PATTERN DISCOVERY, VISUALIZATION AND INTERACTION DATA ANALYTICS IN A PROCESS-AWARE MULTI-TABLETOP COLLABORATIVE LEARNING ENVIRONMENT

By

Parham Porouhan

ID: 5419100001

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ABSTRACT

Dissertation Title	: Pattern Discovery, Visualization and Interaction Data Analytics in a Process-Aware Multi-Tabletop Collaborative Learning Environment
By	: Mr. Parham Porouhan
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Co-Advisor	: Professor James G. Williams, Ph.D.

This dissertation builds on the intersection of educational process mining and the automatic analysis of student's collaborative interaction data previously collected from a networked multi-tabletop learning environment. The main focus of the study was to analyze and interpret the data using several process mining techniques in order to increase the instructor's awareness about the students' collaboration process with respect to specific quantitative indicators as follows: participation (consisting of participation density, participation rate and participation dynamics metrics), interaction (consisting of interaction density and interaction dynamics metrics), time performance (including the number of time intervals between the activities as well as the duration of idle/inactive periods), similarity of tasks (symmetry of actions) and division of labor (symmetry of roles).

The empirical findings showed that high performance groups exhibited increased tendencies to perform tasks simultaneously (together) or alternatively (between group peers). Moreover, high performance groups also showed increased tendencies to interact with objects created by their other fellow group members. Although both groups showed long waiting times at the beginning of a task, high performance groups were mostly brainstorming while low performance groups were playing an idle role. High performance groups showed increased tendencies to work on the same range of actions 'together'. Quite the opposite, low performance groups showed increased tendencies to work on a dissimilar range of actions 'individually'.

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1.0 INTRODUCTION

Although the majority of readers might be familiar with most of the issues and concepts relating to process mining techniques and its algorithms, some of the terminology used in the present study might not be understood by some readers they are explained below. Moreover, there was a need to explain briefly without any emphasis on the technical design specifications and infrastructure requirements as to how the developed system was capable of automatically and unobtrusively capturing, collecting and formatting the students' individual and collaborative activities in terms of MXML-formatted event logs (datasets) supported by the Instructor Dashboard. Therefore, before discussing the empirical part of the research which is the main objective of the study we provide a list of the most important definitions, abbreviations and terminology used in forthcoming sections as follows:

1.1 Preliminaries, Definitions and Abbreviations

Collaborative learning is commonly referred to as a situation in which small groups of students work together (through face-to-face conversations or computer discussions) to search for a common solution, meaning or understanding, and to create an artifact based on their understanding in the learning process (Chiu 2004 ; "Collaborative learning" 2015 ; Harding-Smith 1993). Computer-Supported Collaborative Learning (CSCL) is an educational method in which the learning process is practiced through social interaction via a personal computer (PC) or usingthe Internet. This type of pedagogical approach is commonly referred to the construction and sharing of knowledge among students by using technology as a common resource or as the main tools of communication ("Computer-supported collaborative learning" 2015 ; Stahl 2006).

According to Dillenbourg (1998) in the definition of Computer-Supported Collaborative Learning (CSCL), a pedagogical situation is called collaborative when a group of students —who are more or less at the same level of status, skills, knowledge, expertise, development, and so on can work together and perform the same range of actions toward a common or shared goal (i.e., not by competing with each other toward a conflicting goal). Dillenbourg (1998) explains that although the terms Collaboration and Cooperation are often mistaken and misunderstood as two synonyms, there is a huge difference between them considering the degree of division of labor among peer group members. In cooperative learning situations, students divide the main task into sub-tasks, each group member tries to accomplish a sub-task individually, and finally these sub-tasks are assembled and presented in the form of a final output. However, in collaborative learning situations, students try to accomplish the main task together in a completely collective and spontaneous manner. Therefore, five main features that distinguish the term Collaboration from Cooperation are based on the following factors:

1. Symmetry of participants' status (with regard to their community)
2. Participants are allowed to perform a similar range of actions
3. Symmetry of participants' prior knowledge, expertise, skills, development, etc.
4. Participants attempt to reach a common goal but not throughcompetition
5. Low and spontaneous division of labor

Interactive Table Computers (Tabletops). A multi-user interactive table computer, or a table PC, or an interactive tabletop is a full-featured large-display portable all-in-one computer which is equipped with multi-touch features and capabilities that can be used by up to six individuals on a table's top (Ackerman 2013 ; "Table computer" 2013). According to Dillenbourg and Evans (2011), interactive tabletops include five main different types of systems as follows:

(1) Touch-Interface systems in which the position (and track) of fingers is detected (i) using a contact point among conductivity layers, (ii) using an infrared camera inserted below the tabletop capable of detecting heat points, (iii) through an overhead depth camera inserted above the tabletop where computer vision methods (and image processing algorithms) recognize fingers and their traces. In

Section 2.3 and Section 2.4 of the study, we have explained more about these kinds of tabletop systems and the differences between them. Some of the publications and research by Dietz and Leigh (2001), Schmidt et al. (2010a), Ackad et al. (2012), Klompmaker et al. (2012), Blažica et al. (2013), Martinez-Maldonado et al. (2012a ; 2014) and others were conducted toward these capabilities.

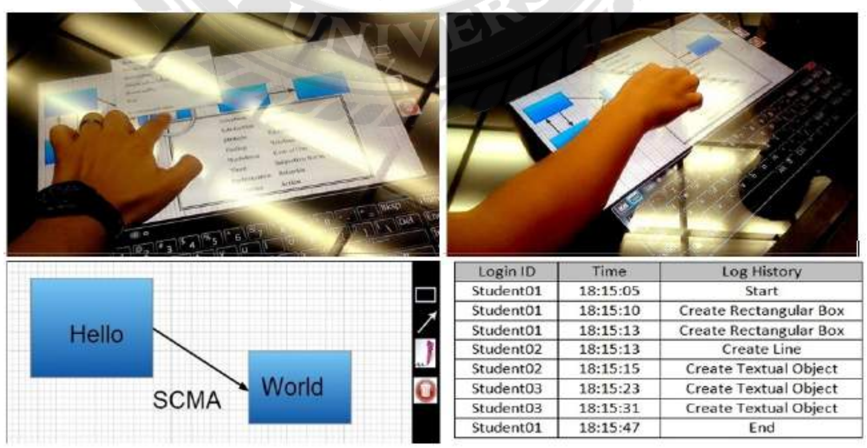
(2) Tangible-Object systems in which the position of tangibles (or physical objects) on the interactive surface is detected by a camera inserted above or below the tabletop by recognizing the tangibles by means of “fiducial markers” or radio frequency (RFID) tags embedded within the tangibles. In Section 2.2 and Section 2.4 we have provided some examples of the Tangible-Object systems in the works done by Tanenbaum and Antle (2009), Oppl and Stary (2011), Marquardt et al. (2010), Klompmaker et al. (2012), Jermann et al. (2009), etc.

(3) Small Gadget-Supported systems in which digital pens, digital gloves, digital wristbands, digital armbands, and so on are used in order to write or draw on the interactive surface of the tabletops. The position of these kinds of small electronic gadgets are normally recognized by radio signals, external hardware or through a camera embedded in them. In Section 2.3, we have provided some examples of the electronic Gadget-Supported systems such as the works done by Collins and Kay (2008), Kharrufa (2010), Meyer and Schmidt (2010), Marquardt et al. (2010), etc.

(4) Paper-Interface systems in which paper sheets (similar to tangible objects) are inserted on the surface as an interaction input. The work done by Do-Lenh et al. (2009) referenced in Section 2.2 studied and compared the effects of a Paper-Interface tabletop for both individual and collaborative learning. (5) Gestural-Interface systems in which the position or track of fingers and hands are recognized by special cameras in them (without any need for direct interaction or contact with the surface). In Section 2.3 we have mentioned two examples of the Gestural-Interface systems developed by Ballendat et al. (2010) and Annett et al. (2011).

Popular Interactive Tabletops. Microsoft's Tabletop touch platform so-called Microsoft PixelSense (or formerly named Microsoft Surface) started development in 2001. PixelSense has the ability to interact with both the user's touch and their electronic devices (“Microsoft PixelSense” 2015 ; “PixelSense” 2015). In the same year, Mitsubishi Electric Research Laboratories (MERL) also began development of a multi-touch, multi-user Tabletop called DiamondTouch which was able to differentiate between multiple simultaneous users (“DiamondTouch” 2015 ; Wong 2007). SMART Table® 442i is a collaborative learning tool that facilitates learning by allowing up to 8 students to interact with activities collectively and simultaneously on the multi-touch surface (“SMART Table collaborative learning center” 2013).

Concept Maps. A concept map is a diagram that illustrates specific relationships among components, elements or concepts. It normally depicts information and ideas with regard to circles or boxes (or textual objects) which are connected with each other through labeled arrows in a hierarchical structure (“Concept map” 2015 ; Novak 1998). Several possible uses of concept mapping in learning situations are briefly mentioned in Chapter 2.



Login ID	Time	Log History
Student01	18:15:05	Start
Student01	18:15:10	Create Rectangular Box
Student01	18:15:13	Create Rectangular Box
Student02	18:15:13	Create Line
Student02	18:15:15	Create Textual Object
Student03	18:15:23	Create Textual Object
Student03	18:15:31	Create Textual Object
Student01	18:15:47	End

Figure 1.Sample screenshots of the designed Online Concept Mapping Application (OCMA) for Theory of Reasoned Action (TRA) task.

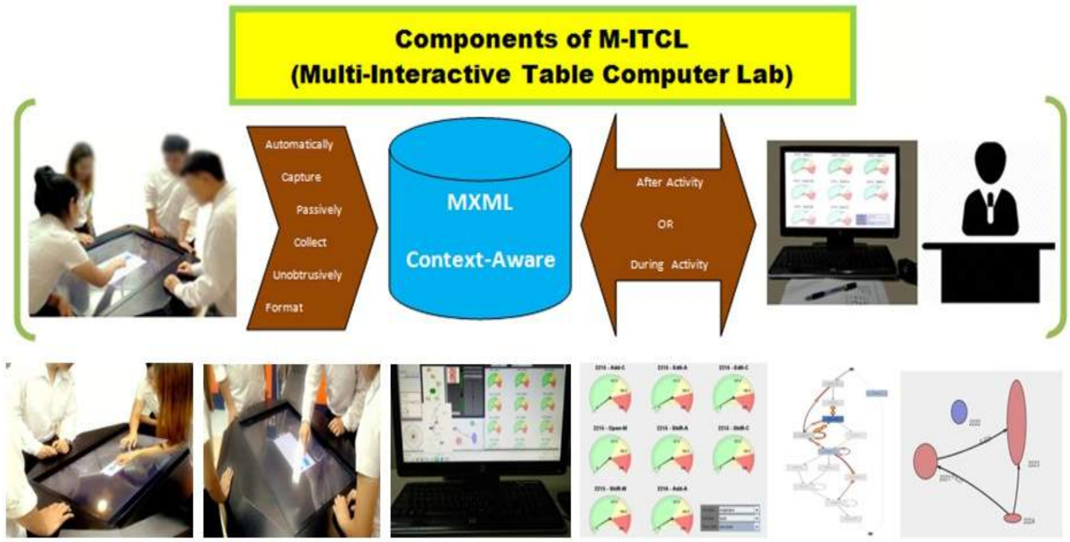


Figure 2. Components of the developed Multi-Interactive Table Computer Table Lab (M-ITCL) setting (Adopted from: Martinez-Maldonado, 2014).

Online Concept Mapping Application (OCMA). In this study, a concept mapping application was designed (written in Python and using Tin Can API) with the purpose of allowing students to draw a concept map that corresponds to their collective understanding about the assigned task. The design principles of the developed application includes: (1) ability to integrate objects that students build prior to working at the Interactive Table Computer, (2) ability to provide personalized content for each student in accordance with the vocabulary of concepts and the links they used in former assignments, or a pre-defined list of suggested terms/words extracted from the instructor's key/master concept map. As shown in Figure 1 (up), the concept mapping application allowed instructors to import and apply previously built individual concept maps (or so-called key/master models) into the system. This feature significantly minimized the need for typing text using a keyboard and reduced clutter by making the concept mapping process as simple as possible, (3) ability to support simultaneous user actions, (4) ability to support real-time multi-user collaboration via an online Internet connection, (5) ability to provide the same controls and features for all the peer group members equally, (6) ability to provide an easy and friendly User Interface (UI) through four main drawing tools on the right-hand side of the design canvas referred to as: draw a concept (component) tool, draw a link (arrow) tool, delete an object tool, and create a textual object tool, (7) ability to resize, move or merge created objects, (8) ability to support and work with popular browsers on any Operating System, and most importantly (9) ability to provide two types of access (i.e., user/student access and admin/instructor access).

As shown in Figure 1 (down-left), using the user/student type of access, students can individually or concurrently create, remove or edit objects/artifacts on the design canvas. Moreover, the instructor also has the advantage of monitoring the primary aspects of the application's environment through a simple toolbox called Log History. Figure 1 (down-right) shows an example of the admin/instructor type of access where the instructor can easily observe and monitor the history logs of the ongoing (or completed) actions of the students in terms of the "type of executed action", "time", and "student's Login ID". Although the admin/instructor feature may slightly increase the instructor's awareness of the students' task progress, the data and the primary information provided here are too elementary, imperfect and incomplete in order to investigate the entire collaboration process with respect to appropriate quantitative indicators in more detail. For this reason, we later developed the Instructor Dashboard (ID).

Theory of Reasoned Action (TRA). This is a model commonly used for the investigation of the relationship between behavior, behavioral intention, attitude toward the behavior, and subjective norms (or external factors). The Theory of Reasoned Action (TRA) model consists of four main constructs as follows: behavior, intention, attitude, and subjective norm (Fishbein and Ajzen1975 ; "Theory of reasoned action" 2015). In this research, the instructor chose a concept mapping activity so as to investigate the topic of "Theory of Reasoned Action" as part of the class for that week. Using the designed concept mapping application in the Multi-Interactive Table Computer Lab environment, the students were asked to build a Theory of Reasoned Action (TRA) model for the prediction of behavioral intention, spanning predictions of attitude and predictions of behavior.

Instructor Dashboard (ID). In this study, ID is a tool with the capability to generate real-time reports of the on-task progress of small groups of students in the Multi-Interactive Table Computer Lab (M-ITCL) setting. The main objective of the Instructor Dashboard (ID) is to generate more detail-oriented reports from the collected event logs (datasets) in order to increase the instructor's awareness about students' collaboration process (with respect to 6 dimensions which will later be explained in Section 1.4) in addition to the flow of knowledge building during (or after) the assigned concept mapping tasks.

Multi-Interactive Table Computer Lab (M-ITCL). In this study, M-ITCL is a networked-based learning environment composed of two interactive tabletops (equipped with the online concept mapping application) in addition to the Instructor Dashboard (equipped with process mining tools). The Multi-Interactive Table Computer Lab (M-ITCL) was applied with the purpose of developing a system that is capable of differentiating which student is touching what, in an automatic and unobtrusive manner. As shown in Figure 2, the M-ITCL was a networked-based system composed of two interactive tabletops (equipped with the Online Concept Mapping Application—OCMA), Instructor Dashboard, small groups of students and an instructor. After registration, students enter their e-mails in order to log in to the system. The developed system was capable of automatically and unobtrusively capturing, collecting and formatting the student(s)' collaboration and interaction data in real-time and based on specific collaboration indicators (i.e., contexts or processes) which will be explained in Section 1.2 and Section 3.1 of the study. The collected data were converted into MXML-formatted event logs in order to be used and analyzed by the Instructor Dashboard (equipped with process mining tools and techniques). The resulting quantitative information of group work (both raw and analyzed) increased the instructor's awareness about the students' collaboration activities as well as the flow of knowledge building during the assigned task. The obtained students' (collaboration and interaction) data also could: (1) help the instructor to improve the management and coaching style in the class, (2) help the instructor to improve the teaching style in the class based on the feedback received regarding the students' performance during the task, (3) enable the instructor to quickly make informed decisions during the class, (4) enable the instructor to improve and transform the traditional grading system which traditionally was only based on the final outcomes accomplished by students (i.e., only based on the final concept maps created by students), (5) transcend the students' assessment process from a merely final-outcome-based approach to a more collaboration-interaction-based system, (6) provide a more detailed and more effective feedback to the students based on their collaboration activities during the task, (7) provide instructors with meaningful insights as to which groups of students might need more support and attention, and which groups can be left to work by themselves, and (8) provide students (and group members) a new source (or tool) for self-regulation and self-awareness about the extent of their participation and interaction during the assigned task (Dillenbourg et al. 1997 ; Dillenbourg et al. 2011 ; Dillenbourg and Evans 2011 ; Dillenbourg and Jermann, 2010).

1.2 Background of Problem

As shown in Figure 3, this research is founded on the intersection of four areas. The first area contains collaborative learning which can significantly increase the thinking skills of students by activating specific learning mechanisms that cannot be acquired via individual learning situations (Martinez-Maldonado et al. 2012b ; Martinez-Maldonado 2014). Collaborative learning between small groups of students can also generate a more positive attitude towards the subject matter by improving critical thinking, reducing task workload, and increasing students' retention (Berland and Reiser2009 ; Felder and Brent 1994 ; Johnson and Johnson 1986). As a result, learning collaboration and argumentation skills can be very important and essential for value generation in educational scenarios (Scheuer et al. 2010).

The second area contains interactive Table Computers. Symmetry of work space where a group of students attempt to learn something together is one of the most important features of a collaborative situation (Dillenbourg 1998). Interactive Table Computers provide a work space that offers equal opportunities of participation for each student; which makes them perfectly suited for collaborative learning scenarios and situations especially when working with virtual content and digital resources that students can use to build a problem solution (Piper and Hollan 2009). Interactive Table Computers have the ability to increase the students' awareness about their actions since the surface is large, created artifacts also are large, fellow users are more aware of each other's action and the table supports concurrent input touch points (Clayphan et al. 2011 ; Rogers et al. 2009 ; Rogers and Lindley 2004). Therefore, interactive Table Computers provide new opportunities to support collocated collaboration and to capture the digital footprints (datasets) of students' interactions (Rogers and Lindley 2004).

The third area includes concept mapping as a technique that can help students create visual representations of the structure of their understanding about almost any knowledge domain and provide meaningful learning (Novak 1990). Concept maps are a way to expand logical thinking and learning skills by finding connections and helping students see how individual ideas can build a larger whole ("Concept map" 2015). Therefore, in this paper we linked collaborative learning with a concept mapping activity. The availability of concept maps and their usage in learning and collaborative learning settings are briefly discussed in Section 2.2.

The fourth area contains educational process mining which is a new field in the educational data mining discipline, and it is used to discover patterns in educational datasets (event logs) with the purpose of developing methods to better understand and analyze students' learning habits and behaviors as well as the factors affecting their collaborative performance. Educational process mining techniques are able to find distinguished patterns, visual representations or process models based on the order of student's actions and with the aid of timestamps (Hicheur-Cairns et al. 2015 ; Martinez-Maldonado 2014 ; Pechenizkiyet al. 2009).

