Mapping eLearning Preparation to Training Objectives in a Multinational Exercise: A Q-Matrix Approach

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ABSTRACT

Multinational training exercises are an important component of developing joint preparedness. Exercise participants increasingly receive eLearning training prior to and during the training event – in this case, planning and conducting a combined and joint Crisis Response Operation (CRO) using Standing Operating Procedures (SOP) within a NATO-led operation – and the efficacy of the eLearning materials depends at least in part on how well they are aligned with the training participants' needs. Methods for aligning eLearning with training exercise objectives generally are based on the judgment of domain experts. However, domain experts face a large challenge in determining where their training materials most impact performance, particularly in highly complex domains. We propose a new approach, based directly on trainee data. We evaluate the alignment between eLearning and training by analyzing data on both individual participant eLearning use and training unit performance on specific objectives. We frame this measure of alignment as a Q-matrix, a representation of the links between two sets of constructs. Q-matrices commonly are used in cognitive diagnostic testing and intelligent tutoring systems to represent the links between latent student skills and specific performance items. We use Q-matrices to represent the connections between the use of specific eLearning modules and unit training achievement. We propose a concrete heuristic for this mapping procedure based on time-on-task and performance ratings. Applying this heuristic to data from a multinational training exercise with participants from 12 countries, we examine how well a set of three eLearning training modules enhances trainee performance on conducting current operations as well as mid-term and long-term planning. Mapping exercise training objectives with eLearning courses in this manner can enable real-time prediction of exercise performance.

ABOUT THE AUTHORS

Biljana Presnall is Vice President of the Jefferson Institute. In her role as lead software systems architect, she has over 15 years of experience in designing and developing distributed learning solutions, simulations, courseware, and learning technologies for government and academic stakeholders. She specializes in international development, deploying digital tools, and integrating them with research and education systems to transform societies by empowering engaged access to information. Currently, she leads the digital team on a Department of Defense R&D project to mature the operational integration of ADL in exercises (MADLx).

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BACKGROUND

This research was conducted in the context of Combined Joint Staff Exercise (CJSE19), an exercise run by the Swedish Armed Forces and Swedish National Defense College with international participation from 12 countries (Sweden, Finland, Estonia, Austria, Switzerland, USA, Georgia, Norway, Germany, South Korea, UK, and Latvia). The overwhelming majority of the 753 trainees were student officers from Sweden (62.5%) and Finland (29.6%). No other participating nation's contribution topped 5%.

The training audience was temporarily assembled into seven teams, each with specified roles on an operational and tactical level. Besides the training audience, the exercise included an OTT (Observer and Training Team), which supported the exercise and provided direct contextual support for the training audience[1]. The training audience could access the online courses necessary to perform adequately at the exercise; the courses were recommended but not prerequisite. When the exercise began, participants received time-framed tasks. At the end of each day, they were debriefed by qualified observers attempting to present nonbiased conclusions[2]. Dedication and commitment to a shared goal among team members was one of the key elements of the exercise, and trainee performance was scored accordingly, following the training objectives for each team. There were 37 objectives divided into three main areas with some overlaps: Current Operations (CO), Mid-Term Planning (MTP), and Long-Term Planning (LTP).

In its nature, team learning has unique attributes[3] which differ from individual learning, and we assumed some conditions as optimal for the purposes of this research. These pre-conditions include, but are not limited to, the non-biased role of the observers and the level of English language proficiency of the participants (the official language of CJSE).

