# Efficient tracking of Web-based collaboration dissonance using Quality Control Analysis (QCA)

**Sofia J. Hadjileontiadou & Leontios J. Hadjileontiadis**

Demokritos University of Thrace, Xanthi, Greece
Aristotle University of Thessaloniki, Thessaloniki, Greece

ABSTRACT: This article presents an approach for tracking and analysing Web-based collaboration dissonance automatically, given the assumption that divergence in peers' collaborative activity causes dissonance at both the group and individual levels. By employing quality control analysis, the proposed method tracks unusual patterns and tendencies in peers' collaborative activity. This information, in turn, triggers appropriate feedback towards a more balanced collaboration among peers. Experimental results from an environmental education case study prove the potentiality of the proposed approach to customise the feedback to peers' needs and to predict possible bias in the collaboration dissonance across the collaboration activity set. Due to its implementation simplicity, the proposed approach could easily be intergraded in many computer-mediated collaborative environments.

## INTRODUCTION

Web-based, asynchronous and written collaboration takes place among participants who normally have divergent characteristics, ie collaborative skills. In such cases, providing support may enhance the quality of the collaborative procedure. Recent studies in collaboration ground the design of this support on the analysis of participants' collaborative interactions, which explicitly employ the above skills [1]. Thus, the designing of a supporting system foresees three primary procedures, namely:

- Monitoring collaborative interactions and acquisition of collaborative data.
- Analysing these data by employing either statistical analysis of the collaborative interactions [2]; and/or intelligent inferences upon the quality of the collaborative activity by means of quantitative indicators [3].
- Providing appropriate feedback based on the analysis results.

Computer mediation for Web-based collaboration allows the automation of all of the above procedures, lending flexibility and adaptive characteristics to the supporting system, thereby enhancing the quality of peer collaboration.

Prior to the adoption of any analysis procedure, the unit of analysis should be defined. In particular, the analysis unit could include the individual's and/or the group collaborative performance [1]. From a Distributed Cognition (DC) perspective, a group may be considered as a joint cognitive system that builds up and maintains a shared understanding of a collaborative activity [1]. On the other hand, from a Socio-Constructivistic (SC) view, each individual has his/her own perception of his/her collaboration activity [1]. When a divergence of peers' collaboration activity exists, a cognitive dissonance is produced at both the above units of analysis [4]. This dissonance produces pressure for change that requires remedy actions to reduce it. A balance of peers' collaborative activity may satisfy this need at the group level. When this balance results from the self-tuning of an individual's attitude to the collaborative activity, it then leads to the action of revising his/her position within the group [4]. Under this perspective, the analysis of collaborative performance focuses on the calculation of the divergence of peer collaboration activity by utilising collaborative data. On the other hand, the feedback content challenges individual conceptual change towards diminishing this divergence.

The notion of convergent conceptual change has been explored in the literature by means of several methods, ie the detection of divergence of syntactic and semantic information [5]; distinguishing beliefs using networks [6]; the use of a confidence indicator that measures the discord between the understanding of two elements of knowledge [7]; conversational interaction analysis [8]; and an exploration of self-affirmation conditions using neural networks [9]. However, these approaches investigate the conceptual change as far as the content of the collaborative activity is concerned.

This article presents an alternative approach based on a Quality Control Analysis (QCA) of peer collaborative interactions [10]. QCA is a statistical method used to assure the quality of a product or service [11]. Here, QCA is used as a means to find those values of collaboration activity divergence that are beyond the control limits [10]. In this way, collaborative sessions that cause cognitive dissonances to collaborators are detected. By employing rule-firing evaluation procedures, QCA permits the estimation of the tendency of the parameters involved; hence, it could be used (solely or combined with metacognitive data) as a means for the proper adjustment of feedback provided to peers, seen from both the DC and SC perspectives, thereby augmenting peer collaboration activity towards more balanced collaboration.