As a result, a synergy of "collaborative concept mapping through interactive Table Computers" and "analysis of students' interaction data through process mining tools and techniques" was the main motivation for the study. However, collaborative relationships do not always ideally and perfectly occur when students work on a group activity even though interactive Table Computers have been designed and built to support such situations (Kreijns et al. 2003).

Figure3.An overview of the scopes and interactions of the thesis

(Adopted from: Martinez-Maldonado, 2014).

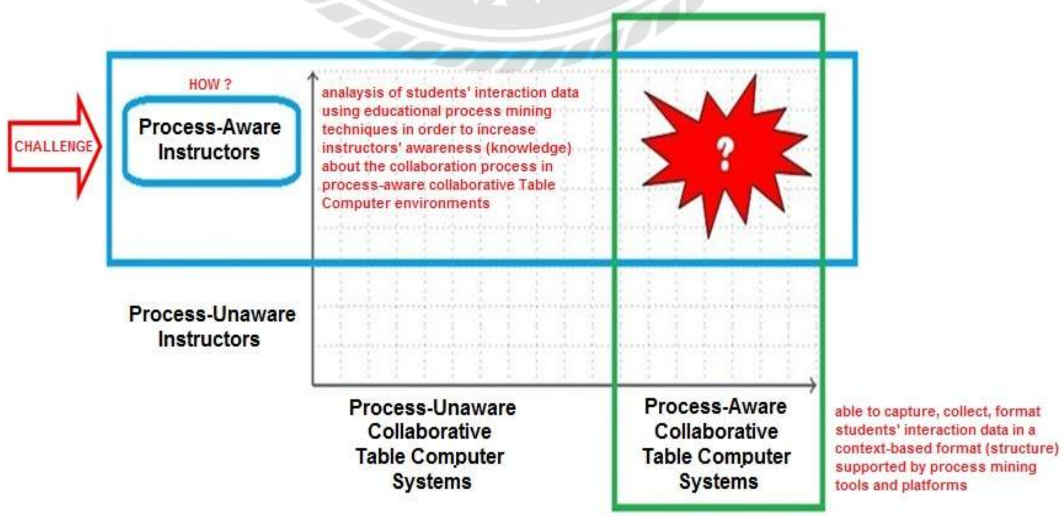


Figure4. The main motivation of the thesis (Adopted from: Burattin, 2014).

Without the provision of appropriate feedback (i.e., mirroring) and self-regulation, students do not always spontaneously collaborate to accomplish the assigned task (Dillenbourg 1998). On the other hand, the role of instructors and facilitators in the classroom is important for helping students to be more aware of their group dynamics with the intention of improving their collaboration skills (Dillenbourg, et al. 2011; Kirschner2001 ;Slavin 1983 ; Webb 2009). Therefore, instructors need resources to improve their awareness about students' collaboration and the flow of knowledge building during small-group learning activities (Dillenbourg et al. 2011 ; O'Donnell 2006). Although the combination of collaborative learning with interactive Table Computers appears interesting, never-the-less group work in learning settings needs to be carefully controlled and monitored by instructors in order to ensure group progress (Dillenbourg and Evans 2011). In reality, instructors mostly care about (and are only aware of) the final artifacts (outcomes) created (accomplished) by groups of students instead of the details of the whole collaborative process. Instructors usually have a short time and inadequate resources to control and monitor all the group activities of students (Zhang et al. 2004) with regard to qualitative indicators (e.g., such as observation, verbal communications, body language, facial integrations and expressions, degree of acknowledgement or disagreement, mutual arguments and discussions and etc.) as well as quantitative indicators (e.g., such as statistical values, hidden markov models, social network visual/graphical representations, frequent itemsets pattern mining, data analytics, clustering algorithms, process mining process models and etc.). In addition, the final artifacts created by groups provide imperfect information about students' collaborative contributions in terms of some quantitative indicators such as, interaction rate, interaction similarity (or handover of task), participation rate, participation density (or number of active members), idle time intervals and waiting time gaps between the performed tasks, level of division of labor, similarity of task and so on in each group of students (Martinez-Maldonado 2014 ; Morgan and Butler 2009). On the other hand, interactive Table Computers alone cannot automatically capture and analyze a student's digital footprints (datasets). Therefore, as shown in Figure 4, there was a substantial need to design, implement and develop Process-Aware Collaborative Computer

Table Systems that provide sufficient information about students' collaboration process based on the interaction data leading to Process-Aware Instructors (Burattin 2014).

The term Process-Aware Collaborative Computer Table Systems was deliberately used and mentioned in order to highlight (and differentiate) those kinds of tabletop-supported (or tabletop-mediated) collaborative learning systems (environments) that can automatically and unobtrusively capture and collect the students' interaction data in terms of a context-based format (and structure) supported by process mining tools and platforms. In the same way, the term Process-Aware Instructors was deliberately chosen and used in order to highlight (and differentiate) those kinds of instructors who increase their awareness (and knowledge) about the students' collaboration process through analysis of the interaction data using process mining techniques and algorithms.To be more specific, the term Process-Aware Collaborative Computer Table Systems stands for those kinds of tabletop-supported (or tabletop-mediated) collaborative learning systems (environments) that can automatically and unobtrusively capture and collect the students' interaction data in terms of a context-based format (and structure) supported by process mining tools and platforms.In the same way, the term Process-Aware Instructors stands for those kinds of instructors who increase their awareness (and knowledge) about the students' collaboration process through analysis of the interaction data using process mining techniques and algorithms. Process-Aware Instructors can improve their grading system (and students' evaluation and assessment process) not only based on the final artifacts (outcomes) created (accomplished) by the groups of students, but by being aware of every student's contribution to the group task progress —in terms of collaborative dynamics and based on several pre-defined quantitative indicators as well. Accordingly, Process-Aware Instructors lead to enhanced performance by monitoring the collaboration process and group progress, and by providing more detailed feedback and helping students to be more aware of the collaborative dynamics of their contribution to the group during the assigned task (Adopted from: Burattin 2014 ; Dillenbourg et al. 2011 ; Morgan and Butler 2009).However, being aware of the fact that the term collaboration process in computer-supported collaborative learning (CSCL) situations is too general and can depend on countless variables and factors such as face-to-face conversations, body gestures, body language, facial expressions, difficulty of tasks, task features, task time, task place, each individual's psychology and personality traits , cultural dimensions and cultural differences, language barrier, the degree of individualism versus collectivism, differences in each individual's learning style, social relationships, social status, interpersonal skills and abilities, daily life hassles, family and personal problems, facilitating conditions and technical support, classroom's temperature and ambient conditions, group size, genetics and heredity issues, health status, gender, sex, domain of individual's expertise, prior experience and level of familiarity with the topic, prior knowledge, and many other factors. In this study we only focused on the analysis of students' collaboration process with respect to specific quantitative indicators (Section 3.1) and dimensions (see Figure 5) as follows:

Analysis of the total time spent to accomplish the assigned task (Section 1.6 and Section 4.1).

Analysis of the types of actions/activities performed during (or after the end of) the assigned concept mapping task (Section 3.2 and Section 4.1).

Analysis of the absolute frequency of the actions/activities (or density of actions/activities) performed during (or after the end of) the assigned concept mapping task (Section 4.1).

Analysis of the rate of the actions/activities performed per second (or activity rate) during (or after the end of) the assigned concept mapping task (Section 4.1).

Analysis of the accuracy of the actions/activities performed during (or after the end of) the assigned concept mapping task (Section 3.2 and Section 4.1).
This is the analysis of the degree to which students' actions are compatible (and matched) with the instructor's key answers (i.e., in this study it is called master concept map model).

Analysis of the impact level of the actions.

This is the analysis of the students' actions with respect to their level of influence (or impact) on the concept mapping task in terms of the high-impact, low-impact or no-impact types of actions (Section 3.2 & Section 4.1).

Analysis of the extent of participation.

This is the extent to which a student actively participates in the assigned concept mapping task. In this study, the extent of participation is divided into two sub-categories: (1) Participation density or number of active students in terms of blocks of activity (Section 4.2), and (2) Participation dynamics or analysis of the participative actions performed with respect to the sequence of their occurrence (by people who did them) over a specific time span (Section 3.2 and Section 4.2) and (3) Participation rate or number of students performing participative actions. As discussed by Dillenbourg (1998 ; 1999), Dillenbourg et al. (2011) and Henri (1992), analysis of the participation among group members can help instructors to increase their awareness (knowledge) about the collaboration process in a more detailed approach in computer-supported collaborative learning situations.

Analysis of the extent of interaction.

This is the extent to which a student works with a concept map object created by another fellow group member. In this study, the extent of interaction is divided into two sub-categories: (1) Interaction density or the absolute frequency of the number of times students (of a group) have worked with a concept map object previously created by their fellow group member during (or after the end of) the assigned concept mapping task (Section 3.2 and Section 4.3), and (2) Interaction dynamics or graphical visualization representation of the number of times students (of a group) have handed over a task to their fellow group members during (or after the end of) the assigned concept mapping task (Section 4.3). According to Dillenbourg (1998 ; 1999), Dillenbourg et al. (2011), Gorse et al. (2006) and Wang et al. (2014), measurement of specific types of interactions (which are characterized as “collaborative”) among students can help instructors to increase their awareness (knowledge) about the collaboration process in more detail in computer-supported collaborative learning situations.

Analysis of the time performance (i.e., modeling of the waiting time gaps between the actions/activities as well as the patterns of idle time versus active time).
This is the analysis of the long waiting time gaps between the actions/activities, as well as the number of time intervals spent in the process (Section 4.4). The durations of activeness versus idleness also are visualized and compared (Section 3.2 and Section 4.4).

Analysis of the extent of symmetry of actions (similarity of tasks).
This is the analysis of the extent to which students perform similar tasks to finish the assigned work. The similarity of task indicator does not consider how students work together on the assigned task but focuses on the activities they perform (Section 4.5). The assumption here is that students doing similar things have stronger relations than students doing completely different things (Social Network Miner 2009). Each student has a “profile” based on how frequently they perform specific works and activities. As discussed by Dillenbourg and Baker (1996) and Dillenbourg (1998), the symmetry of action —or the extent to which the same range of actions is allowed to each student— is one of the important features of successful computer-supported collaborative kerning environments.

Analysis of the extent of division of labor (symmetry of roles).
This is the analysis of the extent to which students work together collectively (i.e., not by splitting the work into sub-tasks, solving the sub-tasks individually, and eventually assembling the partial outcomes into the final artifact.) in order to accomplish the assigned task. According to Dillenbourg (1998) and Dillenbourg et al. (2011), low division of labor is one of the important features of successful computer-supported collaborative kerning environments.

After carefully studying and reviewing significant previous work (Section 2) about how to define and produce a set of quantitative indicators for analysis of collaboration process in computer-supported and tabletop-mediated collaborative learning situations, and after conducting a survey (Section 3.1) regarding the most important factors that influence the performance of peer group members in CSCL environments; 6 dimensions and 15 quantitative indicators were eventually generated through inductive and deductive methods of research.

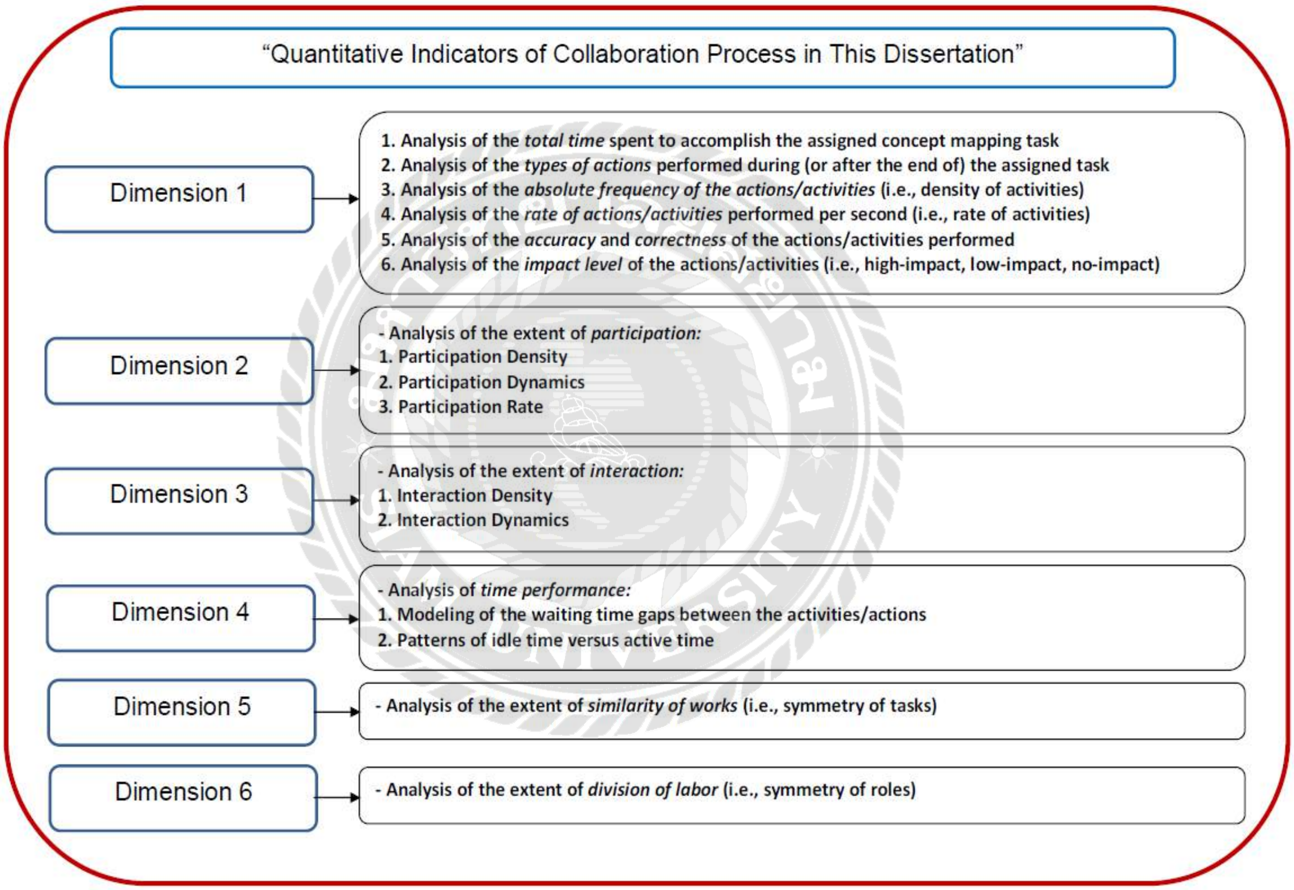


Figure5.Quantitative collaboration process indicators in this thesis (see Appendixes 2-3).

1.3 Questions of the Thesis

Accordingly, the main question of the study is defined as follows:

How can the students' collaborative interaction data be used, analyzed and interpreted in order to increase the instructor's awareness about the collaborative activity process at the Multi-Interactive Table Computers Lab's classroom? (Dillenbourg and Evans 2011 ;Dillenbourg and Jermann 2010 ; Dillenbourg et al. 2011 ; Martinez-Maldonado 2014)

1. During (or after the end of) a class, how can the instructor discover, distinguish and compare general performance differences (i.e., total time, type and absolute frequency of the actions, rate of the actions performed per second, accuracy of the actions, impact level of the actions, etc.) among the High Performance groups and Low Performance groups based on the collected students' collaborative interaction data?

2. During (or after the end of) a class, how can the instructor discover and compare distinguished patterns of participation (i.e., the extent to which a student actively participates in the concept map activity) between the High Performance groups and Low Performance groups based on the collected students' collaborative interaction data?

3. During (or after the end of) a class, how can the instructor discover and compare distinguished patterns of interaction (i.e., the extent to which a student works with a concept map object created by another fellow group member) between the High Performance groups and Low Performance groups based on the collected students' collaborative interaction data?

4. During (or after the end of) a class, how can the instructor discover and compare distinguished patterns of time performance (i.e., analysis of the long waiting times between the activities as well as analysis of the batches of idle time versus active times) between the High Performance groups and Low Performance groups based on the collected students' collaborative interaction data?

5. During (or after the end of) a class, how can the instructor discover and compare distinguished patterns of similarity of task (i.e., the extent to which students perform similar works to finish the assigned task) between the High Performance groups and Low Performance groups based on the collected students' collaborative interaction data?

6. During (or after the end of) a class, how can the instructor discover and compare distinguished patterns of division of labor (i.e., the extent to which the same range of actions is allowed for each student) between the High Performance groups and Low Performance groups based on the collected students' collaborative interaction data?

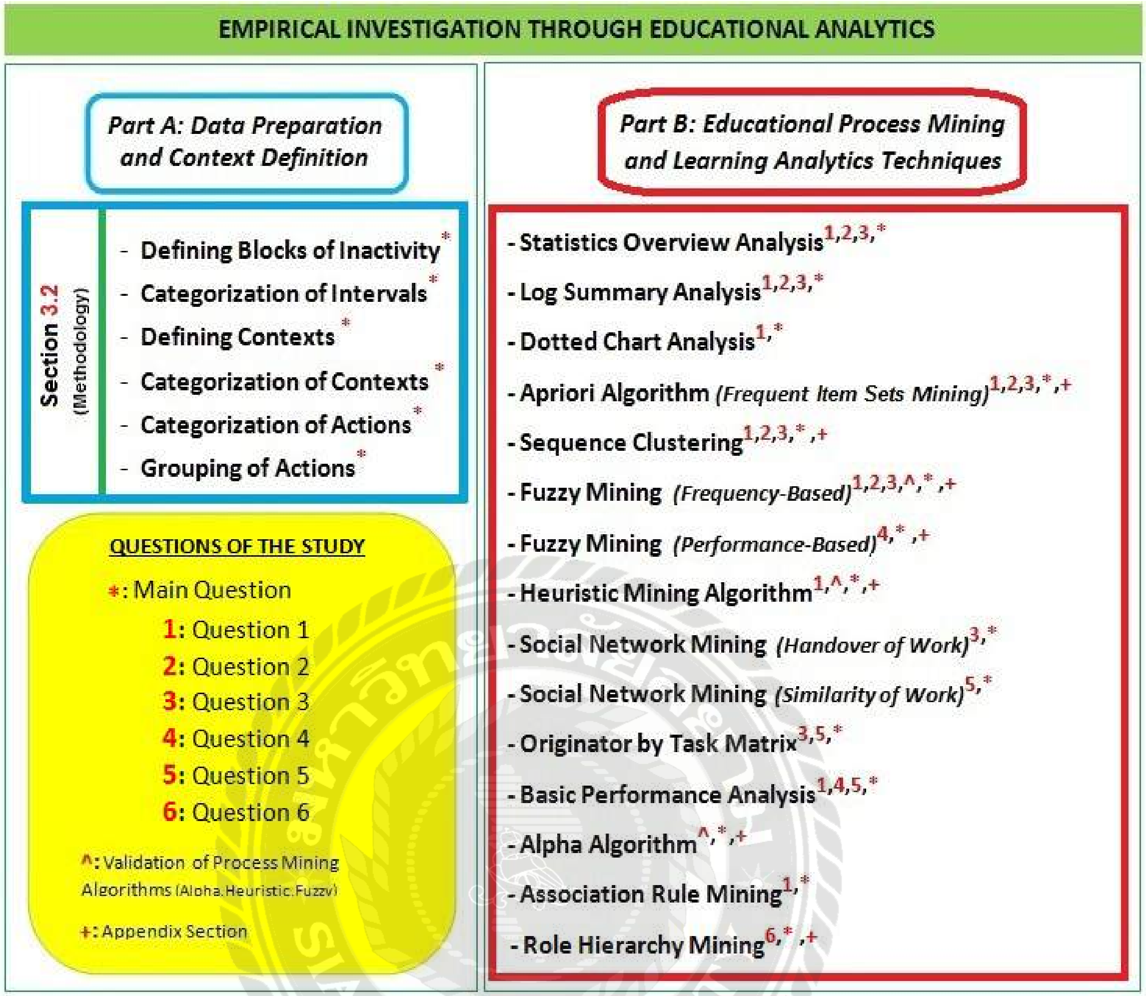


Figure6. Anoverview of the process mining techniques used in this thesis

(see Appendixes 2-3).

