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Empirical evidence from a connectivist Competitive Intelligence Massive Open Online Course (CI cMOOC) proof of concept

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ABSTRACT This study proposes a competitive intelligence connectivist Massive Open Online Course (CI cMOOC) proof of concept and highlights the interactions among content, context and community to explore relevance in CI cMOOC behavior. The CI cMOOC proof of concept was empirically tested with an online purposive sampling to target a qualified audience of similar and dissimilar information-rich cases, providing evidence about content-context-community competing influence on CI knowledge. The results revealed how the CI learning community perceive the capability of a cMOOC to train foreknowledge practices, given the best match between its content and context. The findings outline that tailored learning approach of the instructor influences the CI learning community's satisfaction with the content. The study facilitates theory development in addressing the emerging paradigm of an open intelligence approach to cMOOC collective training. Within boundaries of empirical return on experience of qualified respondents, the research framework strengthens trust in supervised interpretive judgment of CI learners confronted with anticipating competitive challenges.

KEYWORDS Collective training, competitive intelligence, connectivist MOOC, decisional practice, self-regulated learning behavior

1. INTRODUCTION

The key role of interactions in the learning process has always posed a challenge for competitive intelligence (CI) training programs. This paper builds upon a proof of concept related to a connectivist Massive Open Online Courses (MOOC), tailored to the philosophy of connectivism and networking (Daniel, 2012). A connectivist MOOC design enhances learners' networking skills and enables learning gains in terms of autonomy and interactivity across distributed environments (Mackness et al., 2013). Connectivist Massive Open Online Courses (cMOOCs) are innovative learning environments that are capable of scaling learner interactions because they are designed to capture collaborative learning opportunities (Joksimović et al., 2018).

Grounded in rich literature and practice, the focal issue of CI should unlock its substantial influence on decision making by increasing collective exposure to reflective judgments about challenging outcomes. As a domain of expertise, CI fails to persuade decision makers to capitalize on its intangible value in mapping the strategic needs of businesses. Balancing pragmatism and training curiosity with conditioned mindsets, CI should guide strategic choices in deploying learning with future roadmaps, acting as collaborative platforms to train foreknowledge decisional practices. What differentiates competitors is not the strategic information and the way they capture and control it, but rather the way in which the decision is made, especially in terms of the decision-making time. In this context, actionable knowledge of CI delivered within the cMOOC environment enhances competitive responses.

Our involvement in CI research over the last 10 years leads us to speculate whether knowledge on this topic is transferable to interested learners through a cMOOC. This study highlights online community members' perceptions of the process of sharing CI expertise and knowledge. This process is moderated by a new cMOOC conceptualization that provides the basis for interactions between learners who are eager to upgrade their CI knowledge. The goal of this study is to test the CI cMOOC framework to assess its validity as a learning device that addresses both learners' CI skill acquisition demands and pertinent doubts within the community of expertise. The CI cMOOC proof of concept is an explicit attempt to match context-over-content and context-over-community concerns by enabling access to the CI knowledge base while calibrating the pertinence of opportunity-driven CI skills.

As the cMOOC establishes rules to structure elusive CI knowledge, the 3Cs approach (context, content, and community) reframes the active learning landscape of training foreknowledge decisional practices. The proposal of the 3Cs approach to CI cMOOCs resulted from careful consideration of other triple helix analogies. One example is the entrepreneurial university, which is involved in socioeconomic development as well as the traditional missions of teaching and research (Etzkowitz, 2010). Another example is the triple helix system of innovation (Ranga and Etzkowitz, 2013), which consists of R&D and non-R&D innovators, "single-sphere" and "multi-sphere" (hybrid) institutions, and individual and institutional innovators. A third example is the triple helix of knowledge (Bratianu, 2015), which is based on the interrelations between emotional, spiritual, and cognitive knowledge.

The context of the CI cMOOC is crucial because of the limited transferability of CI knowledge. This limited transferability owes to the firm-specific CI process-based identity and its recognizable value as a performance differentiator in real markets. The CI cMOOC content must purposefully match conflicting interests and conflicting objectives of CI capabilities, which are expected to distinctively position players in competitive markets based on the capitalization of actionable knowledge. Finally, structuring the active learning constructs is based on multiple causal links in setting learning objectives and sharing best practices of collaborative sense making within the CI cMOOC community.

In response to decision-making difficulties in stretching strategic vision needs, collaborative training connectivity enables interpretive judgment, highlights the sharing of knowledge about mapping driving and restraining forces, and enhances learners' gains in overcoming concerns over delivering CI skills in real businesses. The 3Cs approach, coupled with concerns over the limited transferability of CI skills to strategic decisions, highlights the need to calibrate a connective CI learning landscape. Acknowledging the complexity of the interrelated disruptive research ambition and specific objectives, this study builds on pertinent team expertise in mixed research methods and managerial practice.

The primary challenge of the CI cMOOC is to address the paradigm shift from the dominant content-based logic to a context-based logic of acquiring and sharing CI knowledge. Beyond the proof of concept, the estimated impact of the CI cMOOC model of active skills transfer is positively moderated by methods of acquiring skills.

The remainder of this paper is organized as follows: Section 2 introduces the relevant theory; Section 3 outlines the research framework, methods, and study procedure; Section 4 presents the findings and their theoretical and practical implications; Section 5 concludes.

2. THEORETICAL BACKGROUND

The broadly accepted definition of CI is the process of gathering and analyzing raw data related to competitors' strategic movements (i.e., CI process inputs) and transforming these data into valuable knowledge (i.e., support for better decisions on market positioning) (Fuld, 1995; Kahaner, 1996; McGonagle and Vella, 2002). Active learning is based on the idea that learners construct their own versions of reality rather than simply accepting the versions that are presented by their instructors (Prince and

Felder, 2006). Given the variety and interactivity of the active learning experiences that are available in most cMOOCs (Bruff et al., 2013), the use of a CI cMOOC within an open community of learners involves design questions that have not been raised in textbooks.

MOOCs emerged as a means of harnessing the potential of technology to transform traditional approaches to education and improve students' active learning (Hew & Cheung, 2014). MOOCs are considered an innovative form of online learning because they enable collaborative learning by encouraging learners to contribute to collective knowledge (Margaryan et al., 2015). MOOCs have revolutionized the education system by making education easily accessible to mass audiences worldwide (Shen & Kuo, 2015).

There are essentially two types of MOOCs: xMOOCs and cMOOCs. xMOOCs are instructive. They are based on traditional e-learning platforms, where the learner is the passive recipient of knowledge. In contrast, cMOOCs are connectivist. They are based on social learning, collaborative intelligence, and Web 2.0 tools (Fidalgo-Blanco et al., 2016).