## BACKGROUND

### Collaboration Issues

A common approach to the collection of collaborative data is the use of a communication protocol materialised by a set of predefined buttons in a participants' workspace [12]. Every participant's interaction takes place through the use of these buttons and, in this way, the system collects collaborative data by means of mouse clicks. These raw quantitative data are weighted to qualitative variables that describe the quality of the collaboration within the group [12]. For instance, when two peers collaborate, the contribution of each to the pair's work represents the quality of the individual collaborative activity, ie $C_n$, $n = A, B,$ where $A$ and $B$ denote the two peers, respectively, normalised by the total collaborative activity, ie $C_{tot} = C_A + C_B$ [12]. Since the analysis unit includes only two peers, the estimated $C_n$ values are complementary and their divergence, ie $dC_{A,B}$, is easily calculated as:

$$dC_{A,B} = |C_A - C_B|, \tag{1}$$

where $|\cdot|$ denotes the absolute value. The definition of upper and lower limits specifies the accepted range of the $dC_{A,B}$ value and differentiates, accordingly, the feedback content. These limits are automatically specified by QCA.

### Quality Control Analysis (QCA)

Quality control tools can be used on almost any production or service process, eg in manufacturing and service industries to monitor the extent to which products or services meet specifications. To do so, a certain quality characteristic is chosen and samples of it are extracted during the ongoing process. Then, the variability in those samples is considered by means of line charts [10]. The charts employed are often classified according to the type of quality characteristic *variable* or *attribute* that they are supposed to monitor. Generally, variable control charts are more sensitive than attribute control charts and may signal quality problems before any actual *unacceptables* occur [10]. Two widely used charts for controlling variables are the R-chart and the X-bar chart [10]. The R-chart is a very popular statistical process control chart that tracks the range of the acquired samples for each sample group (also called subgroups), while the X-bar chart is used to detect those groups that have unusually high or low mean values [10].

According to the characteristic that is to be controlled, a centreline and upper and lower limits are determined by means of statistical principles. In particular, the centreline, $c_L$, denotes, in the case of the R-chart, the average of all ranges, and, in the case of the X-bar chart, the average of all subgroups [10]. The upper and lower limits correspond to the $\pm 3std$ distance from the centreline (*std* denotes the standard deviation), defining the interval where 99% of the sample means falls [10]. If a trend emerges in the area between these lines, or if samples fall outside the limits, then the process is declared to be *out of control*, rejecting the assumption that the current data are from the same population as the data used to create the initial control chart limits. Standard charts require a process that is well defined and in control with minimal measurement error [10]. When these assumptions are not actually met, the aforementioned charts could be approximated by the pseudo-control charts [10]. The latter are preferred for the case of controlling educational processes, where the assumptions for the standard form of the charts are not easily met [11][13]. Motivated by the latter, pseudo-control charts can be applied to collaborative data in order to identify specific abnormalities in peer collaboration to trigger the appropriate feedback.

An evaluation procedure that is often adopted in QCA involves the Western Electric Company (WECO) rules, which are assigned to the employed control charts [14]. The WECO rules provide a means to evaluate the chart line characteristics and possible tendencies. Table 1 presents their activation definition.

Table 1: Definition of the WECO rules [14].

| WECO Rule | Rule Activation Definition |
|---|---|
| R1 | Any point with value $> \lvert c_L \pm 3std \rvert$ |
| R2 | 2 out of 3 points (66.6%) with value $> \lvert c_L \pm 2std \rvert$ |
| R3 | 4 out of 5 points (80%) with value $> \lvert c_L \pm 1std \rvert$ |
| R4 | 8 consecutive points with value $> or < c_L$ |
| T1 | 6 in a row trending up or down |
| T2 | 14 in a row alternating up and down |

NB: $c_L$ : the centreline of the pseudo-control chart; $std$ : standard deviation; $|\cdot|$ : absolute value. T1 and T2 are trend rules [14].

## THE PROPOSED APPROACH

The proposed approach builds upon the information provided thus far. In particular, the use of the pseudo R-chart and X-bar chart is proposed for the realisation of the state of control of the $dC_{A,B}$ value, defined by (1), which is the variable under consideration. In fact, when two peers collaborate in a computer-mediated collaborative environment, such as *Lin2k*, the monitoring of collaborative activity is feasible; hence, data from the collaborative interactions are available [12].