As shown in Figure 7, in this dissertation several process mining algorithms were used with the aim of exploiting and analyzing the students' (interaction and collaboration) data through analytics, process modeling, pattern mining and graphical (or visualization) representation of the collected event logs. These techniques enabled an instructor to look at the data from different angles leading to increased awareness (knowledge) about the collaboration process and group dynamics (Dillenbourg et al. 2011). Figure 6 shows a holistic view of the questions of the study as well as the process mining process discovery techniques used in order to address each question. Several process mining algorithms were used with the aim of exploiting and analyzing the students' (interaction and collaboration) data through analytics, process modeling, pattern mining and graphical (or visualization) representation of the collected event logs.

1.4 Objectives and Contributions of the Thesis

Accordingly, the most important objectives of the study were to address the main question of the study as well as the sub-questions by conducting an empirical investigation of the students' collaborative interaction data and by discovering, distinguishing and comparing the differences between the High Performance groups and Low Performance groups at the Multi-Interactive Table Computer Lab classroom. As a result, a single statement (Martinez-Maldonado 2014) that embodies all aspects of the study was defined as follows:

"To analyze and interpret the students' collaborative interaction data previously captured, collected, and formatted in the Multi-Interactive Table Computer Lab's environment through an empirical investigation of the collaboration process' indicators using process mining techniques in order to increase the instructor's awareness (knowledge) about the collaborative group's activity in such a way to make possible Process-Aware Instructors" (see Appendixes 2-3)

1.5 Participants and Activities of the Study (Case Study)

Overall, 10 tutorial sessions were organized for students of an international undergraduate program during the seventh week of semester 2, 2014. A total of 82 students between the ages of twenty two and twenty five years old attended the tutorial sessions designed for the course: BUS1108: Organizational Behavior. Thirty six of the students (i.e., 44%) were female while forty six of them (i.e., 56%) were male. Only six of the participants were native English speakers while the rest were non-native English speakers (but good enough in English for a non-native speaker). All of the students had prior experience of using computers and the internet (100%). However, none of the students had any prior experience with a collaborative concept mapping assignment via interactive Table Computers and this was their first Multi-Interactive Table Computer Lab (MITCL) experience. To deal with this issue, two types of tutorial sessions were designed. The first activity (90 minutes) was run and practiced as a warm up exercise in order to let the students have a better idea about how different functions and features of the developed Online Concept Mapping Application (OCMA) works in the Multi-Interactive Table Computer Lab's environment. The second activity (30 minutes) was launched and practiced in order to assess and grade the students based on their performance during the tutorial session. In other words, a certain level of success in the first activity was needed (as a pre-requisite) in order to proceed to the second activity. Both activities were set up in the English language. Each tutorial session included 8 to 10 students that were organized in groups of 4 or 5 students (i.e., 18 groups with 4 members, and only 2 groups with 5 members).

The final artifact of the concept mapping activity needed to be a TRA model consisted of six Components (C) and five Arrows (A) in total. A pre-defined list of suggested Words (extracted from the instructor's key/master concept map) and Terms (such as; Intention, Satisfaction, Attitude, Feeling, Usefulness, Time, Performance, Character, Education, Facilitating Conditions, Emotion, Wisdom, Ease of Use, Subjective Norm, Behavior, and Action) was primarily uploaded to the online concept mapping application. The students only needed to connect the constructed Components and Arrows with the appropriate Words and Terms as shown in Figure 1 (up). Consequently, the tutorial agenda was launched as follows (Martinez-Maldonado 2014):

(i) Orientation (20 min.): The instructor divided the students into two groups, gave preliminary explanations about how to work with the Interactive Table Computers and initiated the first activity.

(ii) Activity #1: Demonstration and Q&A Session (90 min.): The instructor demonstrated and explained different components of the online concept mapping application, as well as the interactive table computer. A Question & Answer (Q&A) session was conducted after the instructor's explanations, and then students were asked to build a sample concept map in the Multi-Interactive Table Computer Lab.

(iii) Feedback #1. The instructor stopped/paused all of the Interactive Table Computers and extracted all of the groups' reports concerning the first activity. The instructor conducted a short review discussion about the acceptable solutions and then initiated the second activity.

(iv) Activity #2 (30 min.): From the instructor's evaluation and grading perspective, this was the most important activity of the tutorial sessions as more sophisticated types of questions and concepts were designed for the second activity. The instructor resumed all of the Interactive Table Computers (i.e., the pause mode was ended) and students discussed and concentrated on illustrating the best final solution for their concept maps.

(v) Tutorial Sharing and Feedback #2. Once again, the instructor stopped/paused all of the Interactive Table Computers and extracted all of the groups' reports related to the second activity. Then, the instructor requested every group to share their solution with others in the classroom. After each group clarified their solution map, the instructor reviewed the results of the tutorial, ended the session and evaluated the completed reports of each group behind closed doors.

At the end of the second activity and after assessment of the concept models (i.e., the final outcomes) produced by groups of students, the activity data of all 20 groups (i.e., 82 students) were divided into two main categories of (1) High Performance Groups (with greater or equal to 85% accuracy in creating the final concept models of the Theory of Reasoned Action), and (2) Low Performance Groups (with below 85% accuracy in building the final concept models of the Theory of Reasoned

Action). Accordingly, based on the accuracy of the final artifacts, 13 groups were categorized as groups with high performance while 7 groups were categorized as groups with low performance (Martinez-Maldonado 2014 ; Martinez-Maldonado et al., 2013b).

1.6 Structure (Outline) of the Thesis

This paper is structured as follows. The next chapter (i.e., Chapter 2) of the study describes the state of research in the areas of: (i) indicators affecting the quality of a collaboration process in computer-supported collaboration learning (CSCL) environments (Section 2.1), (ii) similar studies regarding concept maps and learning (Section 2.2), (iii) the most important (and popular) collaborative tabletop systems and their main differences (Section 2.3), (iv) context-aware tabletops for data capture and learning analytics (Section 2.4) and (v) a validity of the three summary of the above mentioned related works as well as their differences with our work (Section 2.5).

Chapter 3 presents the methodology of the study and is divided into five sections: (i) Section 3.1 investigates the validity and reliability of the most significant quantitative indicators affecting the quality of a collaboration process in CSCL situations based on a survey and through inductive and deductive method of research, (ii) Section 3.2 briefly explains the data preparation process as well as the definition of the contexts and alphabets of the study. The section includes: defining blocks of inactivity, categorization of time intervals, defining appropriate contexts, categorization of contexts, categorization of activities and actions/tasks, and finally grouping of actions/tasks, (iii) Section 3.3 investigates the validity of the three popular process mining process discovery algorithms commonly used for collaborative interaction data modeling. This section validates the Alpha, Heuristic and Fuzzy Miner algorithms, and decides which algorithm is more suitable to be used in this study by taking into consideration four criteria as follows; degree of error-free models, degree of replay fitness, degree of generalization, degree of precision, and extent of simplicity of resulting process models. Section 3.4 briefly explains the Association Rule Mining technique via process mining tools and provides some examples for readers. Section 3.5 briefly explains the Frequent Item Sets Mining technique based on the Apriori algorithm and through process mining tools.Chapter 4 presents the results and findings of the study. Section 4.1 compares the general performance differences between the High and Low Performance groups in terms of: (i) analysis of the total time spent to accomplish the assigned concept mapping task, (ii) analysis of the types of actions, analysis of the absolute frequency of activities (or density of activities), (iii) analysis of the rate of actions performed per second (or activity rate), (iv) analysis of the accuracy and correctness of actions, and (v) analysis of the impact level of actions. Section 4.2 compares the most important patterns of participation between the High and Low Performance groups in terms of: (i) participation dynamics, (ii) participation rate, and (iii) participation density. Section 4.3 compares the most important patterns of interaction between the High Performance and Low Performance groups in terms of: (i) interaction density, and (ii) interaction dynamics. Section 4.4 compares the distinguished patterns of time performance between the High and Low Performance groups in terms of: (i) long waiting time gaps between the tasks and activities, and (ii) inactive (idle) versus active (not idle) groups of time intervals. Section 4.5 compares the most important patterns of similarity of tasks (or symmetry of actions) and division of labor (or symmetry of roles) between the High and Low Performance groups in terms of: (i) similar task social network metrics, and (ii) role hierarchy social network metrics.Chapter 5 presents the conclusions and discussions. Chapter 6 identifies the limitations of the current work, and discusses the areas for future research.

2.0 RELATED WORKS (LITERATURE REVIEW)

2.1 CSCL and Indicators of Collaboration Process

In an interesting book written by McGrath (1984), a wide variety of group performance theories, motivational models and group success elements were concisely gathered, defined and explained in detail. According to the book, the level of participation (involvement), behavioral interactions and communication between group members have a significantly high impact on the level of success and performance of the groups.

In research conducted by Henri (1992), a novel analytical model as well as a conceptual framework was proposed in order to better understand the learning process of small groups of students in a computer-mediated conferencing (distance learning) environment from a corpus of messages shared between learners. His results showed that five dimensions (i.e., the extents of participation, interaction, social relationship, cognitive awareness, and meta-cognitive factors) have a significant impact on the performance of small groups of students within the learning process exteriorized in computer-mediated conferencing messages.

In a study conducted by Gorse et al. (2006), the most important factors that affect the behavior of participants and make meetings more effective are discussed and investigated. Their findings showed that the extents of interaction, supportive norms and social leadership significantly influence the participation of small groups during meeting sessions.

In another work conducted by Wang et al. (2014), the importance of interaction and involvement among students (in computer-supported collaborative learning environment) and its relation to the performance of groups was investigated and discussed. The work applied both qualitative and quantitative methods in order to study the role of interactional behaviors, cognitive involvement, and collaborative processes in group performance. The results showed that the extent of interactional behaviors, participation/involvement, and cooperative activities among small groups of students have a significant influence on the performance and motivation of groups.

In several research works conducted by Dillenbourg (1998 ; 1999) and Dillenbourg et al. (2011), the importance of three features as the most important factors affecting the quality of collaboration process in CSCL environments are discussed and presented. These three features include: (1) symmetry (i.e., symmetry in status, symmetry in knowledge, symmetry in prior experience, symmetry in situation, symmetry in actions, symmetry in interactions, symmetry in level of participation (involvement), etc.) , (2) shared goals (i.e., having a common objective), and (3) low division of labor (i.e., symmetry in roles).

2.2 Concept Maps and Learning

In research done by Preszler (2004) when small groups of biology students worked together (in small groups) to accomplish a task via concept mapping, their learning performance was significantly increased.

Novak (1995) suggested that concept mapping can facilitate both teaching and learning processes in positive ways.

Stahl (2006) discussed the group cognition aspects of concept mapping in collaborative learning environments where the interaction of students with other group members and with artifacts was analyzed and investigated.

Gao et al. (2007) argued that concept maps as versatile and multi-purpose tools can support and aid collaborative learning.

Novak and Cañas (2008) explored the relationship between concept mapping and creativity in learning situations and they realized that concept maps can stimulate the generation of ideas and lead to an increase in creativity.

Cañas and Novak (2012) stated that usage of concept mapping in collaborative learning settings and scenarios provides new mechanisms that will improve students' skills. They also indicated that constructing concept maps in collaborative learning situations will facilitate the students' learning process.

Novak and Vanhear (1995), Stahl (2006), Gao et al. (2007), and Chaka (2010) indicated that usage of concept maps in education offers students the opportunity to: facilitate collaborative learning and collaborative knowledge modeling, provide better opportunities to discuss ideas, encourage creation of shared understanding and shared vision among students, facilitate knowledge creation from multiple angles, increase meaningful learning of versatile subjects and topics, increase communication between students, encourage discussions and arguments in terms of agree to disagree, enhance learning and thinking abilities, transform tacit knowledge into team knowledge, identify misunderstandings, reach agreement.

Cambria and Hussain (2012) showed the profound benefits that concept mapping tools and techniques can bring with them in knowledge elicitation.

In addition, several researchers studied the usefulness and applicability of concept maps in learning environments via interactive tabletops. One of the first works in this field was done by Baraldi et al. (2006) who developed an interactive workspace with the purpose of integrating collaboration activities (through wiki knowledge-building) with face-to-face sessions like problem solving or brainstorming scenarios. Their so-called wikiTable was a SDG infrastructure including a software and hardware setup installed in a shared social space capable of visualizing concept maps on a flat table's surface. Their developed system could recognize multiple inputs simultaneously performed by manipulating constructs with bare hands and fingers (or by use of remote devices) on the wikiTable. Some features of the developed concept mapping application via wikiTable were as follows:

- add and remove constructs/nodes.
- draw, modify and delete arrows/links between constructs/nodes.

The wikiTable was synchronized with the wiki repository through a protocol implemented with a XMLRPC interface over HTTP. First, concept maps were built and generated as special wiki pages in XML format. Later, they were visualized in a vector graphics format using a custom XML to SVG conversion. Baraldi et al. (2006) ran their concept map building sessions with more than 30 students of different ages and prior experience in computing within a period of 6 months. The proposed system could not automatically (and unobtrusively) capture and collect students' collaboration data in terms of event logs. Therefore, they used off-line video recordings of the concept map building sessions after the end of activities (not in real-time) in order to analyze the behavior of single-user and multi-user groups. Consequently, the collected collaboration data (based on the video recordings) were only studied and investigated with respect to two dimensions:

(1) average success ratio or measurement of the times in which students' performed actions were correctly recognized by the system.

(2) average time duration or measurement of the average time consumed in order to accomplish the action by students. Their results showed that in the beginning multiple users did not interact simultaneously, but later they found the concept mapping experience via wikiTable interesting and they interacted more simultaneously.

Buisineet. al. (2007) integrated a mind mapping application with a MERL DiamondTouch tabletop and called the resulting system a "Tabletop Mind-Mapping" or "TMM". Although the developed "TMM" system was not as sophisticated as a real concept mapping tool, it could support multi-user horizontal interfaces through interactive shared displays. Students could create a new node in their mind-map with double tap-and-drop interaction on the touchscreen.

The created nodes were editable and their background color was representative of their hierarchy level. The main objective of their study was to compare and evaluate the students' collaborative behaviors within the mind-mapping activity with respect to those students who were using their hands at the interactive tabletops (to create mind-mapping constructs) versus those who were using a control paper-and-pencil condition (to create mind-mapping constructs). After analysis of the students' collaboration patterns, their results showed that the students' verbal contributions were significantly higher in interactive tabletops compared with the in-control conditions. The proposed "TMM" system could not automatically capture and collect students' collaboration data in terms of event logs and in order to analyze and study the students' collaboration data based on observation; both tabletop and control conditions were previously video-recorded offline.

Tanenbaum and Antle (2009) worked on a prototype implementation of a concept mapping application run on interactive tabletops. The main objective of the study was to show how elements of tangible interaction within a concept mapping task via tabletops can help users to better organize and structure their prior knowledge about a domain topic.

Do-Lenh et al. (2009) compared and studied the advantages of interactive tabletops versus traditional personal computers for collaborative concept mapping in learning environments. For the first time, their work analyzes the students' collaboration data with respect to some interesting dimensions/variables such as "amount of speech and words" shared among group members during the task, "nodes' or constructs density" in the final concept maps created by students, "collaboration strategy" chosen by groups of students to accomplish the task, "role assignment" and analysis of leadership in groups, "group process", and extent of students "satisfaction" toward the technology used to finish the assigned concept mapping task. Moreover, they focused on analyzing small groups of students' behavior rather than a singer user investigation. Their findings showed interactive tabletops have no significant advantage over traditional personal computers. However, the findings could be biased because using a personal desktop computer indicates the fact that only one keyboard and only one mouse must be shared among multiple individuals.

Oppl and Stary (2011) studied the benefits of collaborative concept mapping by means of an interactive tabletop. Their data was collected during (and after) the concept mapping activities from 3 different sources: (a) Video recordings of the concept map building process from 2 perspectives (i.e., participants and interactive tabletop's touch screen surface), (b) recordings of the concept map building process by a system, (c) collection of feedback and questionnaires from participants after completion of the concept mapping sessions. In addition, 4 hypotheses and 7 quantitative measures (i.e., in terms of size of concept map, speed of concept map creation, number of concept types used, connectedness, distribution of activity time among participants, turn taking of physical initiative, and discussion time) and 5 qualitative measures were defined and investigated in regard to "effectiveness" of concept map building using a tangible interactive tabletop. Their results showed that interactive tabletops are suitable for building any kind of concept maps whether simple or complex. Based on their findings, interactive tabletops encourage and boost cooperation and cooperative activities among participants compared with traditional screen-based systems such as personal desktop computers. They also found that interactive tabletops facilitate common understanding in learning situations and environments. Therefore, the results of their hypotheses testing found positive relationships between the use of interactive tabletops and cooperative concept map building process. Overall, their work was divided into two main parts. In the first part of the study, 7 quantitative measures were used and defined in order to study behavior analytics of the students during (and after) the concept mapping activities. In the second part of the study, they chose a hypotheses testing approach to understand whether tabletops have any positive effect on concept map construction or not.

