gweon, G. H., Lord, T., Paessel, N., Pallant, A., Pryputniewicz, S. (2021). Machine learning-enabled automated feedback: Supporting students' revision of scientific arguments based on data drawn from simulation. *Journal of Science Education and Technology, 30*, 168-192.
Ligorio, M.B., Cesareni, D., & Schwartz, N. (2014). Collaborative virtual environments as means to increase the level of intersubjectivity in a distributed cognition system. *Journal of Research on Technology in Education, 3*, 339-357.
Ma, X., Wijewickrema, S., Zhou, S., Zhou, Y., Mhammedi, A., O'Leary, S., & Bailey, J. (2017). Adversarial generation of real-time feedback with neural networks for simulation-based training. In *Proceedings of 26th International Joint Conference on Artificial Intelligence (IJAI)*, Melbourne, 2017.
Martin, T., & Sherin, B. (2013). Learning analytics and computational techniques for detecting and evaluating patterns in learning: An introduction to the special issue. *Journal of the Learning Sciences, 22*(4), 511-520.
Meister, J. C., & Willyerd, K. (2020). *The 2020 workplace: How innovative companies attract, develop, and keep tomorrow's employees today*. Harper Business
Morley, D., Bettles, S., & Derham, C. (2019). The exploration of students' learning gain following immersive simulation: The impact of feedback. *Higher Education Pedagogies, 4*(1), 368-384.
Mulliner, E., & Tucker, M. (2017). Feedback on feedback practice: Perceptions of students and academics. *Assessment & Evaluation in Higher Education, 42*(2), 266-288.
NCTVET. (2006). *A coordinator's guide to implementing competency-based education in schools*. Jamaica.
Puentendura, R. (2014). Learning, technology, and the SAMR model: Goals, processes, and practice. Ruben R. Puentendura's blog. hippasus.com/blog/archives/127.
Radloff, A. (2010). Doing more for learning: Enhancing engagement outcomes. Australian student engagement report. Camberwell: Australian Council for Educational Research.
Sharples, M., Taylor, J., & Vavoula, G. N. (2005). Towards a theory of mobile learning. Retrieved from https://www.researchgate.net/publication/228346088_Towards_a_theory_of_mobile_learning.
Shutkin, D. (2019). Representationalism and power: The individual subject and distributed cognition in the field of educational psychology. *Studies in Philosophy and Education, 38*, 481-498.
Stafford, M. (2019). Competency-based learning. Walcutt & Schatz (Eds) In *Modernizing Learning: Building the Future Learning Ecosystem*. Washington DC: Government Publishing Office.
TRADOC G-2, "The Operational Environment and the Changing Character of Future Warfare", Army Capability Integration Center (ARCIC), Campaign of Learning Technical Report. Retrieved from http://www.arcic.army.mil/App_Documents/The-Operational-Environment-and-the-Changing-Character-of-Future-Warfare.pdf.
Wijewickrema, S., Zhou, Y., Bailey, J., Kennedy, G., & O'Leary, S. (2016). Provision of automated step-by-step procedural guidance in virtual reality simulation. In *VRST*, 69-72.
Woods, D. D. & Hollnagel, E. (2006). *Joint cognitive systems: Patterns in cognitive systems engineering*. CRC Press.