The huge potential of xMOOCs to provide training without some of the traditional barriers to participation in elite education (e.g., cost and academic background) should drive differentiation of educational offers (Jordan, 2014). The intense, time-critical competition across elite higher education institutions has led these institutions to adopt xMOOCs as platforms based on viral technologies (McClure, 2014) that are capable of disrupting institutions through potentially high rewards combined with competitive risk (Daniel, 2012).

Despite xMOOCs' successful positioning within traditional Internet-based training programs, some authors have raised serious doubts over xMOOCs' future because of students' low interaction (Yousef et al., 2015; Ospina-Delgado and Zorio-Grima, 2016). Unlike in xMOOCs, instructors in cMOOCs play the key role of facilitating interactions, and learners actively contribute to collectively developing the content (Kaplan and Haenlein, 2016). cMOOCs' frameworks must integrate open intelligence practices, as also mentioned by Patton (2005) and Calof et al. (2017). Inspired by the growing field of open innovation, these practices provide a pertinent approach for addressing this shift from xMOOCs to cMOOCs.

cMOOCs enable learners to tap into collective intelligence communities to create and connect new knowledge through interactions with instructors, experts, and peers (Littlejohn et al., 2012). Self-regulation is a critical aspect of professional CI learning. In cMOOCs, highly self-regulated learners self-evaluate their performance against their own benchmarks and share their success stories with their peers. In contrast, learners in xMOOCs are much less self-regulated and tend to follow the course's instructional pathway (Littlejohn and Milligan, 2015).

cMOOCs require reconceptualization based on new educational variables or different interpretations of existing variables because learners in cMOOCs consider the digital learning context more relevant than the content or community (DeBoer et al., 2014). A certain cMOOC learning format is accepted because a specific digital learning offering is viewed as important only if its use is perceived as having clear benefits (Mertens et al., 2014). The knowledge discovery process within cMOOCs requires the use of mechanisms whereby learners actively build new ideas or concepts based on current and past knowledge and the creation of artifacts to advance and share collective knowledge (Chau et al., 2013). Prior studies have also examined key determinants of technology-mediated learning effectiveness and have proved that active experimentation is crucial because it enables learners to benefit from focal collective knowledge by putting their innovative ideas into practice and sharing outcomes with peers (Hu and Hui, 2012).

In this paper, we show that in CI cMOOCs, context outweighs content and community. A rich body of literature discusses the complex relationships between cMOOCs users' motivations, attitudes, and levels of engagement in a variety of learning contexts (Shapiro et al., 2017). A study of the community of practice's interest in cMOOCs showed that learners' perceptions of context positively moderate the relationship between students' knowledge acquisition while attending a cMOOC and intentions to revisit the content (Huang et al., 2017).

This study builds on prior research by examining whether current contexts and roles of learners influence how they self-regulate their learning style (Zimmerman et al., 2000; Cheng and Chau, 2013). Even if the confidence to participate and learn in a cMOOC is connected to familiarity with the content of the cMOOC and its capacity to share knowledge via a community of practice, studies suggest that the context and current experience of cMOOC participants can influence their self-regulated learning behavior (Hood et. al., 2015). The need for further research on how cMOOCs can better support learners with different backgrounds relies on context (Barnard-Brak et al., 2010). The content of the knowledge construction process of learning communities through interactions is linked to community (Kent et al., 2016). Although cMOOCs are rapidly developing and gaining a prominent global profile, most fail to help learners remain focused on content. This problem occurs because most cMOOC designs do not offer learners an engaging experience. Engaging gamification mechanisms could solve this issue and help create highly effective cMOOCs (Chang and Wei, 2016). Greater cMOOC customization could lead to benefits for learners, who are the primary stakeholders of learning communities. This greater customization could thereby promote open opportunities of collaboration among instructors and across disciplines (Bruff et al., 2013).

As indicated by the Stanford Education Experiment (Leckart, 2012), a potential business model revolves around the ability of cMOOC providers to recommend successful learners to potential employers. The feasibility of this approach may vary across higher education institutions and cMOOC providers, depending on partnerships with employers or the creation of new partnerships through the production of high-profile cMOOCs (Burd et al., 2015).

Given the benefits of high-quality courseware content in business education, there is a need for CI cMOOCs. The future of intelligence studies in business enables the symbiosis of CI cMOOCs with new educational technology. Intelligence studies in business are about how content is built for the surrounding world of any private organization (Søilen, 2016).

The CI cMOOC design framework leverages the role of the cMOOC community, enriching interactions between its members according to their expectations and experience (Yousef et al., 2015; Ospina-Delgado and Zorio-Grima, 2016). Collaborative sense making of engaging a cMOOC target in active learning bridges the gap between decision-making literature and intelligence analysis (Baber et al., 2016). The CI cMOOC learning design overcomes the theoretical, methodological, and managerial mismatch of prior cMOOC practices by developing an active learning environment that fosters a willingness to change routines. This active learning environment is achieved by leveraging the capacity of CI to make sense of changing mindsets to encourage inquiry and experimentation (Moore et al., 2007). As prior studies have shown (Karagiorgi and Symeou, 2005), CI cMOOCs aim to foster motivation among learners, provide the opportunity for learners to develop foreknowledge decisional practices, and cope with problematic situations.

According to the active learning approach to training future CI skills, learning content challenges for cMOOC design are essential for achieving the outcome of overcoming the current vulnerabilities of poor instructional value added and inducing self-regulated learning behavior among learners from different contexts.

3. RESEARCH FRAMEWORK

CI cMOOC proof-of-concept constructs tailored to Lewin's force field model consist of the primary driving forces and restraining forces that condition the behavioral approach to CI cMOOC outcomes. The knowledge gap relates to the core factors that should be considered when developing a CI cMOOC. The methodological approach provides the understanding of the ability of a CI cMOOC's key features to train foreknowledge decisional practices.

The CI cMOOC proof of concept requires proxies to bridge the aforementioned knowledge gap. These proxies can be obtained using a data feedback tool that is built according to Lewin's framework. The proof of concept can be empirically tested against a sample of qualified target respondents who are interested in CI-based decisional problems.

We used purposive sampling to target a qualified audience with features of similar and dissimilar information-rich cases. This approach enabled ex-post data analysis of CI cMOOC learning benefits and enriched the CI knowledge base. The convenience sample consisted of 100 qualified learners who were enrolled in various business training MOOCs, where they gained experience in dealing with connectivist learning platforms.