Following the modelling of collaborative activities, as proposed by Hadjileontiadou et al, the normalised quality of the individual collaborative activity, $C_n$, can be estimated [12]. Consequently, the $dC_{A,B}$ value can further be estimated using (1). According to the structure of *Lin2k*, the estimation of the $C_n$ values takes places at the end of a step (usually six exist) within a collaboration session (a series of sessions construct the whole collaboration activity set). Consequently, the $dC_{A,B}$ value can be estimated for each step and the pseudo-control R-chart and X-bar chart can be constructed for each collaboration session. By employing the WECO rules, an evaluation of these charts can trigger appropriate feedback that could gradually lead the collaborative activity within the control limits across the collaborative activity set. Feedback may be either of an encouraging character, ie propose sustaining the quality of the collaborative activity, when the $dC_{A,B}$ value is accepted, or of an alerting nature, when the $dC_{A,B}$ value is out of control. When feedback is provided at the end of collaborative sessions, it acquires a formative character by gradually coaching peers to improve their collaborative skills towards a balanced level of collaboration. The end of the session is followed by a Web-form that records peers' beliefs of their collaborative performance [12].

Combining the results from QCA with a statistical analysis of these metacognitive data could further enhance feedback content. The latter includes the estimation of the user's trend of improvement, ie the percentage of questions answered by the user regarding the foreseen improvement in his/her collaboration activity at the next collaboration session from the total available questions included in the Web-form [12]. Figure 1 shows a working scenario of the proposed approach during one collaboration session.

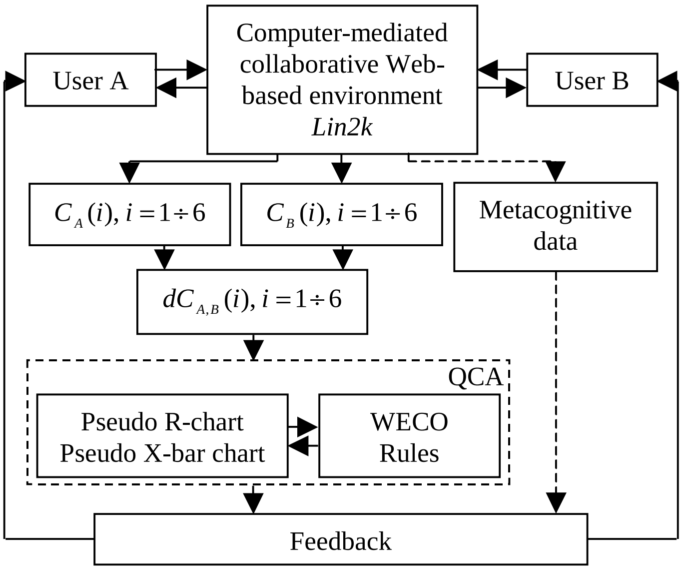


Figure 1: A schematic diagram of the proposed approach for a collaboration session with six steps.

## A CASE STUDY

The proposed analysis was tested involving 38 randomly selected civil engineering students in their 6th semester enrolled in the Department of Civil Engineering at the Aristotle University of Thessaloniki (AUTH), Thessaloniki, Greece. They collaborated in pairs (19 groups) on a case study in the field of environmental engineering. Web-based collaboration was realised using the computer-mediated collaborative environment of *Lin2k* [12]. The whole collaboration set consisted of six sessions with six steps per session, organised according to the task content. In order to test the efficiency of the proposed approach, the 19 groups were split again. The 13 groups, at the end of each session, received feedback regarding their collaboration dissonance, while the six remaining groups, received no such feedback. After the third session, the 13 groups used the *Lin2k* Web-form to provoke metacognitive activity in order to combine QCA with metacognitive data analysis. This Web-form included 33 questions that concerned the quality of the contributions, argumentation, attitude to collaboration and coordination issues [12]. The whole analysis was implemented using the MS *FrontPage 2000* and the *Matlab* Server 6.1.