In an interesting research conducted by Martinez-Maldonado et al. (2013a), a classroom equipped with multi-user multi-touch Tabletops and a teacher monitoring/orchestrating tool (so-called MTDashboard) were designed, launched and tested with the purpose of increasing the teacher's awareness toward small groups of students' learning activities during the assigned concept mapping tasks. The designed teacher monitoring/orchestrating tool was capable of capturing collaborative aspects of students' activity while they worked in small learning groups to construct concept map models. The MTDashboard proposed in their work was displayed at a handheld device in order to empower the teachers with the ability to manage their time and energy more effectively at multi-tabletop classrooms.

2.3 Collaborative Tabletop Systems and Their Differences

Context-aware Tabletops (or Process-Aware Computer Tables) refer to a general class of multi-user, multi-touch, and multi-interactive systems that can sense their physical environment. In Process-Aware Tabletops (Computer Tables), the collected contextual data are defined as process instances. Three main aspects of context-aware systems are as follows: (a) user differentiation, (b) user identification, (c) user localization (Robles and Kim 2010 ; Martinez-Maldonado 2014).

2.3.1 User Differentiation Systems. The context-aware tabletop systems that work based on user differentiation are capable of differentiating and distinguishing every touch an individual performs on the interactive surface —even though the system may not directly recognize the name or identity of the individual performing the touch, the identification process is typically carried out by human judgment or based on an external system. The most commonly used context-aware system for user differentiation in the field of interactive tabletop (Table Computer) research is the DiamondTouch (Dietz and Leigh 2001). A set of antennas embedded in the DiamondTouch tabletop transmit signals. These signals are coupled through the chairs and users to receivers in such a way as to differentiate the parts of the interactive surface each individual is touching. Later, the information can be used for learning analytics and educational data mining purposes by a personal computer or an external device. The second popular approach for user differentiation in the field of tabletop (Table Computer) contains the systems that are equipped with digital wristbands, digital gloves, digital pens, and small digital gadgets. These systems differentiate every tough performed by users through small pieces of hardware that individuals wear on their arms or hands. Some of the works done by Collins and Kay (2008), Kharrufa (2010), Marquardt et al. (2010) and Meyer and Schmidt (2010) were conducted in this manner as shown in Tables 10- 13. Although the idea of wearing digital wristbands, digital gloves, digital pens, and small digital gadgets for user differentiation in interactive tabletop systems appears interesting, they are hard to implement in real-life learning environments due to their high cost and limitations in the interaction space.

The third approach for user differentiation in interactive tabletop (Table Computer) systems consists of applying vision systems on top of the interactive surface. Martinez-Maldonado et al. (2012a) developed a system to seamlessly differentiate and locate users around the interactive tabletop by pairing the tracked user with an identifier.

Their proposed system used Smartphones as a tracking tool by inserting them over the interactive surface and synchronizing them with the tabletop. Their proposed model was capable of collecting and capturing group members of students' interactions based on an overhead sensor installed on top of the interactive tabletop and by using weighted greedy search algorithm to track the position of every student's fingers, body and arms. They captured the speech and verbal participation of the group members as an important dimension of the collaboration process as well.

In a similar way, Ackad et al. (2012) developed a system that could continuously and seamlessly track any touch performed by any student during the activity sessions. The students' personal devices were paired with the interactive tabletop in order to associate each student's touch with an identity.

Klompmaker et al. (2012) also developed a system capable of differentiating and tracking multi-touch interactions of individuals using an overhead Kinect Camera (sensor).

2.3.2 User Identification Systems. The context-aware tabletop systems that work based on the user identification are capable of recognizing and authenticating each touch with the individual who performed it. Some researchers have used biometric technology and biometric for user identification in their studies. Schmidt et al. (2010a) developed a novel user identification system (so-called HandsDown) that could differentiate characteristic features of the users' hands based on a hand contour analysis —and by means of the interactive surface's camera and Support Vector Machines

(SVM) image processing technique. Users directly put their hands on the interactive surface without any need for external devices such as scanners. In a similar work done by Blažica et al. (2013), biometric properties are used for user identification. The developed system can detect 5 or more touchpoints based on a hand contour analysis without any need to external devices.

In another work by Schmidt et al. (2010b), a hand contour analysis technique was used as an enabling user identification mechanism via interactive tabletops. However, one of the users' hands needed to remain on the interactive surface in order to let the system authenticate and track the users.

2.3.3 User Localization Systems. The context-aware tabletop systems that work based on the user localization are capable of recognizing the position or traces of fingers and hands without any need for direct interaction or contact with the surface, and by using special cameras. Annett et al. (2011) developed a Gestural-Interface system (so-called Medus) which used 138 inexpensive proximity cameras/sensors in order to: localize and detect nearby people and their location based on body and arm locations. Ballendatet. al. (2010) developed a Gestural-Interface system that could localize and detect nearby people with respect to their identity, position, traces of movement, and orientation without any need for direct interaction or contact with the surface.

2.4 Context-Aware Tabletops for Data Capture and Learning Analytics

As mentioned earlier, student data can be used: (a) for improving an instructor's awareness about student collaboration and the flow of knowledge building, especially in learning settings and activity sessions with a large number of students which are too challenging (and sometimes impossible for the instructor) to control or monitor the collaborative behavior of every single group member in detail, (b) for defining new parameters and indicators of self-regulation (by students) based on their weak and strong points in the assigned topic, (c) for defining new parameters and indicators for the student's performance assessment and evaluation (by instructors), (d) for improving the student's grading system, not merely based on the final artifacts created by them, but based on the new parameters and variables in regard to analysis of collaborative interactions, (e) for improving performance of instructors based on the analysis of collaborative interactions among students, (f) for providing more support and help to those low achieving students who did not perform well during the current task, and for enabling them to come over their weak points in the next upcoming activity sessions and exams. The intersection of learning analytics and collaborative learning is a huge area with a lot of projects and research in this direction (Siemens and Baker 2012). The main subsets of the above-mentioned intersection include: (a) visualization techniques and graphical illustration of quantitative information of students' collaboration process, (b) Educational Data Mining (EDM) techniques (Baker and Yacef 2009), and (c) educational Process Mining techniques as a sub-category of the Educational Data Mining and Artificial Intelligence. Some of the previous works regarding the learning analytics in collaborative learning environments are briefly mentioned below.

2.4.1 Visualization of Collaboration in CSCL Environments. In a work done by Erickson et al. (1999), they defined Loops (or sociograms of social proxies) in order to illustrate and simulate graphical representations of users based on the amount of conversational activity, size of the group, and who-said-what indication. The Loops illustrate a conversation as a large loop, and the group members as colored dots. Dots within the loop were closely involved in the conversation being observed and dots outside the loop involved those who were in other conversations. The dots of those group members who were active in the conversation (i.e., either listening or speaking) were illustrated near the loop's center. They called the developed system Babble and its main objectives were as follows: (a) to support computer-mediated communication and visibility—within a chat system, an email system, or a newsgroup— by visualizing quantitative aspects of collaborative participation, (b) to increase the users' awareness about participative aspects of their actions and conversation styles, (c) to let the users self-regulate and improve their contribution as a result of their increased awareness about their actions and conversation features (i.e., accountability).

Jermann et al. (2009) followed a similar approach like the one mentioned above based on the Collabograms to simulate and visualize students' interactions in a CSCL environment equipped with Tinker Tables. They proposed a descriptive account to study whether there is a relationship between the spatial position of students and the type of manipulations they perform or not. They compared the groups of students using a second-by-second interaction coding technique in terms of 4 action types: "getting", "adding", "moving" or "adjusting" of the shelves of Tinker Table. Consequently, the collected data obtained based on the above 4 action types was illustrated and visualized using Collabograms in order to show the social structure of interaction. In their work, they used a camera above the Tinker Table as well as ad-hoc digital sound recorders in order to record and investigate the social structure of the interaction among group members.

Sundararajan (2010) conducted a social network analysis (via sociograms and based on a proposed Participation-Interaction Matrix) of chat and bulletin board conversations in a CSCL environment in order to study the most important factors that influence collaborative learning at both individual and group levels. Their results showed that the students with higher degree of betweenness and centrality performed better during the semester due to higher interaction and participation rates.

In a research conducted by Donath (2002), patterns of teamwork and interaction networks (sociograms) of egalitarian and asymmetric groups in chats and discussions were visualized based on the identity and presence of participation among individuals. These visualizations could help the users to better understand their cyber environment as well as their fellow group members leading to increased social awareness. Kay et al. (2006) followed a similar approach but in a pedagogical collaborative learning setting.

2.4.2 Educational Data mining and Process Mining in CSCL Environments. One of the first works in regard to the analysis of the collaborative learning processes using an educational data mining technique was done by Soller et al. (2002) who applied Hidden Markov Modeling as a machine learning approach in order to assess and analyze instances of effective and ineffective knowledge sharing interaction in an on-line shared workspace consisted of 5 groups of 3 students. The shared workspace allowed the groups of students to collaboratively communicate with each other (in terms of textual conversations) with the intention of solving object-oriented design problems through Object Modeling Technique (OMT).

Talavera and Gaudioso (2004) were two of the initial researchers who considered a synergy of CSCL and EDM in their work with the purpose of discovering and distinguishing patterns of similar behavior based on the e-learning data in a collaborative learning environment. In their work, they used data mining clustering methods through machine learning techniques in order to cluster and classify low-level features from higher-level features rooted in the students' interactions data so as to increase instructor's awareness about the collaborative process in small groups of students via the online learning management system (online LMS).

In a similar approach, Anaya and Boticario (2011) applied machine learning techniques in order to analyze and study students' collaboration process in an e-learning network-based environment during the academic years 2006–2009. Their work studied two main approaches. In the first approach, an unsupervised machine learning clustering technique was used in order to cluster and classify students based on their collaborative interactions and participation rates. In the second approach, a supervised learning technique in terms of decision trees was used in order to construct metrics that increase instructor's awareness about the collaborative process in small groups of students via the developed online learning management system (online LMS).

Perera et al. (2009) applied a Sequential Pattern Mining approach (using k-means clustering algorithm) in order to find, cluster and discover distinguished patterns of behavior among groups of students through online collaborative learning data. Applying a sequential pattern mining approach allowed them to use multiple attributes to study similar groups in an unsupervised learning manner. Moreover, the approach made possible mining the collaborative learning data at both individual and group levels in order to cluster groups of students with similar collaborative behaviors as well as investigating the composition of each group in more detail.

Soller and Lesgold (2007) also applied a Sequential Pattern Mining approach (using Hidden Markov Models) in order to show that their proposed approach performs significantly better than other statistical and computational approaches (such as Decision Trees, Plan Recognition, Rule Learners, and Finite State Machines) for modeling collaboration process in an online collaborative learning environment.

Duque and Bravo (2007) used a Fuzzy model (through a machine learning algorithm) to generate a set of rules in order to cluster and classify different aspects of the collaboration process within a group of students and based on the registration data previously collected in an online learning environment. Accordingly, the generation of a set of rules using fuzzy models made possible offering solutions of a certain quality.

Casillas and Daradoumis (2009) proposed an approach based on Social Network Analysis (SNA), Fuzzy classification, and ontology techniques in order to extract and illustrate the knowledge generated from collaborative interaction of small groups of students through an online distance learning environment. The main objective of their work was to develop a mechanism to analyze and study behavioral patterns of interaction and participation in different collaborative learning scenarios and settings. Their research provided an ontological profile to help the instructor have a better understanding about the students' roles, division of labors (i.e., who-did-what) and task divisions as well.

Reimann et al. (2009) were pioneers who used a Process Mining technique (through Heuristics Miner algorithm) to analyze process models of students in small groups based on an online chat data previously collected in a CSCL environment.

The study of Reimann et al. (2009) had a project-based approach by differentiating the groups of students based on the group processes, number of group members, number of actions performed, and task requirements variables. Their results showed that teams with fewer group members received more instruction during the task and showed more linear decision-making tendencies compared with other groups. Their study could increase the students' awareness about their collaborative performance during the task by providing feedback (i.e., mirroring) on their collaborative decision-making process.

Martinez-Maldonado et al. (2013b) worked on technical advancement and empirical research of a multi-user multi-touch tabletop classroom that was capable of capturing authentic information about students while they worked on tasks by applying artificial intelligence techniques such as data mining (i.e., sequential pattern mining) and process mining (i.e., Fuzzy miner modeling) techniques. Their aim was find novel approaches to differentiate between groups of high and low achievers based on behavioral patterns. Their findings showed that the keywords Parallel and Other appeared more often in high achiever groups compared with low achiever groups. As a result, more than one student often interacted with the artifacts in high achiever groups. Their findings also showed that the keywords NoOwn and Inact appeared more often in high achiever groups compared with low achiever groups. However, the appearance of the keyword Own was similar in both high and low achiever groups. In other words, students in high achiever groups showed a tendency to interact with objects previously created by their other fellow group members. Moreover, based on their fuzzy mining results, both high and low achiever groups shared the same building blocks (or core elements) of activity. However, the structures of transitions among the core elements were different in high and low achiever groups. Also in a very comprehensive and sophisticated dissertation written by Martinez-Maldonado (2014) a total of eight datasets were used in order to introduce a novel approach with respect to both technological infrastructure advancement and empirical results (mostly through machine learning and data mining techniques) with the intention of providing support for instructors by increasing their awareness about small groups of student's collaboration in multi-touch multi-user tabletop classrooms. The work written by Martinez-Maldonado (2014) was the main motivation and inspiration of this dissertation as well.

And finally, in a study conducted by Premchaiswadi and Porouhan (2015a), they initially investigated the main factors that affect the performance of small groups of students in an online distance learning collaborative environment. They used specific keywords and contexts in order to extract the appropriate type of information and knowledge from the collected event log. They also applied several statistical and process mining techniques (i.e., such as fuzzy mining, decision point analysis, heurist mining, social network miner) in order to analyze the students' collaborative behavior with respect to level of interactions and degree of involvement/participation. Accordingly, they applied a qualitative method of research to analyze the semantic and textual contributions of students that were shared in online chat rooms during the group distance learning assignment. Their findings indicated that the level of students' interaction was four times greater in high performance groups compared with low performance groups. Similarly, the degree of students' participation/involvement was three times greater in the high performance groups. The level of students' communication (with respect to number of words shared and typed in chat rooms) was also two times greater in the groups with high performance compared with the low performance groups.

2.5 Summary

After having read through the above-mentioned related works and literature reviews, we found that most of the face recognition algorithms and image processing techniques used in overhead depth cameras (sensors) to track and differentiate a user based on the position of hands and fingers are rather costly and difficult to implement in real classrooms with a large number of students. Moreover, the accuracy and reliability of their user differentiation results also is not always assured and guaranteed. On the other hand, most of the touch-identification systems presented in the user identification section have some usability problems and are highly dependent to special touch sensitive hardware or external devices which make them incompatible with every type of tabletop system used for collaborative learning purposes. In the same way, most of the biometric solutions or

Gestural-Interface systems for user identification are also still very expensive considering their financial cost, management support, and requirements for infrastructure. Accordingly, development of a collaborative multi-tabletop environment that allows small groups of students to collaborate with each other through a networked system could be much cheaper and convenient compared with the offline collaborative tabletop systems that differentiate and authenticate users by means of overhead Kinect cameras (sensors) or small digital gadgets and hardware (such as digital gloves, digital pens, digital wristbands, digital armbands, etc.) or based on biometric traces and gestural movements. Unfortunately, there is currently little research work that addresses the intersection of networked-based collaborative tabletop systems and educational process mining techniques in order to analyze and investigate collaborative process and group progress in online learning environments. Majority of the research work presented in this section has focused on one of the scenarios as follows:

"offline collaborative learning environments equipped WITH interactive tabletops (analyzed and studied through traditional analytics, machine learning, visualization, and educational data mining techniques and tools)"

"networked-based collaborative learning environments, NOT equipped with interactive tabletops, (analyzed and studied through traditional analytics, machine learning, visualization, and educational data mining techniques and tools"

"offline collaborative learning environments, NOT equipped with interactive tabletops, (but analyzed and studied through educational process mining techniques and tools)"

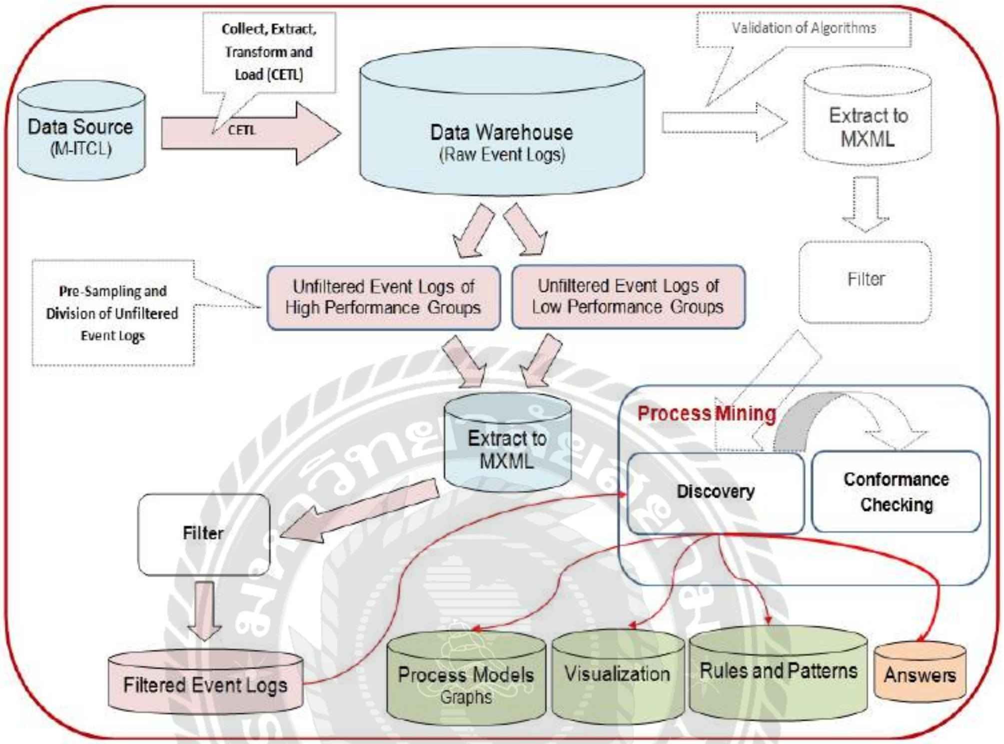


Figure7. An overview of the features that differentiate the developed M-ITCL system from others (Adopted from: Aalst, 2011 ; Martinez-Maldonado, 2014).