The questionnaire was published online on Google Forms and sent through different online platforms. It was shared with scholars via Facebook, LinkedIn and other social media

Figure 1 Active learning landscape with the 3C- CI cMOOC device.

groups and pages dedicated to CI. The questionnaire had three sections, one for each element of the 3Cs research framework (content, context, and community). The items in the questionnaire were stimuli to which the respondents reacted. Each driving force item was contrasted with a restraining force item. Therefore, when answering, the respondent had to understand and react to the combined effect of two stimuli. The reported answer was not necessarily the same as it would have been if these two stimuli were not linked when answering.

When making sense of respondents' varying perceptions of items embedded in the research framework, the right interpretation of expected outliers is crucial. The existence of flaws in understanding learning connectivity's influence on sharing CI concerns raises the following research question: How does the target CI learning community perceive the capability of a cMOOC to train foreknowledge practices, given the best match between its content and context?

Table 1 CI cMOOC proof of concept constructs tailored to Lewin's force field model. Source: primary research.

Driving forces (positive for change)	**Restraining forces (obstacles to change)**
Content	
Ability to maximize the value of CI knowledge transfer based on highly interactive cMOOC content	CI cMOOC users' limited engagement with interactive content
Benefits of online multimedia resources embedded in CI cMOOC	Limited skills to deal with online multimedia resources embedded in CI cMOOC
Capability to properly address CI skills acquisition needs	Limited capability to address CI skills acquisition needs
Accessibility of CI cMOOC platform via mobile technology	Lack of CI cMOOC platform accessibility via mobile technology
Ability to embed a CI strategic behavior self-assessment tool in cMOOC	Limited capability of learners to understand the outcomes of the self-assessment tool embedded in cMOOC
Context	
Use of a serious game to foster CI cMOOC users' interest	Difficulties in assessing rich interactions within the CI cMOOC serious game
Trust in CMOOC instructors' CI background	Limited information about cMOOC instructors' CI background
CI skills acquisition through cMOOC	Low proficiency in CI skills acquisition through cMOOC
High interest in acquiring and developing CI skills	Limited interest in acquiring and developing CI skills
Capability to overcome learners' conflict of priorities	Limited capability to overcome learners' conflict of priorities
Community	
Potential for self-organized CI learning community	Learners' limited interest in belonging to self-organized CI learning community
Capability of CI cMOOC to enable the exchange of tips to acquire CI skills	Limited capacity of CI cMOOC to exchange tips to acquire CI skills
High interest in sharing CI skills	Limited interest in sharing CI skills
Ease of building a solid CI culture based on strategic thinking	Difficulties in building a solid CI culture based on capturing talent
Ability to support peer facilitator roles in the CI cMOOC community	Difficulties in enabling peer facilitator roles in the CI cMOOC community

3.1 Frame-related issues and areas of focus of the CI cMOOC proof of concept

The pertinence of leveraging active learning constructs of easily accessible actionable knowledge on CI still needs to be explored. Making sense of multiple causal links between the design of a cMOOC dedicated to active learning of competitive intelligence insights and pivoting around identified commonalities of supply and demand for cMOOCs, this current design framework's distinctive mission is meant to prove an innovative instructional program's capacity to adapt to change.

The key proposition of the 3C –CI cMOOC research framework relies on visualization with a Venn diagram of the interactions between the structural components of the instructional device (Figure 1). The mission statement with the adopted learning behaviour of the same is to enhance the learning gain by training its signaling role, when future CI decision makers should take leadership and make sense of the conflicting information generated with content, community and context.

Reflecting on the aforementioned causal links, the conceptual logic of the cMOOC design framework requires Lewin's force field analysis (1946) as a tailored method to highlight its pertinence, considering context, content, and community. Therefore, this study advances the CI cMOOC proof of concept research framework by deploying the constructs of the 3Cs framework (content, context, community) tailored to Lewin's force field model (Table 1).

The proposed cMOOC should capture the attention of potential users by providing professional CI content. The highly interactive content, enriched with multimedia resources, represents a driving force to achieve the aforementioned goal. However, highly interactive content could also be an inhibitor for certain target audiences that struggle to use specific tools embedded in the cMOOC. A major expected intangible advantage of CI cMOOCs is the ability to effectively address CI skills acquisition needs. The key issue is the ability of the online learning culture promoted by the CI cMOOC to unlock the potential of talented people. The trend toward mobile learning through CI cMOOCs and embedded strategic CI behavior self-assessment tools are also relevant issues in the framework's content section.

The goal of the CI cMOOC's conceptual and methodological framework would be incomplete without addressing contextual relevance. Integrating a serious game in the CI cMOOC could raise users' awareness and interest. However, the serious game's limits in the assessment process, beyond the simple output of a game grading system, must be clearly identified. Building trust in cMOOC instructors' CI background creates huge opportunities that could be captured during learners' CI skills acquisition and development processes. Because of the need to overcome learners' conflicts of priorities, a limited capability to deal with this issue could negatively affect CI cMOOC adoption.

Incorporating valuable insights from the salient literature, the current conceptual model coherently depicts the CI cMOOC constructs related to community as driving forces. These constructs are supporting self-organized CI learning communities of practice, stimulating interest in sharing CI skills, empowering learners to collaborate by highlighting peer facilitator roles, and enabling collective sense-making efforts to develop strategic thinking.

3.2 Conceptual architecture approach and hypotheses

To extend the debate in the CI knowledge community, the primary research question is addressed using two hypotheses, which are rooted in a novel conceptual architecture. Making sense of structuring knowledge creation within CI learning environments, the framework-related hypotheses are based on a novel methodological toolkit.

> *H1: The overall strength of the driving forces is greater than the overall strength of the restraining forces in the CI cMOOC 3Cs framework.*

The CI target audience, which is sufficiently qualified in terms of expectations and demands, tends to replicate the learning environment clustering to make sense of supervised collective intelligence training. Nevertheless, there are wide gaps in less risk-free environments for decisional practices. These gaps become challenges once the real business restraining forces have been confronted. Community is rooted in cultural grounds of valuing CI learning. Accordingly, we anticipate serious managerial challenges in adopting foreknowledge decisional practices on behalf of CI skills.

The Lewin's force field approach to the 3Cs of CI cMOOCs lends support to the current conceptual framing model, showing that the model coherently anchors the CI cMOOC constructs to train foreknowledge decisional practices. The discovery of all relevant recommendations regarding CI cMOOC actionability requires deeper reflection upon structuring knowledge and adjusting the methodological toolkit. H1 is supported by Lewin's force field approach. However, the CI cMOOC proof of concept still needs testing for actionability.

H2: A greater influence of context (instructor's support for learning) is associated with higher quality CI community of knowledge and higher satisfaction with content.

We propose an original data modeling framework test of truth to test whether there is support for a derived hypothesis. If H2 is supported, the empirical testing calls for further research to enrich our understanding and provide new knowledge on behalf of the assumption that context overcome both content and community. Furthermore, if H2 is supported, this study contributes to managerial practice by providing strategic decision assistance.