Measure of Success

In the Exercise Evaluation (EXVAL) Introduction, EXVAL Director Col. Jan Mortberg stated that the exercise would be considered successful if the participating individuals and teams achieve the following objectives:

• ***Enhanced ability of acting as Commanders (COM) and staff members in an international staff environment during a combined and joint Crisis Response Operation (CRO)***

•***Enhanced understanding of planning and conduct of a CRO, including high levels of conflict in Joint Operations Area (JOA)***

•***Enhanced understanding of using Standing Operating Procedures (SOP) within a NATO-led operation***

[1] Hedlund, Erik & Börjesson, Marcus & Österberg, Johan Team Learning in a Multinational Military Staff Exercise, 2013
[2] Rudolph, J. W., Simon, R., Dufresne, L., & Raemer, D. B. There's no such thing as "nonjudgmental" debriefing: A theory and method for debriefing with good judgment, 2006
[3] Salas, E., DiazGranados, D., Klein, C. C., Burke, S., Stagl, K. C., Goodwin, G. F., & Halpin, S. M. Does team training improve team performance? A metanalysis. Human Factors, 50, 903-933. doi:10.1518/001872008X375009, 2008

Method

Earlier research demonstrated that aligned learning objectives from online courses improve performance in simulations[4]. The Q-method creates a matrix-based model that represents latent relationships among observed binary variables[5]. In learning science there is an increasing interest in discovering Q matrices empirically.

The online eLearning pre-training was available two months prior to the exercise with three major courses:

- Course A: Learning about the context of the exercise
- Course B: Learning about the simulation tool
- Course C: Learning about the observer tools

All courses were xAPI enabled and sent user experience data in a real-time stream to a Learning Record Store (LRS), from which we retrieved the data. Observer data were collected by the exercise organizer and were available after the exercise for analysis.

First, we used the Q-matrix method to identify links between participants' performance during their pre-training and to map them with the training objectives. We also examined each eLearning course's time components: initialized or completed prior to the exercise start, and initialized or completed after the start. We linked these data points with the seven teams' performance on the training objectives during the exercise, dividing them into three main areas: Current Operations (CO), Mid-Term Planning (MTP), and Long-Term Planning (LTP).

The total number of 753 exercise participants included the support groups and observers; we followed only the 319 trainees who took part in online preparation. Each of the seven training groups included a portion of our targeted trainees, but we do not know if they were the total trainee population of each team.

We considered each team separately to minimize the error for trainees within a given unit, and we created a separate Q-matrix for each team. For example, Team One comprised nine members. We had data on both eLearning preparation and course timing for each team member. However, each member shared the same team result against the respective training objective.

To utilize the binary Q-matrix, we used the following formulas for performance in eLearning course preparation and team performance in the exercise to transform the actual data values to binary:

if(course score>50% && exercise performance>50%) Q-matrix value = 1

if(course score>50% && exercise performance <50%) Q-matrix value = 0

if(course score<50% && exercise performance >50%) Q-matrix value = 0

if(course score<50% && exercise performance <50%) Q-matrix value = 1

The trainees had period of two months before the exercise to conduct online preparation as well as one opportunity during the exercise to do so. We examined when they initialized online courses with the following formulas:

if((initialized before==1 && exercise performance >50%) || (initialized before ==0 && exercise performance <50%)) Q-matrix value = 1

[4] Presnall A., Radivojevic V. Learning analytics with xAPI in multinational exercise, IITSEC 2018
[5] Barnes, Tiffany & Bitzer, Donald & Vouk, Mladen. Experimental Analysis of the Q-Matrix Method in Knowledge Discovery, 2005

if((initialized before ==0 && exercise performance >50%)|| (initialized before ==1 && exercise performance <50%)) Q-matrix value = 0
if((initialized after==1 && exercise performance >50%)|| (initialized after ==0 && exercise performance <50%)) Q-matrix value = 0
if((initialized after==0 && exercise performance >50%)|| (initialized after ==1 && exercise performance <50%)) Q-matrix value = 1

For the total time spent on each of the preparation courses:

if (total time > 45” && exercise performance >50% Q-matrix value = 1
if (total time < 45” && exercise performance >50%) Q-matrix value = 0
if (total time > 45” && exercise performance <50%) Q-matrix value = 0
if (total time < 45” && exercise performance <50%) Q-matrix value = 1

Performance

The performances for each course were not valued equally, as course A was the easiest to achieve >50% success with a median of 100% achievement. At the same time, it demonstrated the lowest effect on training success.