## RESULTS AND DISCUSSION

Figure 2 illustrates the QCA results when applied to $dC_{A,B}$ values derived from six groups collaborating without receiving any feedback regarding their collaboration dissonance during their collaboration activity. In particular, Figure 2a shows the pseudo-control R-chart and X-bar chart, while Figure 2b depicts the corresponding WECO rules for these two charts, respectively. From Figure 2a, it is clear that group #5 is beyond the control limits in the R-chart and that group #1 is out-of-control in the X-bar chart. This is also confirmed by the WECO rules in Figure 2b, where the estimated activation level of R1 has reached the threshold level in both charts. In addition, the estimated activation level of R4 and T1 from the R-chart is high (65%), showing a tendency for adopting a bias (R4) and a direction towards an out-of-control state (T1). The latter is also seen from the activation level of T1 (65%) from the X-bar chart, where the activation level of R3 is also high (65%), showing again a tendency to reach the control limits.

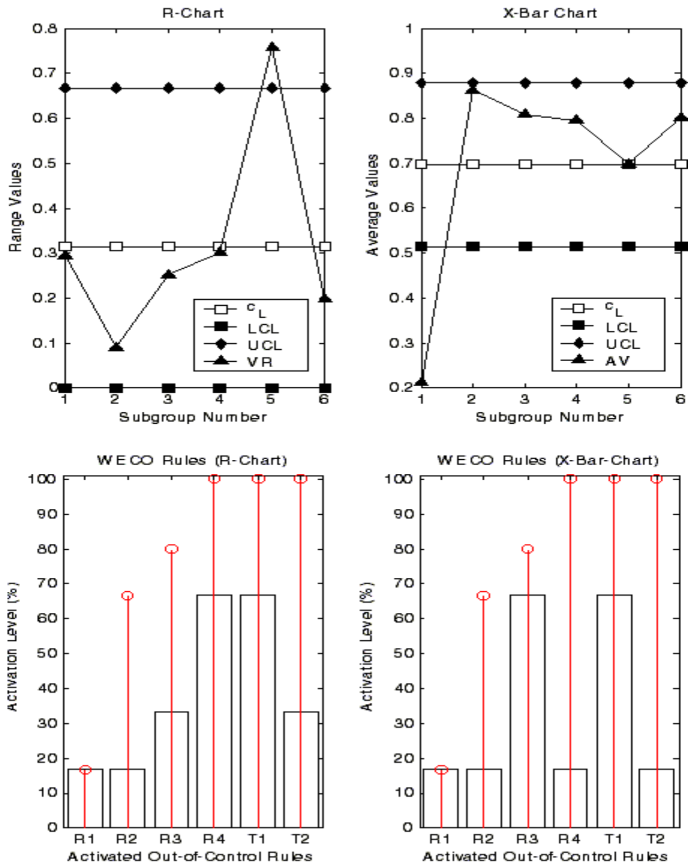


Figure 2: The results from QCA collaborative data acquired from six groups collaborating without receiving any feedback regarding their collaboration dissonance during their collaboration activity. 2a (top): The pseudo-control R-chart and X-bar chart. $c_L$ : the centreline; LCL: Lower Control Limit; UCL: Upper Control Limit; VR: Variable Range; AV: Average Value of all subgroups. 2b (bottom): the WECO rules: the stem denotes the threshold level for activation of each WECO rule (see Table 1), whereas the bar denotes the estimated activation level derived from the pseudo-control charts of 2a.

Figure 3 shows the QCA results when applied to the $dC_{A,B}$ values derived from the 13 groups that received feedback regarding their collaboration dissonance during their collaborative activity. This feedback is triggered by the QCA results combined with metacognitive data analysis provided by *Lin2k*. Specifically, Figure 3a shows the pseudocontrol R-chart and X-bar chart, while Figure 3b depicts the corresponding WECO rules for these two charts. From Figure 3a, it is clear that none of the groups is out-of-control, both in the R-chart and the X-bar chart. This is also confirmed by the WECO rules (Figure 3b), where the R1 and R2 rules are not activated at all, while the range of the estimated activation level of R3, R4 and T1 is kept quite low (5-30%). Increased values can be seen in the estimated activation level of T2, in both charts (55-70%), showing a tendency for alternation around the centreline. As the R-chart and X-bar chart show, this alternation is kept close to the centreline and far from the upper and lower limits.