3.3 CI cMOOC construct reconfiguration

The proof of concept approach to CI cMOOCs means building upon the theory development process of CI cMOOC behavior by exploring antecedents of performance. It is assumed that, from the perspective of causality studies, the content variables represent the "personality" of the CI cMOOC; the context variables represent the "specialized as opposed to generic" learning process in which the CI cMOOC will be used; and the community variables represent the "behavior" of the CI cMOOC (i.e., its interaction with learners). Conceptually, content and context are independent variables that influence community but do not influence each other. We do not expect the CI cMOOC content to influence the context in which it will be used and vice versa. This can be expressed by Lewin's equation, where behavior is a linear function of personality and context.

The 30 questions were sorted into three groups of 10 matching pairs of items (stimuli). Each pair was formed of a driving force (D) and the corresponding restraining force (R). The variables were labeled as follows: CNT_Di and CNT_Ri (i = 1,…,5) for the pairs of items related to cMOOC content (CNT); CTX_Di and CTX_Ri (i = 1,…,5) for the pairs of items related to cMOOC context (CTX); and CTY_Di and CTY_Ri, (i = 1,…,5) for the pairs of items related to cMOOC community (CTY). In Lewin's force field analysis, it is assumed that the true stimuli to which the respondent must react is the pair of driving and restraining forces. Therefore, the following three groups of auxiliary variables were defined as follows:

CNT_DRi = CNT_Di - CNT_Ri, (i = 1,…,5);
CTX_DRi = CTX_Di - CNT_Ri, (i = 1,…,5);
CTY_DRi = CTY_Di - CNT_Ri, (i = 1,…,5).

3.4 Methods

The methods must match the observational nature of the data, which were gathered from a convenience sample rather than from a random sample or planned experience. A priori, the data were grouped into three clusters with predefined meanings. The methods had to be capable of determining whether the evidence supported these predefined groupings. For example, are the groups homogeneous? Moreover, can we provide evidence of underlying latent variables that can synthesize these groups of variables and reflect hidden influences in respondents' perceptions? The following statistical methods are concerned: descriptive statistics to characterize individual variables; multidimensional scaling to study the behavior of respondents when answering the questionnaire; Cronbach's alpha to confirm the homogeneity of the groups; principal component analysis to verify the unidimensional nature of the groups; and path modeling and partial least squares structural equation modeling (PLS-SEM) to explore the possible existence of causal relationships between respondents' answers. For the PLS-SEM, we used the "*plspm*" package (Sanchez, 2013) and the "*gesca*" package (Hwang and Takane, 2015) in R. For all other analyses, we used SPSS version 17.

4. FINDINGS

4.1 Force field analysis

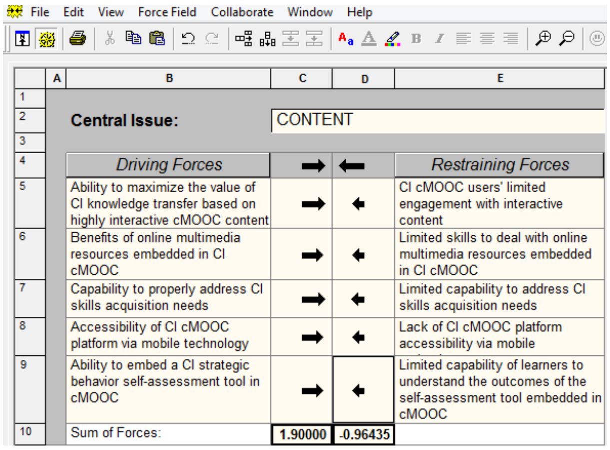
First, analysis was performed using the outputs from the Force Field Tool in the PathMaker software. The average scores for the labeled CI cMOOC constructs were computed in Excel and then transferred into PathMaker software to be converted into strength arrows (Figures 2, 3, and 4).

The partial score for content (Figure 2) supports H1 (driving forces = 1.90; restraining forces = -0.96). The score was computed using the ranking of the following driving and restraining forces as perceived benefits in terms of content: accessibility of interactive content and mobile technology; willingness, curiosity, and engagement of respondents to continually upgrade their preliminary CI skills; and expectations and new actionable CI knowledge.

The partial context score (Figure 3) (driving forces = 1.91; restraining forces = -1.02) fails to provide unequivocal support for H1. Restraining forces were perceived as barriers, mostly because of confusion in the acquisition and development of CI skills and because of the limited benefits of active learning interactions. However, perceptions of driving forces still reflect respondents' interest in acquiring CI skills by building trust in further developing CI expertise in a cMOOC environment.

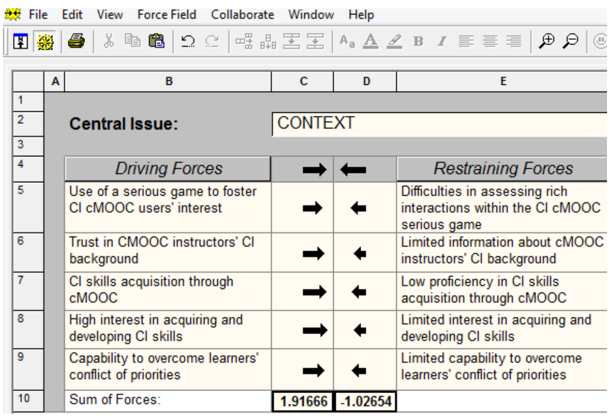
In this study, we analyzed the role of community. The community partial score (Figure 4) was as follows: driving forces = 1.88; restraining forces = -1.01. As expected, community seems to be less of a driver than context. Community was observed to be a less manageable area of change because respondents were sufficiently aware that many CI learning challenges, if not overcome, would magnify the vulnerabilities of CI skills transfer, jeopardizing their actionability in less risk-free environments. Figure 5 shows that the medians of the driving forces were greater than the medians of the restraining forces.