This motivated us to develop a networked-based collaborative environment equipped WITH interactive Computer Tables (analyzed and studied through educational process mining techniques and tools). Our aim was to monitor, analyze and interpret the students' collaboration and interaction data by the Instructor Dashboard equipped with several visualization, analytics, pattern mining, and modeling techniques supported by process mining tools. Figure 7 shows some of the features that differentiates our developed system from others (according to the structure). The process in the networked Multi-Interactive Table Computer Table (M-ITCL) environment initially begins by automatically and unobtrusively capturing, collecting and formatting the students' collaboration data based on the shared tabletop actions that occur using the Online Concept Mapping Application (OCMA) throughout the task session. During the activity, the instructor can use the Instructor Dashboard to monitor (i.e. coach in progress) each group's collaboration process (and progress) in terms of a history log summary, process models, graphical visualization, or numerical formats. After the end of the activity, the interpreted results of the students' interaction and collaboration analysis (both individually and group-based) can help the instructor to provide more support to low achieving students who did not perform well during the assigned task, in such a way to enable them to overcome their weak points during the next upcoming activity sessions and exams (i.e., coaching). Moreover, the instructor can improve the grading and assessment process in a more sophisticated approach not only limited to the final artifacts (outcomes) created (accomplished) by the students. In addition, the overall feedback of the interaction and collaboration analysis can be shown to the students for self-regulating purposes (i.e., mirroring information).

3.0 METHODOLOGY

3.1 Quantitative Indicators of Collaboration Process

In order to identify the most significant quantitative indicators that can be used in order to improve (and increase) awareness of the instructor about the quality of the collaboration process (as well as group progress) and to use these indicators for real-time (or post-hoc) analysis; a quantitative survey was conducted using a random sample of 192 undergraduate students aged 19–25.In other words, the development and identification of these indicators in real-time (or post-hoc) was needed during (or after the end of) the online concept mapping activities in the Multi-Interactive Table Computer Lab classroom where participants (both instructors and students) can observe the output of the analysis based on the specific quantitative indicators, to improve and benchmark the quality of learning/teaching or collaborative processes. After reviewing the secondary data related to the "Theories of Groups" (McGrath 1991), "Theories of Groups Performance and Interaction" (McGrath 1984), Theory of Group Cognition (Stahl 2006), and based on definitions of collaboration in CSCL environments described by Roschelle's and Teasley (1995), Dillenbourg (1998), Morgan and Buttler (2009), Dillenbourg and Jermann (2010), Dillenbourg et al. (2011), Dillenbourg and Evans (2011), and Martinez-Maldonado (2014); eight independent indicators and one dependent indicator were chosen and defined for the initial Conceptual Framework of the survey as follows:

Extent of Participation (independent variable) is defined as the extent to which a student actively and voluntarily participates in a concept map construction process by creating objects or performing activities (or actions) through a networked tabletop classroom. In this study, the extent of participation is identified in terms of "participation density", "participation rate" and "participation dynamics" and is measured through several process mining techniques as mentioned earlier in Section 1.2 and Section 1.3.

Extent of Interaction (independent variable) is defined as the extent to which a student works with a (concept map) object previously created by another fellow group member during a concept map construction process in a networked tabletop classroom. In this study, the extent of interaction is identified in terms of "interaction density" and "interaction dynamics" and is measured through several process mining techniques as mentioned earlier in Section 1.2 and Section 1.3.

Degree of Division of Labor and Similarity of Task (independent variable) is defined as the degree to which different parts (objects) of a concept map model are constructed and built by different peer group members during a concept map construction process in a networked tabletop classroom. In this study, the degree of division of labor (or symmetry of roles) is analyzed through the process mining role hierarchy mining technique and is represented in terms of "high division of labor" and "low division of labor" as mentioned earlier in Section 1.2 and Section 1.3. Similarity of task is the extent to which students perform similar tasks to finish the assigned work. In this study, the degree of similarity of tasks (or symmetry of actions) is analyzed through the process mining social network analysis technique (i.e., similar work metric) as mentioned earlier in Section 1.2 and Section 1.3.

Time Performance (independent variable) is defined as the extent to which a student perceives that the total assigned time to construct a concept map model, and the time gaps and interval batches of waiting time (idle time) between the actions (tasks) performed by peer group members have an impact on the quality of collaborative group performance. In this study, time performance graphs (models) and patterns are analyzed through process mining fuzzy mining (performance-based) and basic performance analysis techniques as mentioned earlier in Section 1.2 and Section 1.3.

Task Difficulty (independent variable) is defined as the degree to which a student perceives the concept map construction assignment via tabletops is hard and difficult.

Group size (independent variable) is defined as the total number of peer members in a small group during a concept mapping activity in a networked tabletop classroom.

Prior experience (independent variable) is defined as a student's previous experience in any concept map construction activity in a networked tabletop classroom.

Gender (independent variable) refers to the sexual identity of a student participating in a concept map construction activity in a networked tabletop classroom.

Collaborative Performance in CSCL (dependent variable) is defined as the extent to which a final artifact (concept map model) created by a group of students is correct and every group member has made individual contribution to the group artifact (task).

Table 1. Reliability analysis of the collaboration indicators based on Cronbach's Alpha

Indicators	Cronbach's Alpha	Number of Items
Extent of Participation (independent indicator)	0.924	10
Extent of Interaction (independent indicator)	0.857	10
Division of Labor and Similarity of Tasks (independent indicator)	0.829	8
Time Performance (independent indicator)	0.879	5
Task Difficulty (independent indicator)	0.835	4
Group Size (independent indicator)	0.815	4
Prior Experience (independent indicator)	0.786	6
Gender (independent indicator)	0.778	3
Collaborative Performance in CSCL (independent indicator)	0.853	3
Total(independents and dependent)	0.850	28

As shown in Table 1, the reliability analysis of the proposed conceptual framework with regard to the Cronbach's Alpha (α) shows a fair reliability for every single indicator, as well as a total reliability of

85% for all of the indicators (both dependent and independent) and items (i.e., questions) of the survey.

Table 2. Bivariate correlation analysis of the collaboration indicators

Indicators		Correlations
Collaborative Performance in CSCL	Pearson Correlation	1
	Sig. (2-tailed)	
Extent of Participation	Pearson Correlation	.302(**)
	Sig. (2-tailed)	.000
Extent of Interaction	Pearson Correlation	.200(**)
	Sig. (2-tailed)	.005
Task Difficulty	Pearson Correlation	.074
	Sig. (2-tailed)	.307
Prior Experience	Pearson Correlation	.103
	Sig. (2-tailed)	.157
Time Performance	Pearson Correlation	.185(*)
	Sig. (2-tailed)	.010
Division of Labor and Similarity of Tasks	Pearson Correlation	.185(*)
	Sig. (2-tailed)	.010
Group Size	Pearson Correlation	.011
	Sig. (2-tailed)	.884
Gender	Pearson Correlation	-.067
	Sig. (2-tailed)	.356

** Correlation is significant at the 0.01 level (2-tailed).

* Correlation is significant at the 0.05 level (2-tailed).

In order to measure the linear correlation (or the level of dependency) between the indicators; the Pearson product-moment correlation coefficient (2-tailed approach) was used. The correlations between the eight independent indicators and 1 dependent variable are illustrated in Table 2. Considering the results of the Pearson Correlation coefficients (2-tailed approach); four indicators of "Task Difficulty", "Prior Experience", "Gender" and "Group Size" were not supported and removed from the initial conceptual framework due to their low correlation coefficients. As a result, the total number of independent indicators was reduced from eight to four (highlighted in yellow).

Table 3.The results of ridge linear regression analysis

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-8.356	1.908		-4.378	.000
Extent of Participation		.582	.112	.334	5.197	.000
Extent of Interaction		.744	.167	.293	4.466	.000
Division of Labor and Similarity of Tasks		1.102	.309	.233	3.569	.000
Time Performance		.456	.152	.192	2.998	.003

a Dependent Variable: Collaborative Performance in CSCL

As shown in Table 3, using the Ridge Regression Analysis technique, we could estimate the coefficients of the linear equation, involving four independent variables (i.e., "Extent of Participation", "Extent of Interaction", "Time Performance", and "Division of Labor and Similarity of Tasks") that best predicted the value of the dependent variable. As a result, the most significant indicators of collaboration in CSCL were as the following, respectively: Extent of Participation (with significance level of 0.000 < 0.05 and t value of 5.197 > 2.0), Extent of Interaction (with significance level of 0.000 < 0.05 and t value of 4.466 > 2.0), Division of Labor and Similarity of Tasks (with significance level of 0.000 < 0.05 and t value of 3.569 > 2.0), and Time Performance (with significance level of 0.003 < 0.05 and t value of 2.998 > 2.0).

The resulting coefficient of determination (i.e., R Square) indicated that 71.3% of the variance in the dependent variable is predictable from the four independent variables as shown in Table 4.

Table 4.The results of the coefficient of determination (R Square)

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.844[a]	.713	.691	.86866

a Predictors: (Constant), Extent of Participation, Extent of Interaction, Time Performance, Division of Labor

3.2 Data Preparation, Defining Tasks Contexts, and Data Collection

The Instructor Dashboard (equipped with myInvenio, ProM and Disco Fluxicon process mining tools) was designed with the purpose of assisting an instructor for generating real-time reports of the on-task progress of each small group in the Multi-Interactive Table Computer Lab classroom's environment. From a data capture perspective, the Instructor Dashboard had instant access to the synchronized data received from the Online Concept Mapping Application (OCMA) supported by the Tin Can API platform while students were working on creating concept map objects via the networked-based Table Computers during the assigned task. Detailed explanations of the technical infrastructure requirements of the developed system falls beyond the objectives of this study and will be presented in another paper. The reports of the Instructor Dashboard displayed on a handheld device enabled the instructor to easily and closely monitor a group's progress during the concept map construction activity. Moreover, the tool allowed the instructor to explore the nature of information that the instructor wants to see with respect to specific structures and labels. The preliminary raw data of the Instructor Dashboard —in this study it is called a report— was composed of a lengthy sequence of actions whereas each element was labeled (Martinez-Maldonado 2014) as: {Construct, ActionType, Subject, Possessor, TimeStamp, Correctness}, where (1) Construct can be: a Component (concept), an Arrow (line) or a Menu (window). (2) ActionType can be: an Add (i.e., build/create a component or arrow), a Del (i.e., remove/delete a component or arrow), a Shift (i.e., move/shift a component or arrow), an Edit (i.e., add/edit a text object in a component or arrow), a Scroll (i.e., scroll up or down the list of suggested components through the menu window), a Mix (i.e., merge/mix two components or arrows), an Open (i.e., open the menu window), or a Close (i.e., close the menu window). (3) Subject is the student who executes the action and (4) Possessor is the student who builds and owns a Construct (i.e., Component, Arrow or Menu). (5) TimeStamp is the time when the action takes place. (6) Correctness indicates whether the executed action is compatible with the key elements of the instructor's master concept map or not. Therefore, Correctness can be: a Correct (i.e., when the created component or arrow is completely matched with the key elements of the instructor's roadmap) or an InCorrect (i.e., when the created component or arrow is not matched with the key elements of the instructor's roadmap).

Some examples of the primary reports include: {"Component F", "Del", "4", "4", "14:26:11", "Correct"}, when Student #4 correctly deletes the redundant Component F (which was created by himself previously) from the main map at 14:26:11 o'clock; or {"Arrow D", "Shift", "3", "4", "12:41:08", "InCorrect"}, when Student #3 incorrectly moves an arrow (which was created by Student#4 previously) at 12:41:08 o'clock; or {"Menu", "Open", "3", "3", "11:25:18","Correct"}, when Student #3 correctly opens the menu window at 11:25:18 o'clock.

Table 5.Data design and definition of Contexts

Object	Activity Type		Context 1	Context 2	Context 3
Component-C *Arrow-A* *Menu-M*	*Add-C,A* *Edit-C,A* *Shift-C,A,M*	*Del-C,A* *Mix-C,A* *Open-M* *Close-M*	*Simultaneous* *Another* *Same*	*Possess* *NoPossess*	*Correct* *False*
Inactivity Interval- Idle	*Short Inactivity-IdleShort*	*Long Inactivity-IdleLong*			

Adopted from: (Section 5.1, "Sequence mining", Martinez-Maldonado et al. 2013b ; Section 8.7.2, "Methods: Sequence Mining and Process Mining", Page 179, Martinez-Maldonado 2014 ; Page 12, Premchaiswadi and Porouhan 2015a)

3.2.1 Defining Blocks of Inactivity (or Idle Time). Considering the intervals of inactivity during the concept map construction activity, one of the following scenarios may occur: (1) students may have productive discussions together, (2) students may have off-task chatting together, or (3) students may be completely quiet and idle and not involved in any conversation or contribution to the task.

Since in this study, a speech detection technique was not used to capture and analyze the verbal communications of the students, it was crucial to consider the intervals of idle time and inactivity instead (Martinez-Maldonado 2014; Martinez-Maldonado et al., 2013b ;Premchaiswadi and Porouhan 2015a). Moreover, as discussed in Section 3.1, consideration of "Time Performance (i.e., time gaps and idle times)" is crucial in the analysis of the collaboration process in CSCL environments.

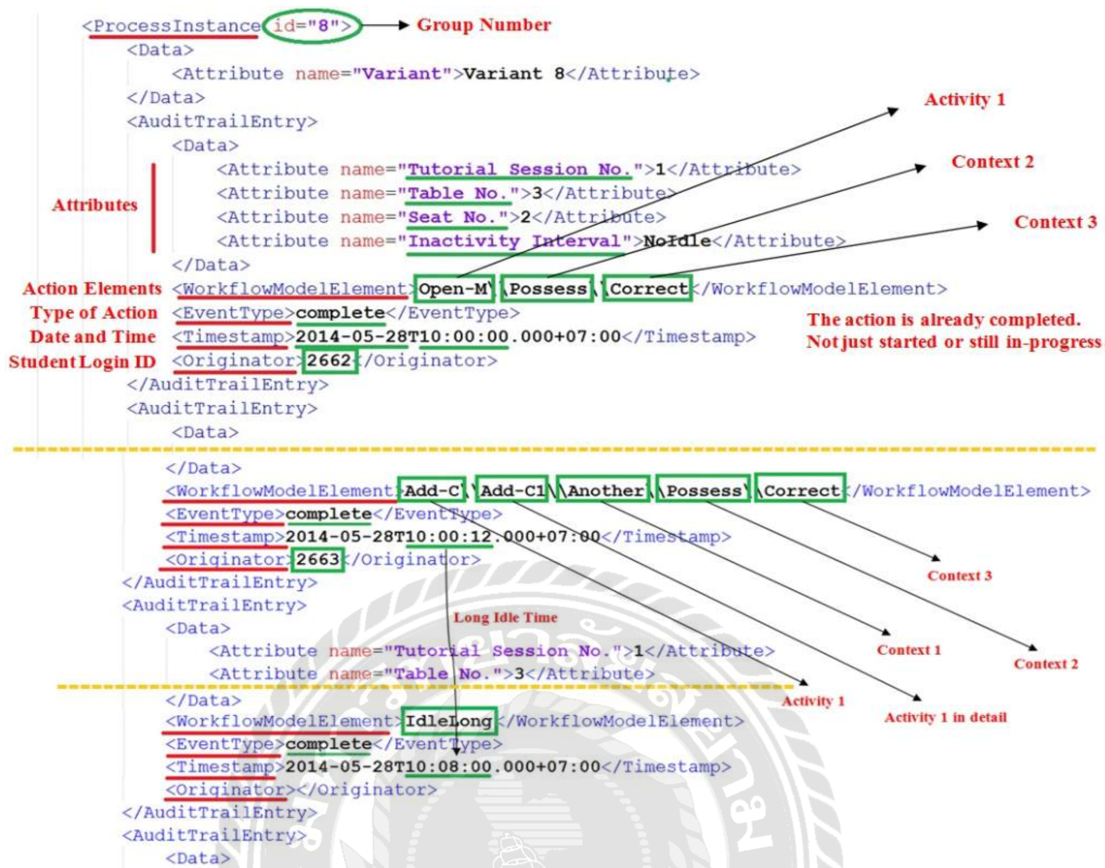


Figure8. A sample screenshot of a MXML-formatted event log captured from the M-ITCLsetting.

In this research, periods over 16 seconds were assumed as an interval of idle time. However, the intervals of idle time were also divided into two main groups as follows: (1) short idle time, and (2) long idle time. A short interval of idle time was defined when the time gaps are between 16 and 27seconds. On the other hand, a long interval of idle time was defined as time gaps longer than 27 seconds.

3.2.2 Defining and Categorization of Contexts. As mentioned earlier in Section 1.2 and Section 1.4, the definition of the term collaboration process in computer-supported collaborative learning (CSCL) situations is too general and can depend on countless variables and factors. Section 3.1 showed that the “Extent of Participation” and “Extent of Interaction” are two of the most significant indicators that can affect the “Collaborative Performance” (or degree of Correctness and Contribution) of groups in CSCL situations. Therefore, there was a need to define and use limited Contexts and Alphabets in order to address the above mentioned issues within the collected data. Accordingly, as shown in Table 5, three contexts (i.e., Context 1, Context 2 and Context 3) were defined and applied in ways to enable the instructor to better investigate and study the “Extent of Participation”, “Extent of Interaction” and “degree of Correctness of actions performed by the students” during the online concept map construction activity in the M-ITCL classroom. All of the learning events and actions were stored, captured and collected in the form of the format:

{(Activity Type+Object)⟶(Activity Type+Sub.Object)⟶(Context 1)⟶(Context 2)⟶(Context 3)}

Context 1 attempts to represent the sequence or order of the actions performed by the students at the interactive Table Computers. Such actions can take place:
simultaneously (or in parallel) with other students’ actions (keyword: Simultaneous)
in-turns when the prior action is done by another student (keyword: Another)
as a series of actions performed by the same student in sequence (keyword: Same)

Context 2 tries to clarify the ownership of the actions with respect to:
the actions that students execute on the objects created by themselves (keyword: Possess)
the actions that students execute on the objects created by their other fellow group members (keyword: NoPossess)

Context 3 tries to represent the correctness of the actions with respect to:
the actions that are compatible with the instructor’s key/master concept map (keyword: Correct)
the actions that are not compatible with the instructor’s key/master concept map (keyword: False)

The developed system was capable of automatically capturing, collecting, storing and formatting the students' (interaction and collaboration) data in terms of MXML event logs. A MXML-formatted event log consisted of:

a Process which is a mandatory field and it includes information about the execution of the processes,

a Source which is an optional field and it includes additional information regarding the source program that generated the log,

a Data which is an optional field and it includes information about the additional data elements (Dongen et al. 2005 ; Aalst 2011).