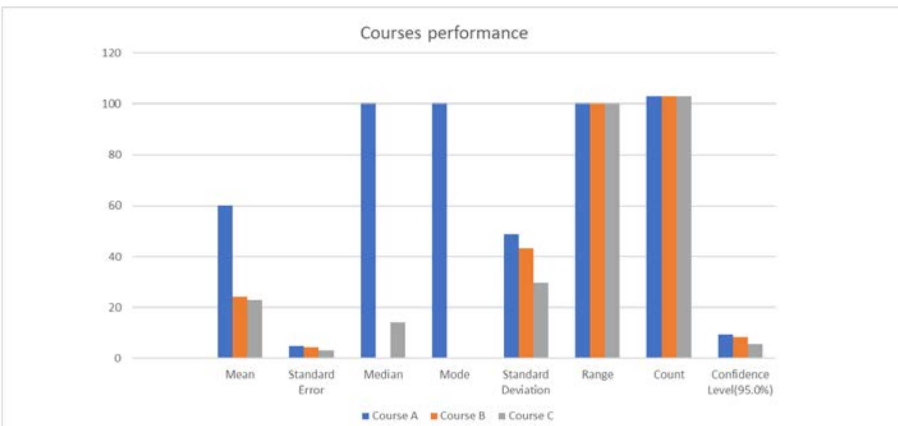

Figure 1: Performances in eLearning

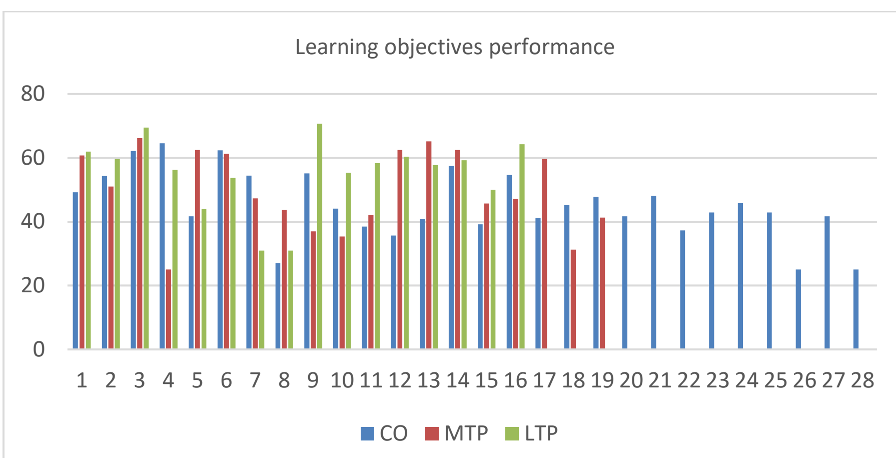

Figure 2: Performances in exercise

This was especially evident for Current Operations (CO) objectives, where success in the courses did not correspond with poorer results in the exercise.

For all training teams, a minimum of 50% achievement in eLearning courses correlated with higher achievement in all areas of the exercise.