Consequently, a tendency for alternation around the centreline gives the effect of feedback on the groups to sustain their collaboration dissonance within the control limits, mostly close to the centreline.

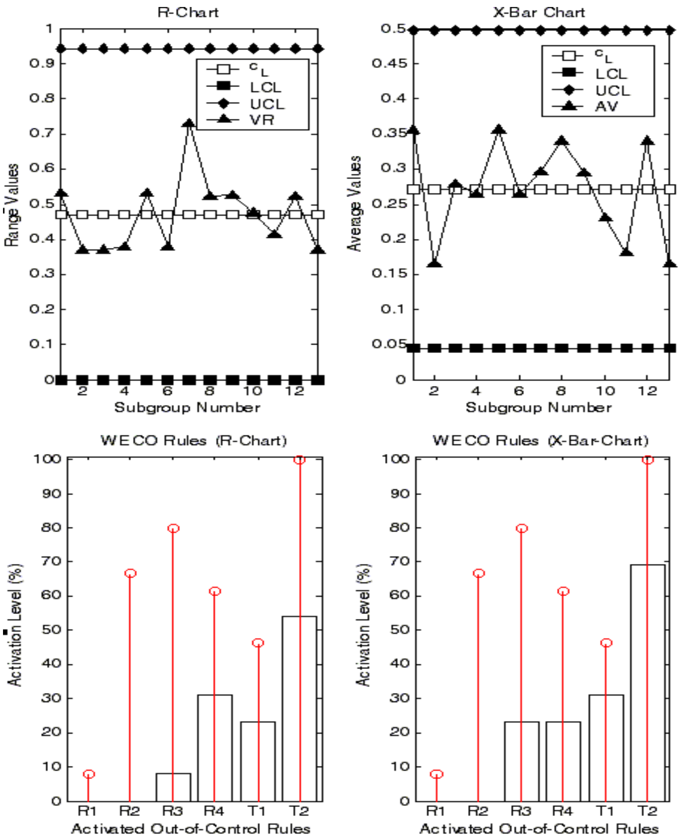


Figure 3: The results from the QCA collaborative data acquired from 13 groups receiving feedback during collaborative activity (4th session). 3a: The pseudocontrol R-chart and X-bar chart. 3b: The WECO rules (legend same as in Figure 2).

Similar results have been obtained when the feedback provided to peers was based on QCA only, ie no metacognitive data analysis was employed (sessions 1-3). This means that QCA plays the main role in the feedback triggering procedure, whereas the metacognitive data contribute to its further refinement. More specifically, QCA clearly identifies those groups that are (or tend to be) out-of-control and specifies the general category of the feedback messages, eg encouraging or warning type, etc. The metacognitive data analysis, then, narrows down the messages from the triggered category to ones with more specific content, such as *You have a correct perspective of the way you collaborate with your peer. Continue in the same way*. In this way, the collaboration dissonance is efficiently controlled within the control limits and the collaborators have an accurate view of the quality of their collaboration.

The simplicity of the proposed approach provides its online implementation in a Web-based collaboration environment, facilitating collaboration of distant peers. QCA highlights possible trouble areas in collaboration dissonance and the feedback is guided to correct identified problems, and not to try to detect unusual patterns. In this way, peers can rely on the collaboration environment and collaborate more freely, since they *a priori* know that the system systematically detects any unusual patterns of collaboration dissonance and guides them towards a within-control limits collaboration activity. Nevertheless, large-scale application of the proposed tool should be employed to further justify the promising results presented here.

## CONCLUSIONS

An automated way of tracking collaboration dissonance during Web-based collaboration using quality control procedures is presented in this article. The proposed approach efficiently identifies unusual patterns in peers' collaborative activity and triggers appropriate feedback messages that could guide peers towards a more balanced collaboration.

Furthermore, it reveals possible tendencies and bias in the collaborative activity field, acting as a prediction tool, hence, obviating out-of-control collaboration patterns. Moreover, its implementation simplicity makes it an attractive tool for the online facilitation of Web-based collaboration between peers over some distance. Finally, its modular design allows its integration in any computer-mediated collaborative environment, provided the availability of collaboration dissonance data.

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