Figure 8 shows a sample screenshot of a MXML-formatted event log for Group #8 of the study generated during (or after the end of) Tutorial Session #1 of the concept mapping construction activity where students were sitting at Table Computer #3 in the Multi-Interactive Table Computer Lab (M-ITCL) classroom. Having browsed through the sample MXML-formatted event log shown in Figure 8 (up), it is clear that Student #2662 has correctly started the concept map construction task by opening the Main Menu at 10:00:00 AM (2014-05-28). Therefore, the system has stored and collected the first event in the direction of the format:

{ (Activity Type+Object)⟶(Activity Type+Sub.Object)⟶(Context 1)⟶(Context 2)⟶(Context 3)}

{ (Open-M) ⟶ (…) ⟶ (…) ⟶ (Possess) ⟶ (Correct) }

Due to the fact that the action Open-M does not need any more clarification about the type of action performed (i.e., does not need any sub-action to be defined) and due to the fact that Student #2662 was the first person who initiated the concept mapping task (i.e., before him/her there was no one else doing anything); the system has automatically skipped (Activity Type+Sub.Object) and (Context 1) elements. In Figure 8 (middle), we can see that 12 seconds later at 10:00:12 AM another student (Student 2663) has correctly added the first Component of the concept model. Therefore, the system has stored and collected the second event in the direction of the format:

{ (Activity Type+Object)⟶(Activity Type+Sub.Object)⟶(Context 1)⟶(Context 2)⟶(Context 3)}

{ (Add-C) ⟶ (Add-C1) ⟶ (Another) ⟶ (Possess) ⟶ (Correct) }

Due to the fact that the action Add-C needs more clarification about the type of action performed; the system automatically uses the sub-action Add-C1 in order to identify the number of the component created. Similarly, because this is the first time C1 is been created, therefore Student #2663 is defined as the person who possesses (Possess) the object. Moreover, due to the fact that before Student #2663 somebody else performed an action (i.e., Student #2662); the system has defined and saved the second event done and executed by as Another.

Table 6. Categorization of actions based on the level of importance

High Impact actions	**Low Impact actions**	**No Impact actions**
Add a component/arrow *Delete* a component/arrow *Edit* a component/arrow	*Shift a component/arrow* *Mix* two components/arrows	*Open* or *Close* menus *Scroll/Shift* menus

Adopted from: (Section 4, “Study Design and Data Description”, Martinez-Maldonado et al. 2013b ; Section 8.7.1, “Study Description”, Page 178, Martinez-Maldonado 2014 ; Page 13, “Categorization of actions”, Premchaiswadi and Porouhan 2015a)

After the second event (Add-C1), we can see a long waiting time gap until the third event has occurred. Therefore, because the waiting time gap was longer than 27 seconds; the system has automatically defined and stored a new action named as IdleLong. As shown in Figure 8 (down), the type of the third event occurred during the concept map construction activity is not shown clearly here, but what we are sure of is that the third event has happened 1 second after the end of the long waiting time (or IdleLong action). And this is how the system recognizes and identifies the short and long time gaps of idleness (inactivity) in terms of IdleShort and IdleLong type of actions, respectively.

3.2.3 Categorization of Actions. In order to analyze the students' actions with respect to the level of influence or impact on the concept mapping assignment; three categories of actions (shown in Table 6) were defined as follows: (1) high-impact actions, (2) low-impact actions, and (3) no-impact actions.

High-impact actions were defined as those types of actions that can significantly or substantially change the content or structure of the concept map. Such actions typically deal with edit, creation, or deletion of the components, arrows or textual objects.

Conversely, low-impact actions were defined as those types of actions that only can change the layout (or formation) of the concept map, which are important for the activity, but not really essential. In this paper, low-impact actions typically dealt with moving or shifting the components or arrows.

No-impact actions were defined as those types of actions that have no influence on the content or formation of the concept map, such as, opening and closing the main menu window, or scrolling up and down through the main menu.

3.2.4 Grouping of Actions. Subsequent to the categorization of actions; three new groups of actions were defined as follows: (1) HighOnly types of actions are those that consist of at least one high-impact action; (2) LowOnly types of actions are those that consist of at least one low-impact action; and (3) NoImpact types of actions contain at least one no-impact action (Martinez-Maldonado 2014). As mentioned earlier in Section 1.2 and Section 1.3; analysis of the impact level of the activities/actions performed by the student is one of the quantitative indicators and dimensions (see Dimension 1) of the collaboration process (quality) in this work.

3.3 Process Mining Algorithms (Validation)

Process mining is a new and fast-growing process management technique that provides process discovery, process modeling, and conformance checking (or auditing) of business processes based on datasets (event logs). The main idea in process mining is to extract and interpret knowledge from datasets (or event logs) collected from an information system (Aalst 2011). Such event logs typically consist of cases, events, time stamps, resources and other additional data in terms of attributes. Many process discovery process mining techniques are capable of producing process models in various forms, such as Petri nets, C-nets, YAWL-models, BPMNmodels, EPCs, and so on.

In this study, several process mining techniques, models and algorithms — using myInvenio (which is an online process mining tool), ProM 5.2 and ProM 6.4.1 (which are Open Source frameworks for process mining algorithms) and Disco (which is a process mining toolkit from Fluxicon) — were applied with the purpose of extracting knowledge from the event logs captured in the Multi-Interactive Table Computer Lab classroom. Using Disco (Fluxicon), the datasets were initially converted into the MXML and XES process mining standard formats suitable for ProM 5.2 and ProM 6.4.1, respectively. As mentioned earlier in Section 1.6, the collected datasets (event logs) were divided into two main sets; event logs of the high achieving groups and event logs of the low achieving groups. We started analyzing with an inspection of the statistical details about processes in each group by providing a general overview of information about the number of cases and events in the datasets, number of active students, number of interactions, and the time frames covered, as well as performance charts about the case duration and so on.

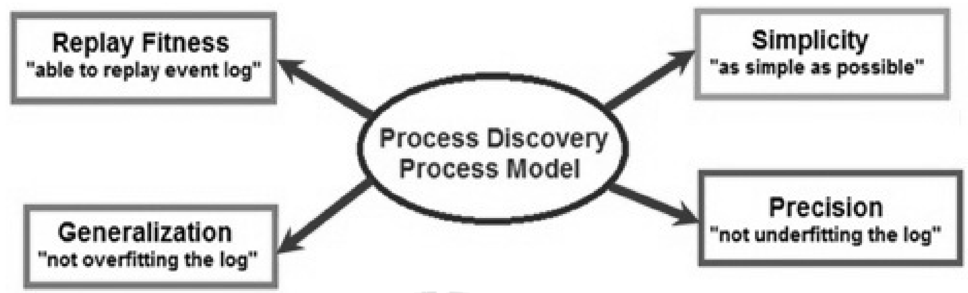


Figure9. Four quality dimensions of a good process discovery process model (Adopted from: Aalst 2011 ;Buijs 2014 ; Buijs et al. 2012).

We used Social Network Analysis visualization (graphical) representation techniques in order to further investigate the extent of Interaction Dynamics, Division of Labor (or symmetry of roles), and Similarity of Tasks (or symmetry of actions) among peer members in each group. We also applied Alpha, Heuristic miner, and Fuzzy miner algorithms in order to discover and compare process maps between both High and Low Performance groups. However, before inception of any process modeling using the above-mentioned algorithms (i.e., Alpha algorithm, Heuristic miner and Fuzzy miner), there was a need to know which of them was more qualified to better discover and predict the behavior of students during (or after the end of) the assigned task (i.e., Activity #2 of TRA concept map construction session) within the Multi-Interactive Table Computer Lab classroom.Figure 9 shows four quality dimensions of a good process model generated by process mining process discovery algorithms in terms of:

Replay fitness. It refers to the extent in which the discovered model/graph can correctly and accurately reproduce (or replay) the cases recorded in the event log.

Simplicity. It refers to the degree of complexity, readability and understandability of the discovered process model/graph. Process discovery algorithms often are divided into two types of process models: (a) Spaghetti-like process models, which are very complex and complicated (i.e., normally include a lot of noises and discrepancies) and are very hard to read and interpret. (b) Structured process models which are very straightforward, organized and easy to read/interpret them.

Precision. It quantifies the fraction of the behavior allowed by the discovered process model/graph which is not observed/found in the event log. In other words, a resulting process model has optimal precision if it allows for only minimally more behavior than observed/found in the event log.

Generalization. It refers to the extent to which the discovered process model/graph will be able to reproduce (i.e., replay) and predict future behavior of the event logs traces and processes.

However, most of the processes mining discovery algorithms in real-life situations are not capable of addressing all of the above mentioned four quality dimensions at once (Bujis 2014 ; Bujis et al. 2012). Table 40 shows a qualification analysis of the Alpha, Heuristic Miner and Fuzzy Miner process discovery algorithms based on the event logs collected in Activity #2 of the study with respect to five criteria.

Table 7.Qualification analysis of the process mining process discovery algorithms

Algorithm	Error-free	Replay Fitness	Precision	Generalization	Simplicity
α-algorithm	□	✗ (67.31%)	✗	✗	✓
Heuristic miner	✓	✗ (93%)	✓	✗	✗
Fuzzy miner	✓	✓ (100%)	✓	✓	✓

Adopted from: (Bujis 2014)

The error-free criterion investigates the extent to which the discovered process models (graphs) can be executed without errors. The results show that Heuristic miner and Fuzzy miner algorithms produced error-free models on the collaboration data collected from Activity #2 of the M-ICTL classroom for all 20 groups (i.e., both HP and LP groups) of students. The α-algorithm created a process model (graph) that was 'relaxed' error-free (shown by a yellow square) which means all of the processes could be finished without any error but some extra work remained anyhow. As shown in Table 7, Fuzzy miner algorithm resulted in generation of rather simple process models with good precision (i.e., allow only minimally more behavior than observed in the event log) and generalization. The Heuristic miner algorithm resulted in the generation of process models with good precision (i.e., allow only minimally more behavior than observed in the event log), but with poor generalization and simplicity. The Alpha algorithm resulted in the generation of process models with good simplicity, but with poor precision (i.e., allowed only minimally more behavior than observed in the event log) and generalization.

Table 8.Validation analysis of the process mining process discovery algorithms

		Modeled Behavior (α-algorithm)		Modeled Behavior (Heuristic miner)		Modeled Behavior (Fuzzy miner)	
		High	Low	High	Low	High	Low
Real Behavior	High	11	2	13	0	13	0
	Low	4	3	1	6	0	7

Adopted from: (Martinez-Maldonado 2014 ; Martinez-Maldonado et al., 2013b)

Moreover, a validation of the algorithms using a confusion matrix for both High Performance and Low Performance groups was tested and illustrated in Table 8. Based on the validation analysis; the produced Fuzzy miner models/graphs (via myInvenio, Disco Fluxicon and ProM) for the High Performance groups (i.e., 13 groups) could differentiate all of the high achieving cases correctly with 100% level of fitness. Similarly, the produced Fuzzy miner models/graphs (via myInvenio, Disco Fluxicon and ProM) for the Low Performance groups (i.e., 7 groups) could differentiate all of the low achieving cases correctly with 100% level of fitness. Taking into account both of high and low achieving groups, the average amount of the replay fitness (or validation measure) for the resulting Fuzzy miner models/graphs was 100%.

The generated Heuristic miner models/graphs (via ProM) for the High Performance groups (i.e., 13 groups) could differentiate all of the high achieving cases correctly with 100% level of fitness. The generated Heuristic miner models/graphs (via ProM) for the Low Performance groups (i.e., 7 groups) could differentiate only 6 of the low achieving cases correctly. Therefore, the level of replay fitness for the low achieving groups (using Heuristic miner algorithm) was 86%. Considering both of the high and low achieving groups, the average amount of the replay fitness (or validation measure) for the resulting Heuristic miner models/graphs was 93%.

Similarly, the resulting Alpha algorithm models/graphs (via ProM) for the High Performance groups (i.e., 13 groups) could differentiate only 11 of the high achieving cases correctly with 84.62% level of replay fitness. The produced α-algorithm models/graphs (via ProM) for the Low Performance groups (i.e., 7 groups) also could differentiate only 3 of the low achieving cases correctly. Therefore, the level of replay fitness for the low achieving groups was (via ProMα-algorithm) was 50%. Considering both of high and low achieving groups, the average amount of the replay fitness (or validation measure) for the resulting Alpha algorithm models (graphs) was 67.31%.

Therefore, based on both qualification and validation analyses; "Fuzzy Miner algorithm" can better help the instructor by generating quality process models that can be used to discover, compare and distinguish different patterns of collaboration process followed by either High Performance or Low Performance groups during the concept map construction assignment in Activity #2 of the M-ITCL classroom.

3.4 Association Rule Mining

The purpose of the Association Rule Miner technique is to discover association rules from the event log. The approach of the technique in this study was based on the process mining Association Rule Miner technique by using algorithms implemented in the Weka library (Agrawal and Srikant 1994) to generate association rules. Association rules, as the name suggests are the rules that shows associations between various items. These items can be products in your shopping basket, they can be spare parts in an automobile company information system, and many other such examples can be thought of. In the context of ProM process mining tool, these items are the activities in an event log ("ProM" 2009).

An example association rule is:

Add-C1 (Same) =>Add-C2 (Same) [support 2%, confidence=60%]

The above rule gives the information that the student who creates/builds Component 1 of the concept mapping assignment also tends to create/build Component 2 by himself/herself as well.

Rule Support and confidence are two measures of rule interestingness. They respectively represent usefulness and certainty of discovered rules. A support of 2% for the above association rule means that 2% of all the transactions under analysis show that Component 1 and Component 2 of the concept mapping activity are created/built by the same person/student. A confidence of 60% means that 60% of the students who created/built Component 1 also created/built Component 2 by themselves (see Appendix 1 for more details).

In general, if we have an association rule: a =>b then the support count indicates the joint probability of a and b. It is calculated as:

Support (a =>b) = Number of transactions containing (a U b)/ Total number of transactions

Confidence indicates the conditional probability of b given a. It is calculated as:

Confidence (a =>b) = Number of transactions containing (a U b)/ Number of transactions containing a

3.5 Apriori Algorithm (Frequent Item Sets Mining)

In general the discovery of interesting correlation relationships among huge amounts of transaction records and event logs can help in many decision making processes, such as students' collaborative behaviour analysis. These association rules show relationships between various items in the database or between various activities in an event log (in context of ProM). In this study, we used the Apriori algorithm in order to discover associations among items (as well as frequent item sets) in event logs previously collected from the Multi-Interactive Table Computer Lab classroom (see Appendix 1 for more details). The Apriori algorithm follows two steps:

Find all frequent itemsets. An itemset (set of items) satisfying a minimum support value is referred to as frequent itemset or large itemset. This minimum support value is called the minimum support threshold.

Generate association rules from these frequent itemsets. Generate strong association rules from the frequent itemsets. The rules that satisfy both a minimum support threshold and a minimum confidence threshold are known as strong rules. Strong rules are preferred because it is not practical to do an exhaustive search for thousands of potential rules that can be generated from a database. Many of these rules will not be of interest and use because they may be unreliable due to low support or confidence values (Gupta 2007 ; "ProM" 2009). Therefore it is common to generate only those rules that have a minimum specified support and confidence values (i.e., strong association rules).

4.0 FINDINGS AND RESULTS

4.1 General Performance Differences

4.1.1 Analysis of total time and total number of actions performed. As mentioned earlier in Section 1.6, the entire collected data were divided into 2 main sets of High Performance event logs and Low Performance event logs. Initially, we compared the groups based on the total average time taken to finish the assigned task. Out of a maximum 30 minutes of time for the second activity (so-called Activity #2), it took 13.7 minutes on average for the High Performance groups to finish the Theory of Reasoned Action (TRA) concept map creation task. However, for the Low Performance groups, the total average time spent to finish the same task was 24.7 minutes. Therefore, as shown in Table 9, none of the groups consumed the entire 30 minutes allowed to accomplish the Theory of Reasoned Action (TRA) concept map creation task, although the Low Performance groups spent more time (i.e., almost double) to finish the Activity #2. When investigating the details of the total time and total number of actions, we realized that in the High Performance groups (i.e., 13 groups), the maximum duration of time spent was 20 minutes and 12 seconds in Group #10 whereas the minimum duration of time consumed to finish the same tasks was 7 minutes and 14 seconds in Group #2.

Table 9. Comparison of the median and mean time to finish the TRA task

	Median Group Duration	Mean Group Duration
High Performance Groups	13.4 mins	13.7 mins
Low Performance Groups	24.2 mins	24.7 mins

On the other hand, as shown in Figure 10 (top), the maximum and minimum numbers of students' total actions (so-called events) were 45 (in Group #10) and 31 (in Group #4 and Group #11), respectively, in the High Performance groups (Premchaiswadi and Porouhan 2015a). Alternatively, as shown in Figure 10 (down), the maximum and minimum duration of time to finish Activity #2 in the Low Performance groups (i.e., 7 groups) were 29 minutes and 12 seconds (in Group #19) and 22 minutes and 5 seconds (in Group #20), respectively. The maximum number of students' total actions during Activity #2 was 81 actions (or events) in Group #16 whereas the minimum number of students' total actions was 48 in Group #19 of the Low Performance groups.

4.1.2 Analysis of the rate of the actions/events performed per second (average activity rate). As shown in Table 10, the average number of actions (events) executed in the High Performance groups was 35.62 actions (or 1.87 action per minute) whereas the average number of actions (events) executed in the Low Performance groups was 50.28 (or 1.676 action per minute). This means that the students in the Low Performance groups performed more actions and created more events on average (almost 1.5 times greater) than the High Performance groups in total.

Case ID	Events	Duration
1	37	10 mins, 23 secs
2	34	7 mins, 14 secs
3	32	10 mins, 11 secs
4	31	12 mins, 4 secs
5	34	13 mins, 22 secs
6	29	10 mins, 11 secs
7	34	17 mins, 12 secs
8	36	16 mins, 7 secs
9	43	18 mins, 22 secs
10	45	20 mins, 12 secs
11	31	15 mins, 6 secs
12	38	15 mins, 16 secs
13	39	12 mins, 13 secs

Case ID	Events	Duration
14	49	25 mins, 6 secs
15	49	24 mins, 12 secs
16	81	26 mins, 15 secs
17	49	24 mins, 13 secs
18	72	22 mins, 11 secs
19	48	29 mins, 12 secs
20	52	22 mins, 5 secs

Figure 10. Comparison of the total time and total number of events between the High Performance Groups (top) and the Low Performance groups (down).