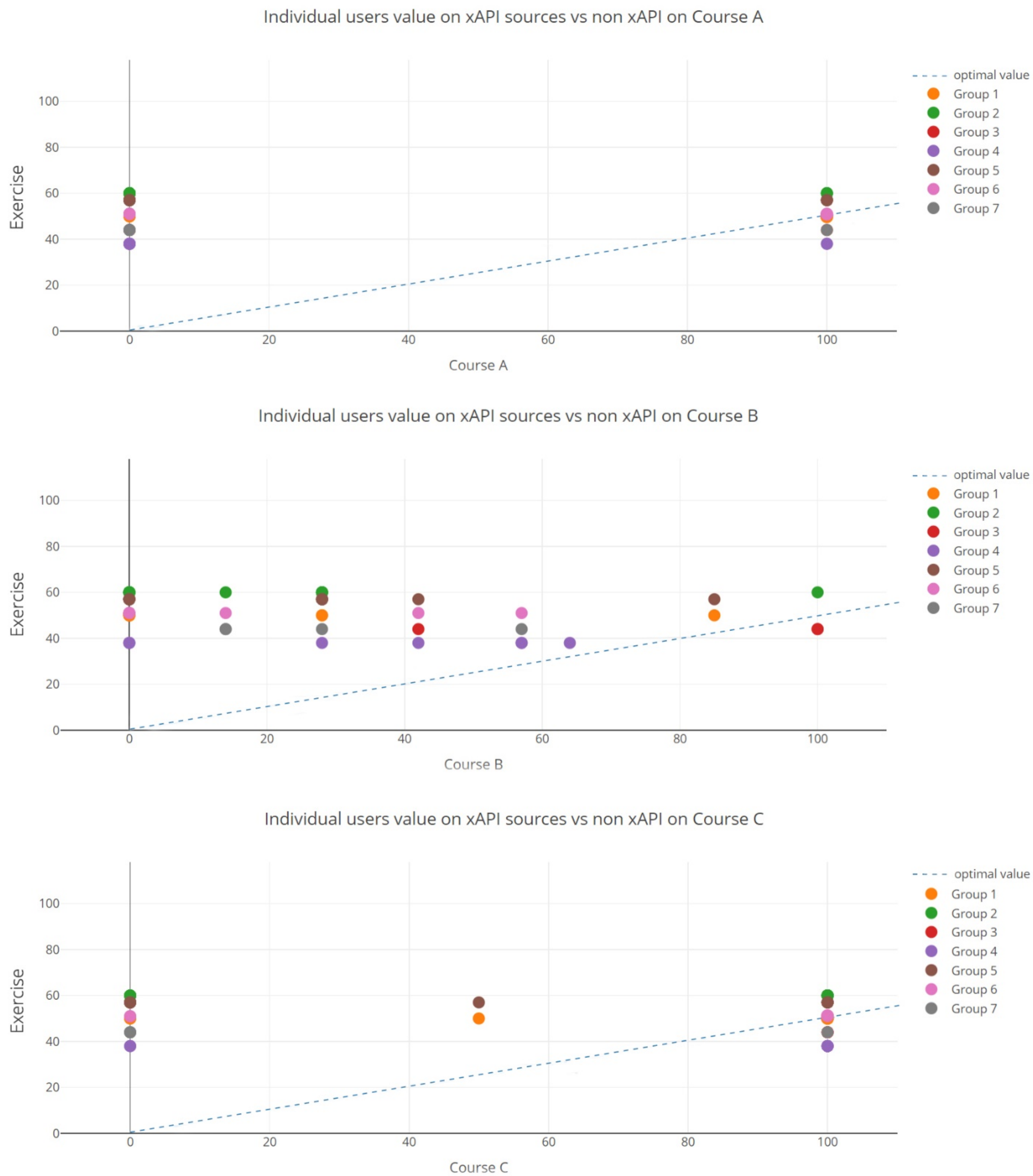

Figure 3: Performances of eLearning (x) compared with exercise performance (y)

Timing

A majority of participants (74%) initiated and completed the courses before the exercise started, but only some course activities were associated with better eventual performance. Specifically, we may associate completion of Course A – which was intended to familiarize participants with the context of the exercise, prior to the exercise start – with better performance within all three main training areas. We saw higher correlation only in the training groups whose focus was to utilize specific knowledge from course B (Simulation tool) or C (Observer tools). We assume that these courses better supported their role in the exercise. If trainees initiated or completed the courses after the exercise began, there was no evidence of impact on the result of their respective training group.

Duration

Trainee time spent on the learning management platform preparing for the exercise ranged from five minutes to two and-a-half hours, with Course A receiving the greatest attention: 53% of participants spent an average of one hour and 10 minutes. However, participants' duration on the platform did not appear to have a significant effect on the overall results of their team.

Q-Matrix Model Extraction

The model creates a matrix representing the relationships between concepts and questions directly from student response data. For our analysis, the eLearning courses and their initialization/completion and total time spent were our concepts, while the exercise objectives were our questions.

The algorithm varies c, the number of concepts, and the values in the Q-matrix, minimizing the total error for all participants for a given set of n objectives. We searched for the best Q-matrix using an algorithm similar to the one used by Barnes, Bitzer & Vouk, 2005[6].