To confirm the validity of the 3Cs approach to CI cMOOC force field analysis, we performed a non-parametric test (Wilcoxon signed-rank test). This test allowed us to objectively decide whether the mean of the driving forces was equal, less than, or greater than the mean of



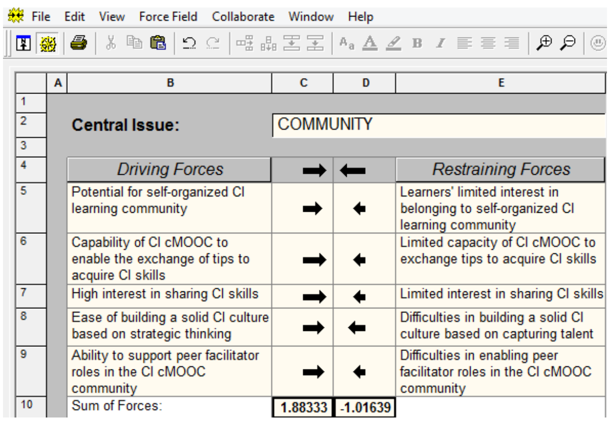
Central Issue:	CONTENT		
Driving Forces	➡	⬅	Restraining Forces
Ability to maximize the value of CI knowledge transfer based on highly interactive cMOOC content	➡	⬅	CI cMOOC users' limited engagement with interactive content
Benefits of online multimedia resources embedded in CI cMOOC	➡	⬅	Limited skills to deal with online multimedia resources embedded in CI cMOOC
Capability to properly address CI skills acquisition needs	➡	⬅	Limited capability to address CI skills acquisition needs
Accessibility of CI cMOOC platform via mobile technology	➡	⬅	Lack of CI cMOOC platform accessibility via mobile
Ability to embed a CI strategic behavior self-assessment tool in cMOOC	➡	⬅	Limited capability of learners to understand the outcomes of the self-assessment tool embedded in cMOOC
Sum of Forces:	1.90000	-0.96435	

Figure 2 Driving vs. restraining forces for content.



Central Issue:	CONTEXT		
Driving Forces	➡	⬅	Restraining Forces
Use of a serious game to foster CI cMOOC users' interest	➡	⬅	Difficulties in assessing rich interactions within the CI cMOOC serious game
Trust in CMOOC instructors' CI background	➡	⬅	Limited information about cMOOC instructors' CI background
CI skills acquisition through cMOOC	➡	⬅	Low proficiency in CI skills acquisition through cMOOC
High interest in acquiring and developing CI skills	➡	⬅	Limited interest in acquiring and developing CI skills
Capability to overcome learners' conflict of priorities	➡	⬅	Limited capability to overcome learners' conflict of priorities
Sum of Forces:	1.91666	-1.02654	

Figure 3 Driving vs. restraining forces for context.



Central Issue:	COMMUNITY		
Driving Forces	➡	⬅	Restraining Forces
Potential for self-organized CI learning community	➡	⬅	Learners' limited interest in belonging to self-organized CI learning community
Capability of CI cMOOC to enable the exchange of tips to acquire CI skills	➡	⬅	Limited capacity of CI cMOOC to exchange tips to acquire CI skills
High interest in sharing CI skills	➡	⬅	Limited interest in sharing CI skills
Ease of building a solid CI culture based on strategic thinking	➡	⬅	Difficulties in building a solid CI culture based on capturing talent
Ability to support peer facilitator roles in the CI cMOOC community	➡	⬅	Difficulties in enabling peer facilitator roles in the CI cMOOC community
Sum of Forces:	1.88333	-1.01639	

Figure 4 Driving vs. restraining forces for community.

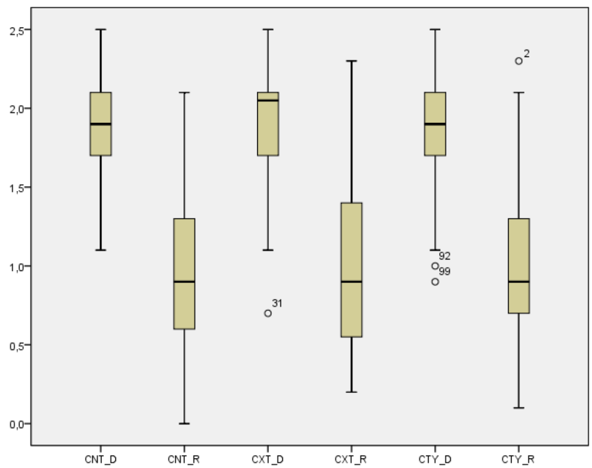


Figure 5 Distribution of medians of driving and restraining forces.

Table 2 Evidence of dominance of driving forces over restraining forces.

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
						Value	Std. Error	Value	Std. Error
CNT_D	100	1.1	2.5	1.898	.3272	-.111	.241	-.452	.478
CNT_R	100	.0	2.1	.969	.4888	.527	.241	-.328	.478
CXT_D	100	.7	2.5	1.922	.3463	-.801	.241	.654	.478
CXT_R	100	.2	2.3	1.023	.5272	.658	.241	-.503	.478
CTY_D	100	.9	2.5	1.875	.3176	-.878	.241	.697	.478
CTY_R	100	.1	2.3	1.019	.4935	.603	.241	-.319	.478
Valid N (listwise)	100								

the restraining forces. At the standard significance levels, the hypothesis of equal means was rejected in favor of the hypothesis that the mean of the driving forces is greater than the mean of the restraining forces. Compiling the partial influence scores of 3Cs CI cMOOC provided by PathMaker software, this study further highlights the in-depth analyses of the research framework.

4.2 Univariate descriptive statistics

Examining the results for univariate descriptive statistics reveals several key findings. In general, the variables representing driving forces had higher medians than the corresponding variables representing restraining forces (Figure 4 and Table 2). The variability of the restraining forces was considerably greater than the variability of the driving forces. This finding means that there was greater consensus among respondents in relation to driving forces than in relation to restraining forces. In addition, the asymmetry of the driving forces was negative (right asymmetry: dominance of larger values), whereas the asymmetry of restraining forces was positive (left asymmetry: dominance of smaller values). Positive values dominated negative values when we considered the net result of the driving force item minus the corresponding restraining force item. Thus, according to respondents, the driving force dominates the restraining force for most variables in the three groups.

4.3 Multidimensional scaling

The preliminary data analysis reveals good reasons to use multidimensional scaling (MDS) to study the meanings of the associations implicit in respondents' reactions to stimuli. MDS illustrates the topology of respondents' reactions (i.e., mental proximities between meanings of concepts) to items embedded in the proposed framework.

The visual mapping of pairwise gaps in Euclidean space provides insights to recalibrate the questionnaire toward assigning common meanings of the CI knowledge base. Furthermore, the CI cMOOC, defined as an interactional space of CI skills transfer, enables collaborative learning among instructors and users.

Using MDS to examine the outputs from these analyses yields several key findings. The points (Figures 6, 7, and 8) are defined as stimuli—the items that the respondents reacted to according to the meaning they attributed to those stimuli/items (interpretation). Therefore, if two stimuli are close to one another in the graph, this implies that all respondents interpreted them in a similar way. Conversely, a large distance between two stimuli in the graph implies that respondents interpreted these stimuli very differently.