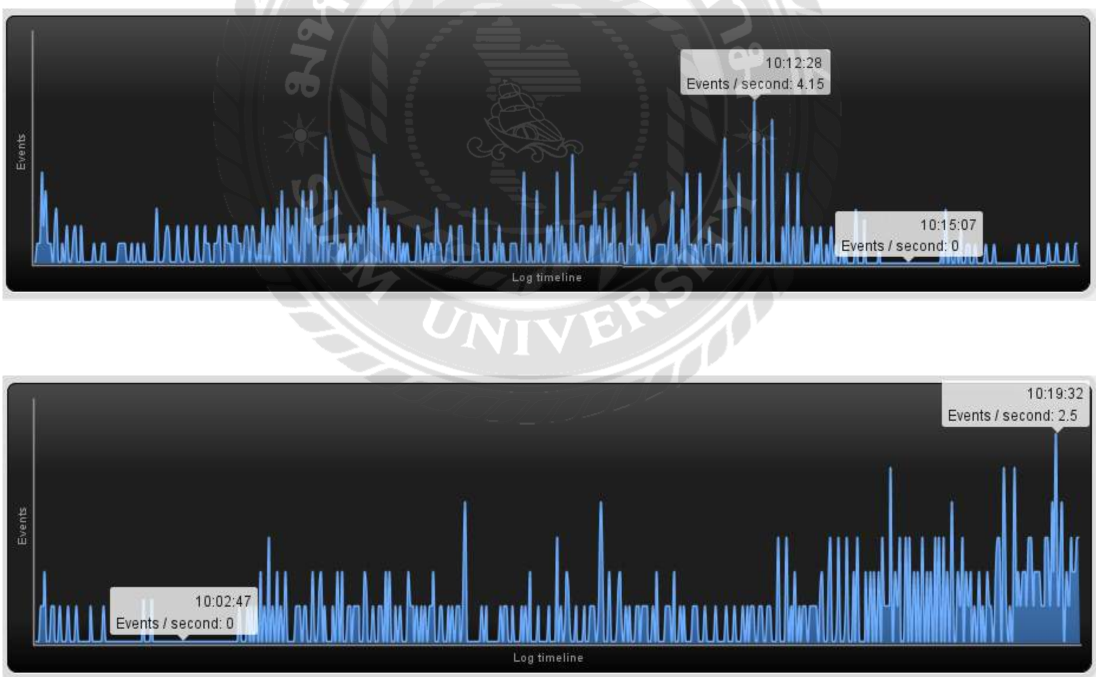


Figure 11. Distribution of the number of eventscreated per second between the High Performance (top) and Low Performance (down) groups.

Table 10. Comparison of the median and mean frequency of events to finish the TRA task

	Median Frequency	Mean Frequency
High Performance Groups	23	35.62
Low Performance Groups	28	50.28

We illustrated the number of students' actions performed over the time (per second) as well. The Y coordinate in Figure 11 represents the frequency (number of actions) while the X coordinate illustrates the time of the tutorial session in Activity #2. The distribution diagram of the High Performance groups significantly demonstrates a very low ratio of actions performed per second a moment just before the end of the tutorial session. On the contrary, the distribution diagram of the Low Performance groups significantly demonstrates a very low ratio of actions performed per second a moment just after the beginning of the Activity #2. Furthermore, in the High Performance groups, the maximum number of the actions per second (ratio) occurred at 10:12:28 o'clock (with 4.15 events per second) while in the Low Performance groups, the maximum number of the actions per second (ratio) occurred at 10:19:32 o'clock (with 2.5 events per second).

4.1.3 Analysis of the types of the actions/events performed. A process mining Dotted Chart Analysis technique was used in order to examine the maximum ratios of actions performed per second (i.e., the peak areas of the distribution diagrams) in both the High and Low Performance groups. As shown in Figure 12 (up), editing a component and editing an arrow (i.e., Edit-C and Edit-A, both selected and highlighted in light blue color) contained the majority of the actions that occurred at the peak area of the High Performance groups (i.e., between 10:12:00 to 10:13:00 AM). This means that during the peak area in Activity #2, the majority of the High Performance groups were "adding text objects" to their already created components and arrows.

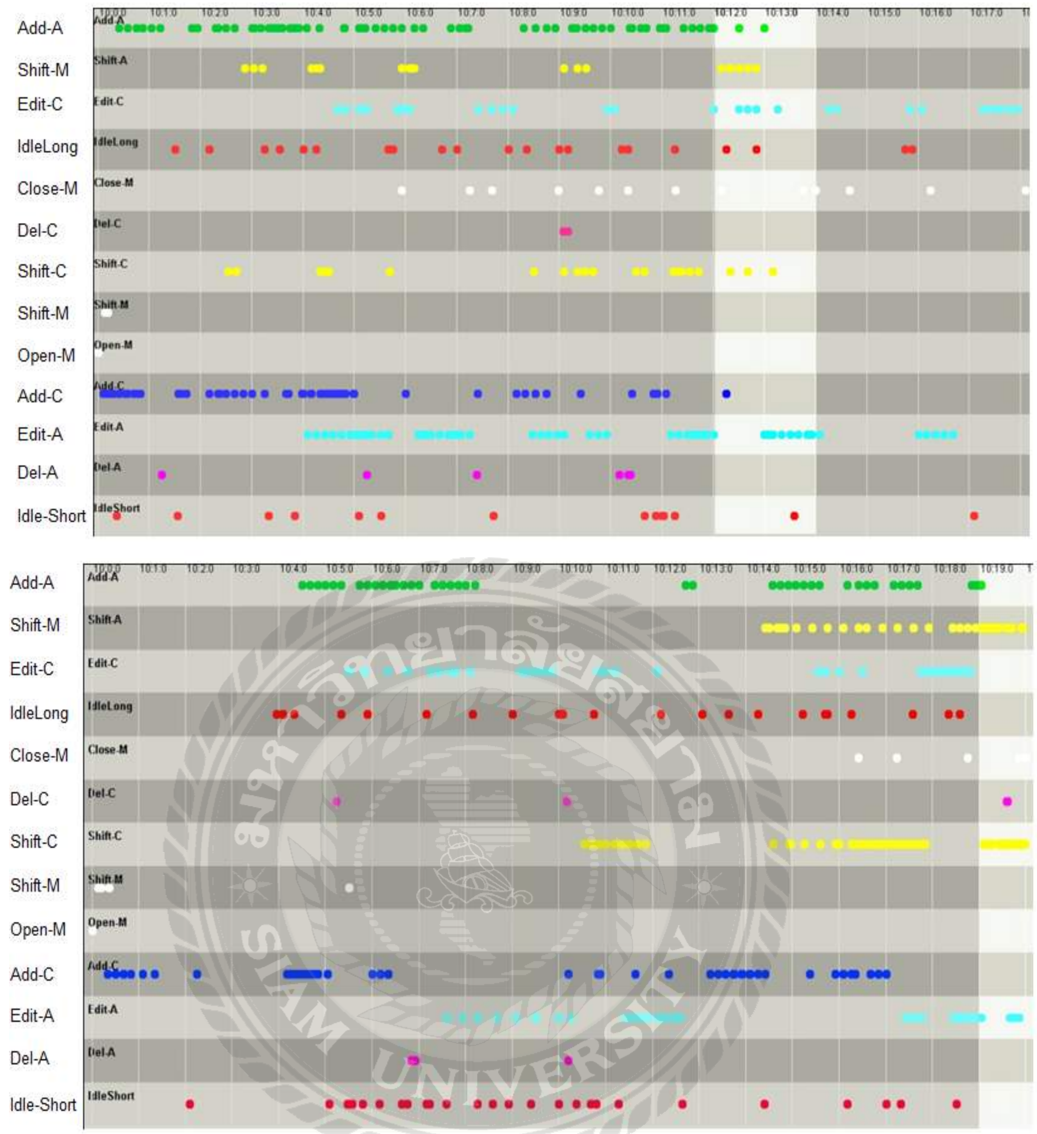


Figure 12.Comparison of the types of actions performed during the peak areas of the distribution diagrams between the High (up) and Low (down) Performance groups.

On the contrary, as shown in Figure 12 (down), shifting a component and shifting an arrow (i.e., Shift-C and Shift-A, both selected and highlighted in the yellow color) contained the majority of the actions that occurred in the peak area of the Low Performance groups (i.e., between 10:19:00 to 10:20:00 AM).This means that, during the peak area in the Activity #2, the majority of the Low Performance groups were only “moving” the created components and arrows from one side to another side.

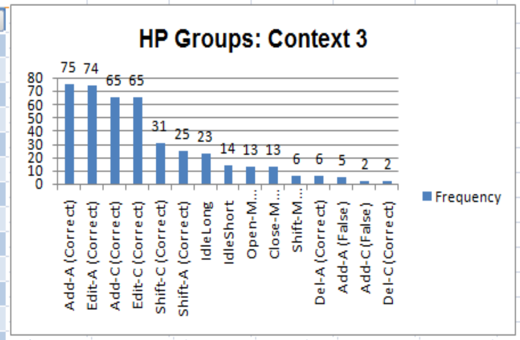
Table 11. Comparison of the resulting top-3 frequent itemsetsbased on Context 3

Frequent Item Sets Mining (Apriori Algorithm)	**High Performance Groups** - Num of Groups: 13 -	**Low Performance Groups** - Num of Groups: 7-
Context 3 *(Top-3 Item Sets)*	1. .{Add-A (**Correct**)}, {Edit-A (**Correct**)}, {Edit-C (**Correct**)}, {Close-M (**Correct**)} *Number of Process Instances (i.e., LP Groups) satisfying this Frequent Items Set : 13	1.{Open-M (Correct)},{ Edit-C (**False**)}, {Add-A (**False**)}, {Close-M (Correct)} *Number of Process Instances (i.e., LP Groups) satisfying this Frequent Items Set : 7
	2. {IdleLong}, {Add-C (**Correct**)}, {Add-A (**Correct**)}, {Edit-A (**Correct**)} *Number of Process Instances (i.e., LP Groups) satisfying this Frequent Items Set : 12	2. {IdleLong}, {Add-C (Correct)}, {Edit-C (Correct)}, {Add-A (**False**)} *Number of Process Instances (i.e., LP Groups) satisfying this Frequent Items Set : 7
	3. {Open-M (**Correct**)}, {IdleLong}, {Add-C (**Correct**)}, {Add-A (**Correct**)} *Number of Process Instances (i.e., LP Groups) satisfying this Frequent Items Set : 12	3. {IdleLong}, {Add-A (Correct)}, {Edit-C (**False**)}, {Add-A (**False**)} *Number of Process Instances (i.e., LP Groups) satisfying this Frequent Items Set : 7

4.1.4 Analysis of the accuracy or correctness of the actions/events performed. A process mining Frequent Item Sets Mining technique based on the Apriori algorithm was used in order to analyze the collected collaborative interaction data with respect to Context 3 (i.e., correctness) of the study. A total of 638 different patterns and clusters of Frequent Itemsets were identified for both of the High Performance groups (with 127 patterns) and Low Performance groups (with 511 patterns). By only focusing on the resulting top-3 patterns of Context 3, we realized that in the High Performance groups all of the actions in the top-3 most frequent itemsets contained the keyword Correct which means they have been executed correctly as shown in Table 11 (left). On the other hand, the resulting top-3 patterns in the Low Performance groups as shown in Table 11 (right) included five actions that were performed incorrectly as they contain the keyword False. In total, the keywords Correct and False (i.e., Context 3) appeared in 89.49% (frequency: 375) and 1.67% (frequency: 7) of the entire dataset for the High Performance groups, while the same keywords appeared in 47.49% (frequency: 169) and 38.76% (frequency: 138) of the entire dataset for the Low Performance groups, respectively as shown in Figure 13 (Up). Therefore, overall the keyword False appeared almost 20 times more (i.e., 19.714 times) in the Low Performance groups. However, by taking into account the number of groups participating in the activity (i.e., 13 HP groups and 7 LP groups), the average number of times the keyword False appeared in the Low Performance groups was almost 34 times more (i.e., 33.757 times) compared with the High Performance groups as shown in Figure 13 (Down).

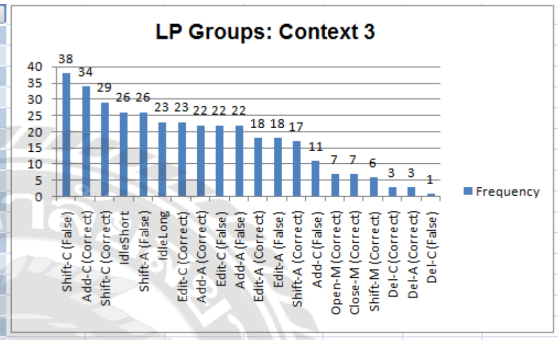
We used the process mining Dotted Chart Analysis technique in order to further investigate the groups' accuracy when deleting objects such as Components and Arrows (i.e., Del-C and Del-A) during the concept map construction activity. As illustrated in Figure 14 (left), the High Performance groups deleted 6 objects correctly (selected and highlighted in the green color) while 2 objects were deleted incorrectly (selected and highlighted in the red color). Therefore, in the High Performance groups, 75% of the deletion/removal actions were performed correctly and were compatible with the instructor's key/master concept map. Quite the opposite was true for the Low Performance groups since only 2 objects were deleted correctly (shown in the green color) whereas 5 objects where removed incorrectly (shown in the red color). As a result, see Figure 14 (right), in the Low Performance groups only 28.5% of the deletion/removal actions were executed correctly.

Activity	Frequency	Relative frequency
Add-A (Correct)	75	17.90%
Edit-A (Correct)	74	17.66%
Add-C (Correct)	65	15.51%
Edit-C (Correct)	65	15.51%
Shift-C (Correct)	31	7.40%
Shift-A (Correct)	25	5.97%
IdleLong	23	5.49%
IdleShort	14	3.34%
Open-M (Correct)	13	3.10%
Close-M (Correct)	13	3.10%
Shift-M (Correct)	6	1.43%
Del-A (Correct)	6	1.43%
Add-A (False)	5	1.19%
Add-C (False)	2	0.48%
Del-C (Correct)	2	0.48%



Overall	Frequency	Relative frequency
Overall (Correct)	**375**	**89.49%**
Overall (False)	**7**	**1.67%**

Activity	Frequency	Relative frequency
Shift-C (False)	38	10.67%
Add-C (Correct)	34	9.55%
Shift-C (Correct)	29	8.15%
IdleShort	26	7.30%
Shift-A (False)	26	7.30%
IdleLong	23	6.46%
Edit-C (Correct)	23	6.46%
Add-A (Correct)	22	6.18%
Edit-C (False)	22	6.18%
Add-A (False)	22	6.18%
Edit-A (Correct)	18	5.06%
Edit-A (False)	18	5.06%
Shift-A (Correct)	17	4.78%
Add-C (False)	11	3.09%
Open-M (Correct)	7	1.97%
Close-M (Correct)	7	1.97%
Shift-M (Correct)	6	1.69%
Del-C (Correct)	3	0.84%
Del-A (Correct)	3	0.84%
Del-C (False)	1	0.28%



Overall	Frequency	Relative frequency
Overall (Correct)	169	47.49%
Overall (False)	138	38.76%

Figure 13.Comparison of the frequency of the occurrence of the Context 3 between the High (up) and Low (down) Performance groups.

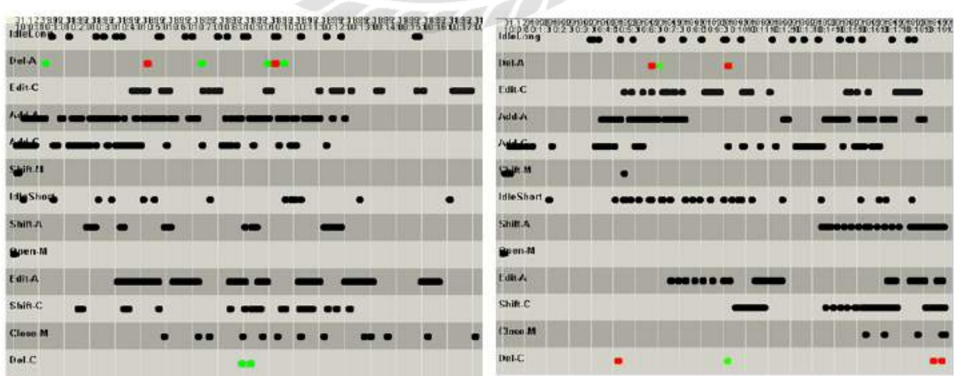


Figure 14.Comparison of the accuracy of the deletion/removal of objects between the High (left) and Low (right) Performance groups.

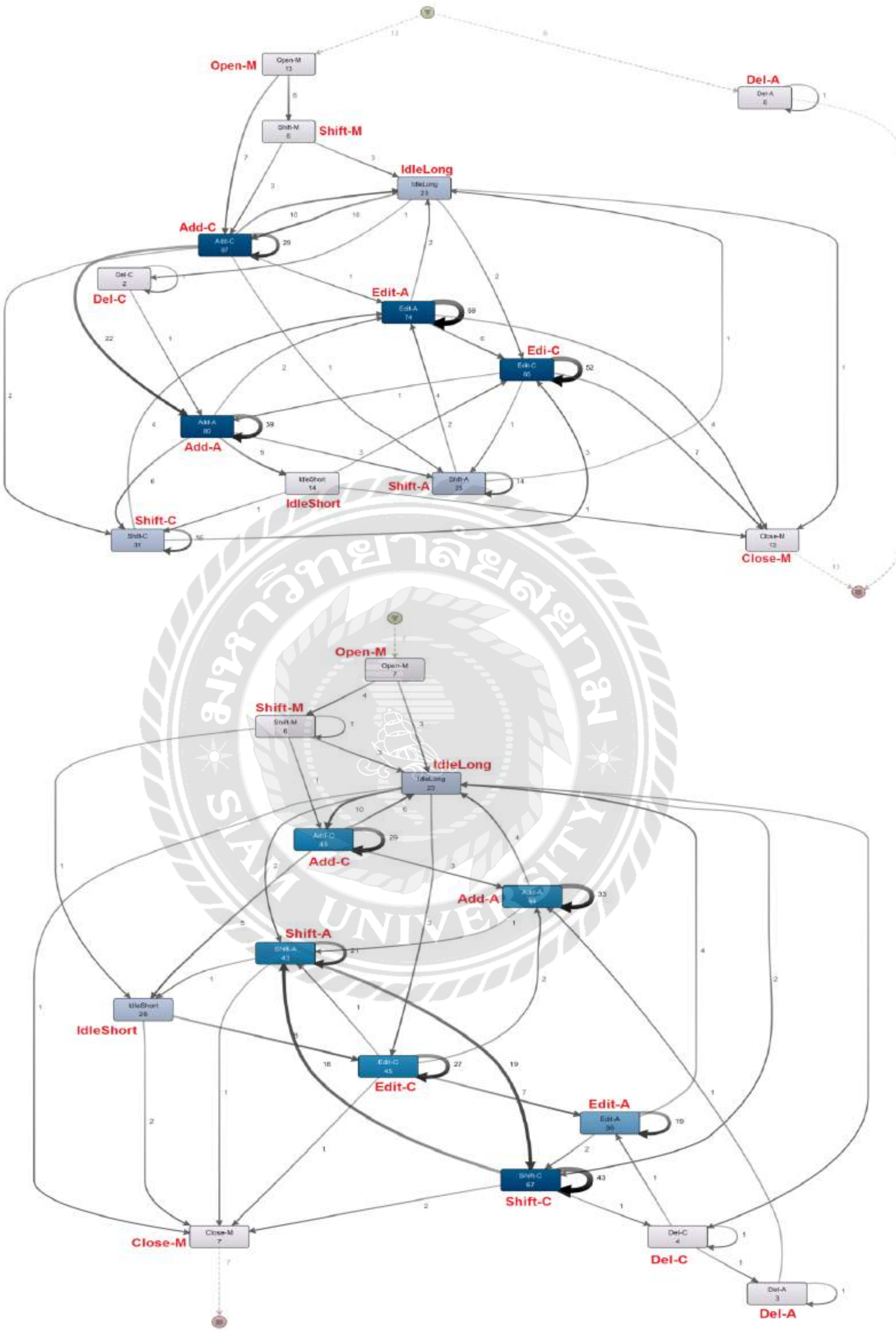


Figure 15. The resulting fuzzy process models based on the absolute frequency of the actions between the High (up) and Low (down) Performance groups.