We computed the total error for the Q-matrix across all trainees, using the following formula:

$$d(p, IDR) = p(q) * IDR(q) \qquad (1)$$

After the error was computed, each value in the Q-matrix was changed by a small amount; if the overall Q-matrix error improved, we saved the change. We repeated this process for all the values in the Q-matrix several times, until the error in the Q-matrix was not changing substantially. After we computed the Q-matrix in this fashion, we ran the algorithm again with a new random starting point several times, saving the Q-matrix with minimum errors to avoid falling into a local minimum.

We started with random matrix and input data of numbers of objectives matched with number of concepts. The matrix works the best if square, so we performed 9 x 9. For this, we randomly selected three learning objectives from each of the training areas – CO, MTP, and LTP – and we observed the behavior of each participant with comparable results. We then applied the Q-matrix with minimum errors to the trainees of the exercise.

Results

Utilizing a Q-matrix, we analyzed data on training exercise participants' eLearning behavior and compared it with the performances of the trainees' units on specific objectives. We reached the following conclusions:

[6] Barnes, T., Bitzer, D., & Vouk, M. Experimental analysis of the q-matrix method in knowledge discovery. In International Symposium on Methodologies for Intelligent Systems (pp. 603-611). Springer, Berlin, Heidelberg., 2005

	Course A	Course B	Course C	Couse A initialized before exercise started	Course B initialized before exercise started	Course C initialized before exercise started	Total time spent on course A>45"	Total time spent on course B>45"	Total time spent on course C>45"
CO#1	0	1	1	1	0	1	1	0	0
CO#2	0	1	1	1	0	1	1	0	0
CO#3	0	1	1	1	0	1	1	0	0
MTP#1	1	1	1	1	1	0	1	0	0
MTP#2	1	1	1	1	1	0	1	0	0
MTP#3	1	1	1	1	1	0	1	0	0
LTP#1	1	1	1	1	1	1	1	0	0
LTP#2	1	1	1	1	1	1	1	0	0
LTP#3	1	1	1	1	1	1	1	0	0

Figure 4: Q-matrix with minimal error

- A performance of **at least 50% on eLearning courses** is associated with overall higher achievement of all training units in an exercise. However, conducting Current Operations (CO) and enhancing the ability of acting as commanders and staff members are the least influenced by performance on Course A (which covers the context of the exercise).
- The eLearning courses demonstrated the greatest efficacy when initialized or/and completed **before the exercise started**. Completion of Course B (knowledge about the simulation tool) and Course C (knowledge about observation tools) affected trainee understanding of using SOP and conducting LTP.
- The eLearning courses showed **no influence** on overall results when initialized after the exercise started. An influence occurred only when specific skills were demanded in CO and MTP from Courses B and C. (This might indicate the best match for on-demand, micro-learning content in support of a similar exercise.)
- The duration of eLearning training does not have any performance impact. Even though the trainees spent the most time learning about the context of the exercise (Course A), we did not see any significant difference in exercise results if trainees spent more time on this training course.

Conclusion

The measures of success of an exercise cannot be proven unless the trainees participate in another exercise, or a live mission or similar crisis. Thus, exploring the empirical elements of the exercise, and utilizing them to predict post-exercise individual and team behavior, provides valuable insights. Mapping exercise training objectives with eLearning courses in this manner can enable real-time prediction of exercise performance and ultimately team and individual behavior in real-life missions.

We recognize that results of our analysis may not apply in every similar multinational exercise, but opens a path for further investigation of methods for better aligning eLearning with exercise training objectives. It also adds to the growing body of research demonstrating the value and efficacy of eLearning as pre-training to enhance exercise performance, to reduce training costs, and to help maximize Return on Investment (ROI) in multinational training exercises.

Overall, the research conducted here helps us to better understand the role of eLearning courses in the development of skills targeted in training exercises; eventually, it may help us understand the development of skills beyond those training exercises and their use in live missions.

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