Figures 6, 7, and 8 show that for content, context, and community, the driving and

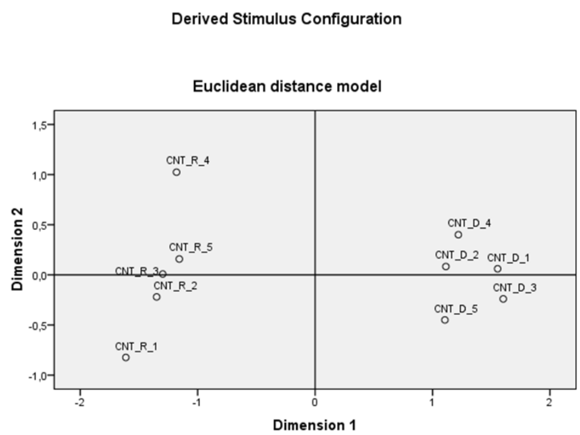


Figure 6 MDS (ALSCAL) proximity of content-related items in terms of respondents' interpretations of their meanings.

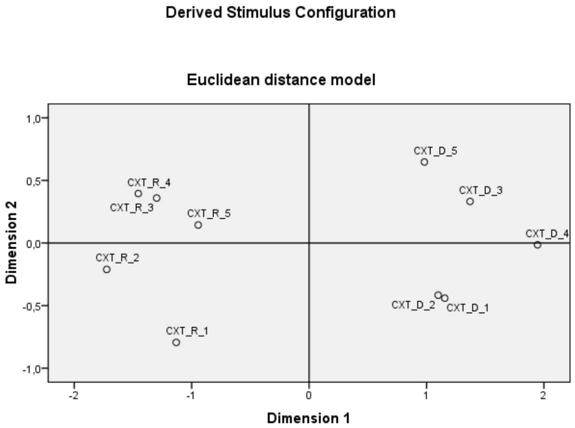


Figure 7 MDS (ALSCAL) proximity of community-related items in terms of respondents' interpretations of their meanings

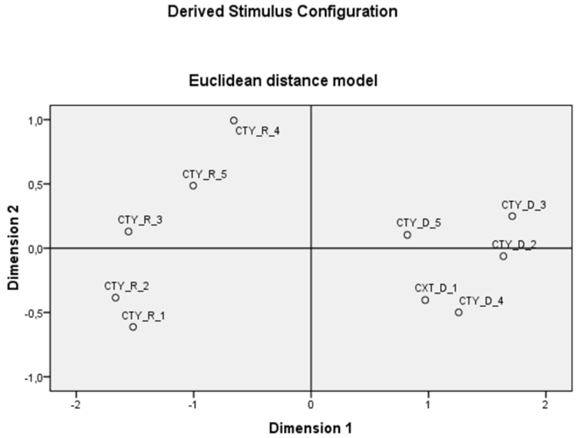


Figure 8 MDS (ALSCAL) proximity of community-related items in terms of respondents' interpretations of their meanings.

restraining forces were clearly interpreted differently by respondents, with driving forces on the right side of the three graphs and restraining forces on the left side. This separation correctly represents the intended opposition of these two types of forces. In relation to the assumed matching between driving forces and restraining forces for each pair, the situation was quite different. Specifically, for the content-related variables, the proximity of the points representing driving forces suggests that respondents struggled to distinguish the meanings of these variables—they form a group with small mutual distances. Consequently, we expect the variables DRi (= Di-Ri) to present some ambiguities for this dataset.

If both driving and restraining forces are projected on the vertical axis, the restraining forces' projections are generally a long way from the corresponding driving forces in the predefined matching. This should not occur if the respondents interpret the intended meaning of matched pairs of driving and restraining forces as expected. In other words, for most pairs, the alignment between driving and restraining forces is broken by respondents' perceptions. There are several possible explanations for this finding. First, the wording of the questions might have meant that different respondents attributed different meanings or that the intended meaning was not understood. Second, respondents might have incorrectly understood the instructions. For example, certain respondents did not associate each driving force with the intended matching restraining force. Finally, the driving force and restraining force items might not have been properly matched, for if they were properly matched, the pairs of items would be vertically aligned.

Respondents' perceptions of driving and restraining forces highlight the expected biased interpretation of the meaning of the 3Cs. Not only were respondents aware of the necessity of the CI cMOOC, but they also recognized the capability of this interactional space to provide support for CI decision practices.

Preliminary findings were used to analyze the alignments that seemed to emerge from the answers based on the proximities in the graph rather than the alignment of driving and restraining forces that resulted from the predefined matching. If the alignment of concepts (in terms of respondents' perceptions) was not the matched pair (D3, R3) but was rather (D3, {R2, R3}), then in subsequent analyses, D3 - (R2+R3)/2 would be used instead of D3-R3. Doing so enabled us to check the legitimacy of the latent variable against the principal component analysis. The associations found by comparing the intended vs. observed meanings of wordings support the assumption that a latent variable for each of CNT_DR, CTX_DR, and CTY_DR could emerge. The principal component analysis should further confirm the relevance of this issue.

4.4 Evidence for latent variables

The first principal component, in conjunction with Cronbach's alpha and the consistency of group correlations, helped check the assumption that the set of variables that formed a group could be represented by one latent variable of which those observed variables were coherent manifestations (Table

3). These latent variables can be interpreted as a common sentiment or attitude among respondents in response to the issues (content, context, and community). Table 3 shows the percentage of variance associated with the first and second principal components for each group of variables (CNT, CXT, or CYT). Table 3 also shows the values for the standardized Cronbach's alpha measure. Calculations were made using SPSS version 17.

Table 3 Percentage of variance associated with the first and second principal components and Cronbach's alpha for the three groups of variables. Var. = group of variables. CA = Cronbach's alpha for standardized items. 1PCV = First principal component variance percentage. 2PCV = Second principal component variance percentage. QV = quotient of variances. QV is calculated with 1PCV/2PCV.

Var.	CA	1PCV	2PVC	QV
CNT	*0.502*	*30.5*	*21.8*	*1.4*
CTX	*0.678*	*41.6*	*18.7*	*2.2*
CTY	*0.680*	*50.1*	*16.1*	*3.1*

The first principal component explains a large percentage of the variance (information) for the CTX and CTY groups of variables. Together with the high Cronbach's alpha values (approximately 0.7), this result suggests that these two groups can safely be synthetized by latent variables labelled LCTX and LCTY, respectively. The situation for the first group (CNT) is less clear. The first principal component explains only 1.4 times more variance than the second principal component does. Moreover, the value for Cronbach's alpha is only 0.5. The large percentage of variance that is explained by the first component suggests that the essential message of this group is captured by just one latent variable (labelled LCNT). Given the low value of Cronbach's alpha, however, we can expect greater error when interpreting this latent variable.

In summary, consistent with the previous results, the homogeneity of the groups CTX and CTY is greater than the homogeneity of the group CNT. It therefore makes sense to represent the meaning of respondents' opinions about CTX and CTY using the latent variables LCTX and LCTY. The homogeneity of CNT is much lower, so it makes sense to synthetize respondents' reactions to this group of variables using one latent variable (LCNT), but this variable should be complemented to account for the extra variability. In other words, the expected error is greater for CNT than it is for CTX or CTY.

4.5 Path analysis and model validation

Given our initial observations and according to the perspective of Lewin's force field model, it makes sense to specify and estimate the path model depicted in Figure 9, expressing the hypothesis that LCTY is a dependent variable explained by LCNT and LCXT. Respondents' reactions to the community concept are explained by their attitudes in relation to the concepts of content (expressed by the latent variable LCNT) and context (expressed by the latent variable LCXT). This hypothesis must be supported or contradicted by the available non-observational data.

The path model shown in Figure 9, following the usual conventions, expresses these beliefs: ellipses represent latent variables, rectangles represent indicators, and arrows represent causal assumptions. LCNT represents respondents' underlying opinions expressed when answering content-related questions. LCXT represents respondents' underlying opinions expressed when answering context-related questions. LCYT represents respondents' underlying opinions expressed when answering community-related questions. CNT_DR_i was computed by taking the differences between the answers to the ith driving force (D_i) and the corresponding restraining force (R_i) for i= 1,...,5.

Because data were observational and no distributional model was assumed, we used partial least squares path modeling (PLS-PM) as the estimation method. Concerns have been raised over the nature of results obtained using PLS-PM. One of the primary concerns is that this method, which is based on an iterative algorithm, assumes convergence for a specific solution. PLS-PM is therefore criticized for failing to guarantee the optimization of specific global criteria. The convergence might be to a local rather than a global optimum.

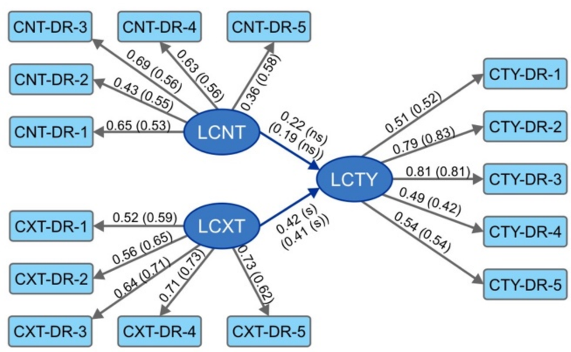


Figure 9 Path model relating latent variables LCNT, LCXT, and LCTY from the perspective of Lewin's force field model.

Generalized structured component analysis (GSCA) was employed to overcome the shortcomings of PLS-PM (Hwang and Takane, 2015).

The model specified in Figure 9 was estimated using both methods. To do so, we employed two R packages: "plspm" (Sanchez 2013) and "gesca" (Hwang and Takane, 2015). The results are presented and discussed simultaneously in the subsequent paragraphs, thereby enabling a comparative study.

The estimations of the structural model (strengths of associations between latent variables) and correlations (loadings) between manifest variables and the corresponding latent variable are expressed by the values along the arrows. The results provided by the "plspm" package are followed in parentheses by the values provided by the "gesca" package (Figure 8). The results are not identical, but they are similar and coherent. The causal relation LCNT -> LCTY is not supported by the data. This relationship was found to be non-significant by both methods at the 1% significance level. The causal relationship LCTX -> LCTY was found to be significant by both methods, with values of 0.42 (0.41). These results were confirmed using 1000 bootstrap samples. The model's goodness of fit for the two methods was similar: 0.3546 (0.3465). The overall goodness of fit was low, but it can be interpreted as acceptable for the purposes of this study.

Table 4 The one-dimensional character of each group of variables. Var = Variable type. Exo = Exogenous. Endo = Endogenous. CA = Cronbach's alpha. DG Rho = Dillon-Goldstein Rho.

Latent	Var	R2	CA	DG Rho	AVE
LCT	Exo	0.00 (0.000)	0.502	0.715	0.319 (0.335)
LXC	Exo	0.00 (0.000)	0.678	0.795	0.422 (0.437)
LCY	Endo	0.326 (0.291)	0.621	0.768	0.415 (0.417)

These results are complemented by the results in Table 4, which presents Cronbach's alpha, the Dillon-Goldstein Rho, and the average variance extracted (AVE; i.e., how much variance of each indicator is explained by the corresponding latent variable). The data in Table 4 confirm the discriminant validity of the measurement model, related to the one-dimensional character of the group of variables associated with the latent variables (Hwang and Takane 2015; Vinzi et al., 2010).

As mentioned earlier, the influence of LCT was non-significant at the 1% significance level. The influence of CTX on CTY was stronger. The respondents' accurate perceptions support the hypothesis that context dominates content, thereby achieving our research goal. The analysis provides preliminary conclusions about the pertinence of the research framework, tested within the empirical boundaries of the purposive sample. CNT homogeneity was much lower. It makes sense to synthesize respondents' reactions to this group of variables (CNT) as one latent variable, but this variable should be complemented to account for extra variability. In other words, the expected error was greater for CNT than for CTX or CTY. Note that respondents seemed puzzled by content-related questions. Before we reach a conclusion, this issue must be analyzed. Does this ambiguity result from an error by respondents or from an error in specification? It makes sense to match respondents' puzzled perceptions of content with divergent views of driving and restraining forces. Actual responders' misfits are reported with limited capability to address CI skills acquisition needs, platform accessibility via mobile technology and the outcomes of the self-assessment tool.

Respondents reactions to CONTENT construct is of upmost importance while higher variance challenges the fitness of foreknowledge decisional practices with unpredictability and not the informative role of CI knowledge base among participants.

The higher expected error of CNT than for CTX or CTY calls for reflection over reported misfits of respondents' perceptions about the satisfaction with content. The following insights should help the respondents to maximize the value of CI knowledge transfer with high interactive cMOOC content, while engaging in collective experimenting of unpredictability with decision aiding techniques.

The CI cMOOC content will be available to learners via personalized accounts and dashboards. The accounts will integrate learners' profiles (short biography, contact details and links to social media profiles) and their e-portfolios (all files submitted during assignments or discussions with their peers and instructors). The customized dashboards will embed the following features: list of modules (videos emphasizing theoretical issues in CI, performed by reputable professors in this field from around the world), webinars (links for joining live webinar sessions, performed by CI practitioners; learners will have the opportunity to view and listen to recordings, if they missed the live webinars), gamification platform access (it will allow learners to self-assess their dominant CI behaviour: intelligence provider, vigilant learner, opportunity captor, or opportunity defender, while being immersed in a serious game, where they make data-driven decisions on specific scenarios), grades (each learner will receive assignments that have to be graded by professors who give video lectures) and technical support (in case a learner requests assistance, he/she will be redirected to the platform support team).

With founded preliminary support for the legitimacy of the latent variable (Section 4.4. Evidence for latent variables), we now focus on the unambiguous interpretation of latent variables for context and community. Although the overall quality for this model is moderate, the primary conclusion based on data from respondents is that context matters more than content when predicting CI cMOOC behavior.

5. CONCLUSIONS, IMPLICATIONS AND FURTHER RESEARCH

The conflictive nature of acquiring CI skills versus CI actionability relies on sharing versus concealing future anticipation, therefore the current research results inform about upgrading and contextualization of decision aiding techniques with CI cMOOCs.

In this study, we address the need to use an integrated CI knowledge system through a cMOOC platform, highlighting content, context, and community issues tested with 100 qualified respondents, who acknowledged their missing CI skills. We are fully aware that the implementation of the CI cMOOC requires further development, especially in terms of funding. Therefore, we evaluate our ideas by creating a proof of concept that will encourage the business community to support the CI cMOOC, which yields benefits for each participant in terms of access to essential information and knowledge to address current micro and macro environmental issues.

Learners' knowledge background and their variety, within the capacity to recall significant experience of contextualization, must be checked against a predictable performance environment for delivering results. That matches the collective intelligence process design approach to intelligently align both role settings of a qualified CI skill individual and the organizational learning environment, a unique recipe prone to autonomously generate foreknowledge decisional practices, such as deploying context-specific CI practices.

The primary outcome of a successful CI cMOOC is its capacity to deliver on its promise, based on validated learnings regarding context-over-content and context-over-community. The instructor's primary role is to trigger the CI cMOOC's learning interactional space, dominated by incentives to challenge CI foreknowledge decisional practices.

The CI cMOOC constructs highlight pre-matched pairs of driving force and restraining force questions for each group of variables (i.e., content, context, and community). The test of medians provides insight into common perceptions of driving forces. It therefore legitimates the collaborative approach to connectivity in sharing concerns, while perceptions of restraining forces highlight the need to reconcile bias in interpretations of future obstacles.

The values of Cronbach's alpha and the estimation based on principal component analysis suggest that there is an underlying latent variable for each group of variables. Each latent variable embodies respondents' reactions to one of the constructs (i.e., content, context, or community). These findings were reinforced by examining the cross-correlations using PLS-PM and GSCA.

Capitalizing on the acquisition of learners' CI skills, the instructor's role is to adopt a sequential approach to CI learning, increasing collective exposure to connective rules of engagement in training CI skills. Acting as a moderator in reflective judgment, the instructor makes sense of collective learning returns on experience to enrich CI content.

The instructor's role is to deter the learner's propensity to avoid real-world challenges so that the learner can seize opportunities by using newly acquired CI skills. The CI cMOOC's specific context of acquiring skills has the greatest impact within the CI community of learning, thereby enabling collective adaptation behavior regarding the interpreter's selection of CI content. Our findings show that CI context adjustability represents the main challenge of the CI cMOOC as an innovative learning device. The CI cMOOC's impact on transferring new skills to foreknowledge practices is conditioned by the similarities between the controlled learning environment and the application of CI skills to real business scenarios.

The accountability of learners' applied CI knowledge is influenced by learners' capacity to replicate the context of learning without instructor mediation, autonomously delivering results in terms of scanning, filtering, interpreting, selecting, reacting, and adjusting to recognizable signs, blind spots, and opportunities. Closing the gap between similarities of risk-free training in an environment of CI skills and dissimilarities within the complexity of delivering results makes sense for developing early warning systems as foreknowledge decisional practices.

An awareness of the gap between the risk-free cMOOC training environment and the real business environment calls for collective learning returns on experience. By purposefully leveraging constructs of active learning, managerial practices of CI configurations to fit CI artifacts and developing organizational design capabilities to anchor patterns of foreknowledge decisional practices.

A proof-of-concept approach to the CI learning landscape requires the reconceptualization of artifacts of learnable and non-learnable CI skills to address significant concerns over the replicability of training foreknowledge decisional practices to deliver results in real businesses. The designed artifact bridges the gap in recognizing a random approach to active learning in CI communities, matching respondents' puzzled perceptions of content, enriched with unique combinations of divergent views about future challenges. The positioning of the CI cMOOC relies upon respondents' future gains in acquiring CI skills to individually delivering upon trained foreknowledge decisional practice within risky business environments.

The viability of the CI cMOOC proof of concept requires further confirmation from the business community regarding the contribution of CI skills to support foreknowledge decision practices. It is expected that CI cMOOCs will match CI communities of learners' gains in terms of businesses' expectations of improvements in foreknowledge decision practices. Nevertheless, learners will be able to display an increasing capacity to confront CI challenges.

Regarding its contribution to theory, this study provides insights into the foundations of decision science in addressing the emerging paradigm of an open intelligence approach to CI MOOC collective training versus a CI approach to delivering pertinent skills. Variability in learners' CI knowledge level should be checked against the real business environment.

The tailored learning behavior approach of the CI cMOOC proof of concept enables learners to deliver results in applying CI skills and highlights the influence of contextual intelligence over content and community. Managerial practice gains strength when replicable CI knowledge recognizes early enough future competitive challenges, enhances trust in moderating risk exposure to support decision making and induces valuable self-regulated learning behavior. One managerial implication is that the CI cMOOCs can enhance the collective intelligence approach to developing foreknowledge decision practices in the organizational learning process by sequentially increasing respondents' exposure to learnable CI skills. Another insightful implication of the study lies with sharing responsibility of CI decision makers to actively engage with instructors and designers, aiming to enrich the cMOOC context of training skills. A social implication resides on enabling the affordability of opportunities provided by the CI knowledge sharing within the CI cMOOC community of learners. Scaling highlights another social outcome, leading to the increase of the future CI cMOOC's social impact.

CI cMOOCs emerge as a disruptor to corporate learning, providing companies with an innovative digital platform design to share CI skill sets, while challenging an outdated corporate culture. CI cMOOCs as a training provider should focus on corporate coaching needs in their endeavor for accurately measuring the impact of CI acquired skills on the companies' outcome. The 3C approach to CI cMOOCs will imply the renewal of the CI content to enhance the CI community interactions, aiming to shape core CI skill sets, while strengthening the impact of CI training outputs over company outcomes.

Scholars should replicate this study to validate the CI cMOOC constructs of discovering knowledge through active learning, transferring knowledge of CI skills, and capitalizing on acquired skills. Further studies should legitimate the value of the CI cMOOC context of applying skills aligned with highly specific competitive pressures.

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