4.1.5 Analysis of the absolute frequency of the actions/events performed (activity density). As mentioned earlier in Section 3.3, both the Alpha and Heuristic Miner algorithms do not guarantee that their resulting graphs (i.e., produced models) can 100% replay all cases in the event log collected from Activity #2 (TRA concept mapping task) in the Multi-Interactive Table Computer Lab classroom. Therefore, in this study we applied both the process mining Fuzzy Miner (ProM) and the Fuzzy Miner (Disco Fluxicon) algorithms in order to deal with the less-structured processes (with a lot of concurrencies) which display a large amount of unstructured and conflicting behavior (Aalst 2011 ; "Fuzzy Miner" 2009).

Figure 15 illustrates the outcomes of the fuzzy process models —showing all of the activities (100%) and 98% of the paths— supported by Disco Fluxicon based on the absolute frequency of actions/events (i.e., number of times groups repeated an action/event in total) for both of the High and Low Performance groups, respectively. To simplify the process model, a threshold of 98% of the paths (but 100% of the activities) was deliberately and purposely applied. By visually comparing the graphs, we realized that there were major differences between both groups with respect to the frequency and disposition of the events as follows First, although the total number of the Low Performance groups (i.e., 7 groups) was almost half of the High Performance groups (i.e., 13 groups), the absolute frequencies of the actions Shift-A (i.e., moving an arrow) and Shift-C (i.e., moving a component) were 2 and 1.7 times more in the Low Performance groups, respectively. Second, only 46% of the High Performance groups (i.e., 6 groups) navigated through the Main Menu Window (i.e., they executed Shift-M action), while 86% of the Low Performance groups (i.e., 6 groups) scrolled up and down through the Main Menu Window (i.e., Shift-M) during the tutorial sessions. Third, in the High Performance groups only 2 times (in total) a component was removed or deleted (i.e., the keyword Del-C was executed), whereas in the Low Performance groups 4 times (in total) a component was deleted. Fourth, in the High Performance groups 6 times (in total) an arrow was removed or deleted (i.e., the keyword Del-A was executed), whereas in the Low Performance groups an arrow was deleted only 3 times (in total). Fifth, activities: {Add-A (80 times), Edit-A (74 times), Add-C (67 times), Edit-C (65 times)} were the most frequent actions, respectively, performed by the students in the High Performance groups, whereas in the Low Performance groups the activities: {Shift-C (67 times), Edit-C (45 times), Add-A (44 times), Shift-A (43 times)} were the most frequent actions performed by the students, respectively.

4.1.6 Analysis of the impact level of the actions/events. Figure 16 illustrates the resulting fuzzy models after applying the Disco Fuzzy Miner algorithm in order to mine the impact level of actions performed by students in the High and Low Performance groups. To simplify the process model, a threshold of 80% of the paths (with 100% of the activities) was deliberately and purposely applied. By visually comparing the graphs we realized that they both share identical core blocks of activity. This was not compatible with the results of Martinez-Maldonado et al. (2013b) as in their work the building blocks of high and low achiever groups was quite different in terms of disposition and layout. As shown in Figure 16 (left), the activity block of "HighOnly-NoPossess" (168 times) had the highest frequency of occurrence in the High Performance groups. This means that students in the High Performance groups exhibited more tendencies to execute high-impact actions (such as adding, deleting, or editing a component/arrow/textual object) on the objects created by their other fellow group members. Quite the opposite was true for the Low Performance groups since the activity block of "HighOnly-Possess" (154 times) had the highest frequency of occurrence. Accordingly, as shown in Figure 16 (right), students in the Low Performance groups exhibited a greater tendency to execute high-impact actions on the objects created by themselves. These findings were compatible with the results obtained earlier through the Sequential Pattern Mining technique by Maldonado et al. (2013b). Alternatively, the Low Performance groups on average (i.e., divided by 7) executed more blocks of actions with no-impact (such as opening or shifting the main menu window). The average frequencies of the "NoImpact-Possess" and "NoImpact-NoPossess" blocks were almost 1.5 times greater in the Low Performance groups compared with the High Performance groups.

Also the Low Performance groups on average (i.e., divided by 7) performed more blocks of actions with low-impact. The average frequencies of the blocks including “LowOnly-Possess” and “LowOnly-NoPossess” were almost 3.5 times more in the Low Performance groups compared with the High Performance groups. These findings were not consistent with the results achieved by Martinez-Maldonado et al. (2013b) since in their research, high achiever groups performed more no-impact actions.

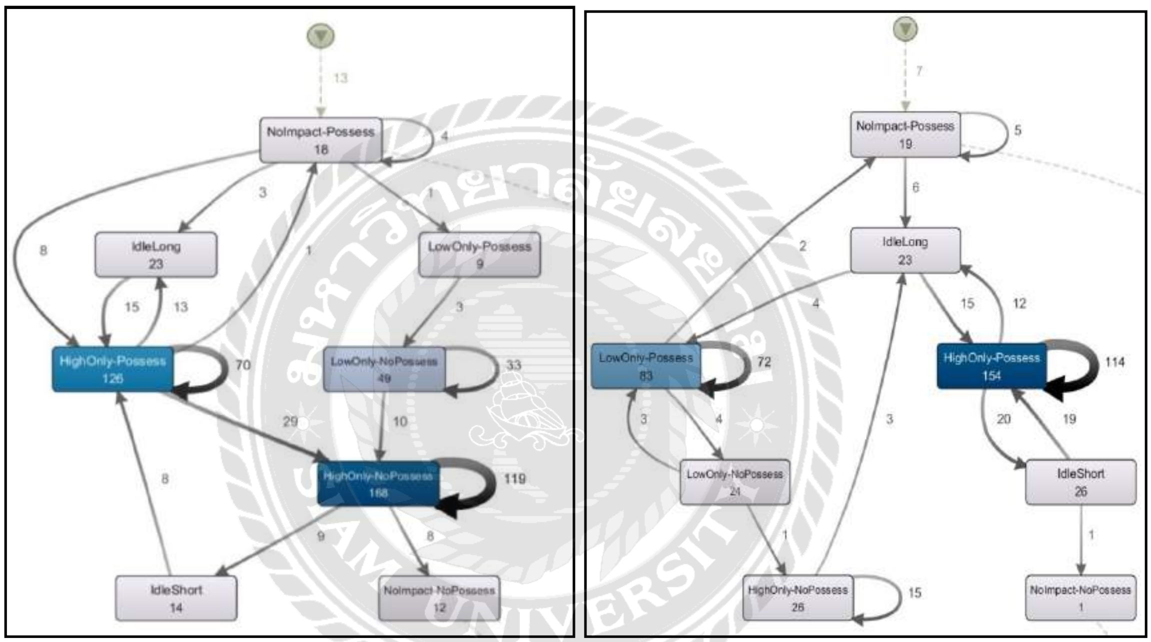


Figure 16. The resulting fuzzy process models based on the level of importance of the actions between the High (left) and Low (right) Performance groups.

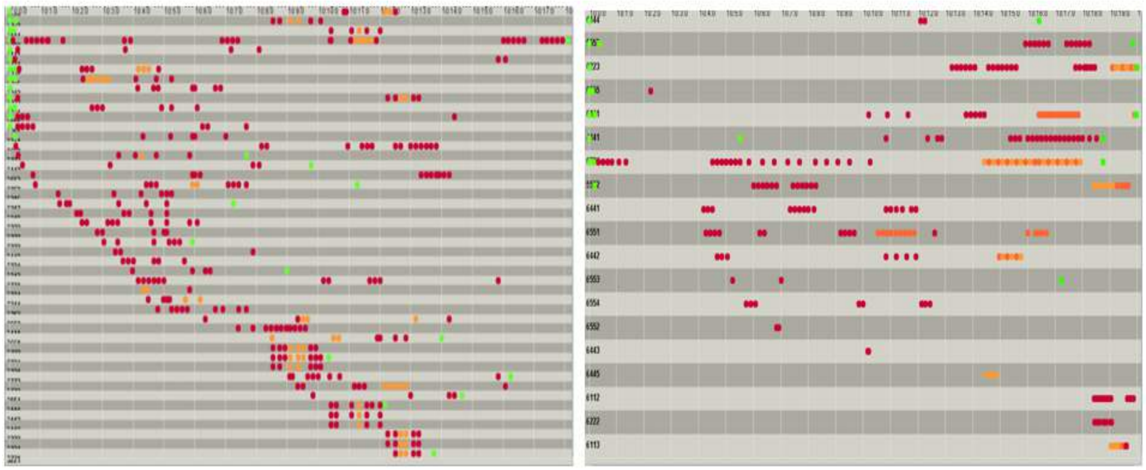


Figure 17.Comparison of the importance of actions over time between the High (left) and Low (right) Performance groups.

Likewise, in order to further investigate the impact level of actions performed by students in both groups during Activity #2 in the Multi-Interactive Table Computer Lab classroom, the Dotted Chart Analysis technique was used to better illustrate the spread of importance of actions performed by students over time. The X-axis in Figure 17 represents the cases (or students) who performed an action at the interactive Table Computer while the Y-axis represents the time of the assigned concept mapping task which was a maximum of 30 minutes in Activity #2.The points highlighted in red represent actions with High Impact, while the points highlighted in orange represent actions with Low Impact, and the points highlighted in green represent actions with No Impact. By comparing both charts for the High Performance groups and the Low Performance groups, once again we can see that the majority of the active students (during the Activity #2) participated in executing and performing actions with High Impact at the interactive Table Computers in the high achieving groups. Alternatively, only a few number of the active students (during the Activity #2) participated in executing and performing actions with High Impact at the interactive Table Computers in the low achieving groups. We will elaborate more on this later in Section 4.5.

Figure 18 shows the resulting fuzzy process models (generated by the Instructor Dashboard via ProM) with overall conformance and cutoff metrics of 75% and 0.2, respectively. Quite different from the Disco fuzzy models, the ProM fuzzy models deal with two fundamental metrics: (1) Significance and (2) Correlation.

"Significance" measures the relative importance of behavior while "Correlation" measures how closely related two events follow one another (Günther and Aalst 2007b).

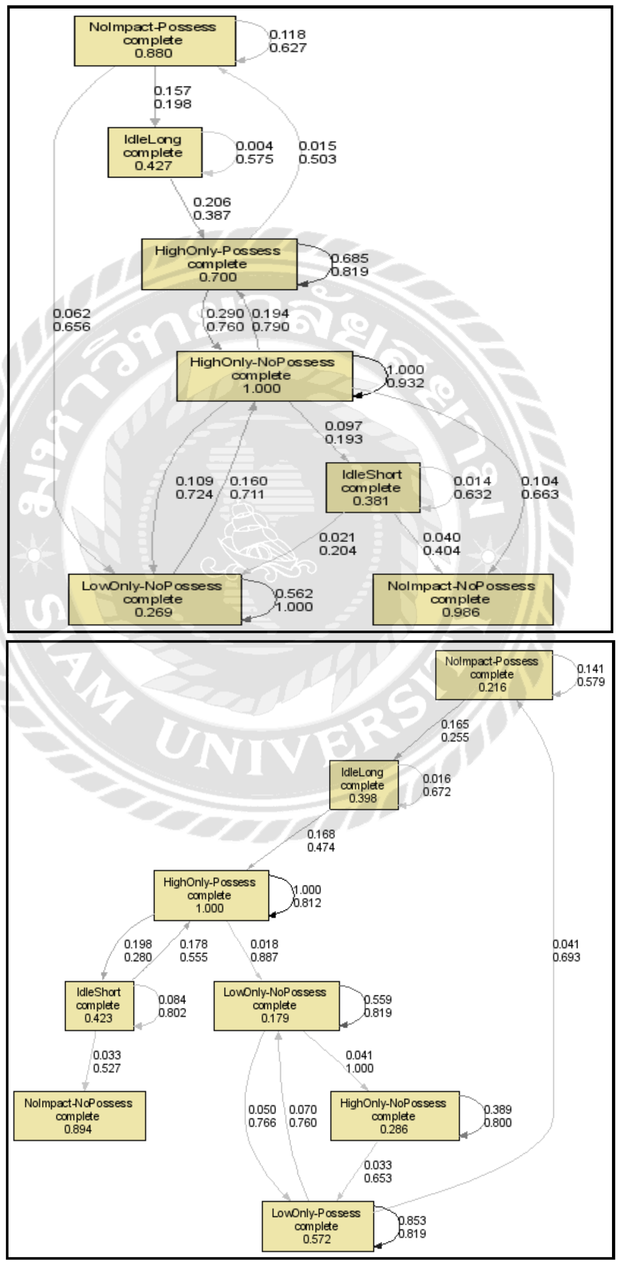
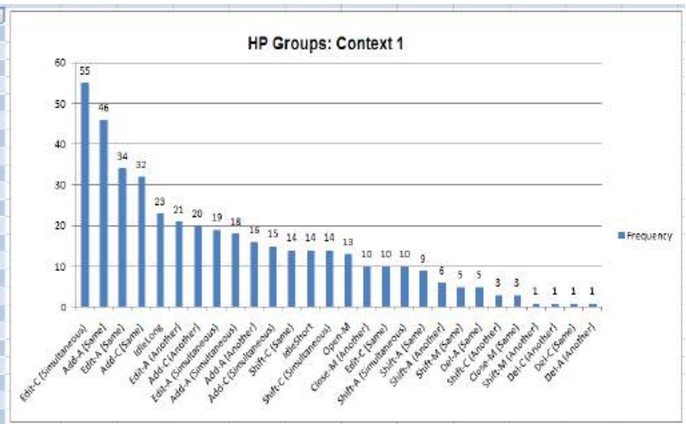


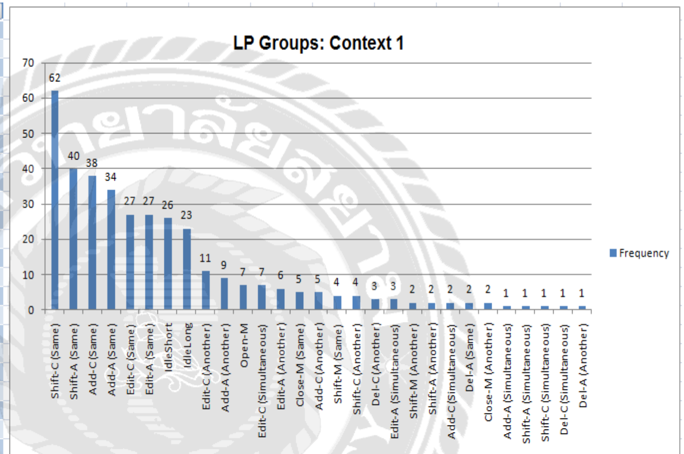
Figure 18. The resulting fuzzy process models based on the significance levelbetween the High (left) and Low (right) Performance groups.

Activity	Frequency	Relative frequency
Edit-C (Simutaneous)	55	13.13%
Add-A (Same)	46	10.98%
Edit-A (Same)	34	8.11%
Add-C (Same)	32	7.64%
IdleLong	23	5.49%
Edit-A (Another)	21	5.01%
Add-C (Another)	20	4.77%
Edit-A (Simutaneous)	19	4.53%
Add-A (Simutaneous)	18	4.30%
Add-A (Another)	16	3.82%
Add-C (Simutaneous)	15	3.58%
Shift-C (Same)	14	3.34%
IdleShort	14	3.34%
Shift-C (Simultaneous)	14	3.34%
Open-M	13	3.10%
Close-M (Another)	10	2.39%
Edit-C (Same)	10	2.39%
Shift-A (Simultaneous)	10	2.39%
Shift-A (Same)	9	2.15%
Shift-A (Another)	6	1.43%
Shift-M (Same)	5	1.19%
Del-A (Same)	5	1.19%
Shift-C (Another)	3	0.72%
Close-M (Same)	3	0.72%
Shift-M (Another)	1	0.24%
Del-C (Another)	1	0.24%
Del-C (Same)	1	0.24%
Del-A (Another)	1	0.24%



Overall	Frequency	Relative frequency
Overall (Same)	145	37.71%
Overall (Another)	79	18.86%
Overall (Simultaneous)	131	31.27%

Activity	Frequency	Relative frequency
Shift-C (Same)	62	17.42%
Shift-A (Same)	40	11.24%
Add-C (Same)	38	10.67%
Add-A (Same)	34	9.55%
Edit-C (Same)	27	7.58%
Edit-A (Same)	27	7.58%
IdleShort	26	7.30%
IdleLong	23	6.46%
Edit-C (Another)	11	3.09%
Add-A (Another)	9	2.53%
Open-M	7	1.97%
Edit-C (Simultaneous)	7	1.97%
Edit-A (Another)	6	1.69%
Close-M (Same)	5	1.40%
Add-C (Another)	5	1.40%
Shift-M (Same)	4	1.12%
Shift-C (Another)	4	1.12%
Del-C (Another)	3	0.84%
Edit-A (Simultaneous)	3	0.84%
Shift-M (Another)	2	0.56%
Shift-A (Another)	2	0.56%
Add-C (Simultaneous)	2	0.56%
Del-A (Same)	2	0.56%
Close-M (Another)	2	0.56%
Add-A (Simultaneous)	1	0.28%
Shift-A (Simultaneous)	1	0.28%
Shift-C (Simultaneous)	1	0.28%
Del-C (Simultaneous)	1	0.28%
Del-A (Another)	1	0.28%



Overall	Frequency	Relative frequency
Overall (Same)	239	67.12%
Overall (Another)	45	11.23%
Overall (Simultaneous)	16	4.49%

Figure 19. Comparison of the absolute frequencies of the participative actions based on Context 1 between the High (up) and Low (down) Performance groups.

As shown in Figure 18 (left) the most significant blocks of activity in the High Performance groups (with regard to the "significance" metric) were as follows:

(1) HighOnly-NoPossess (with the highest significance of 1.000),

(2) NoImpact-NoPossess (with significance of 0.986),

(3) NoImpact-Possess (with significance of 0.880),

(4) HighOnly-Possess (with significance of 0.700),

(5) IdleLong (with significance of 0.427),

(6) IdleShort (with significance of 0.381), and

(7) LowOnly-NoPossess (with the lowest significance of 0.269).

Therefore, similar to the Disco fuzzy models, the resulting blocks of "HighOnly-NoPossess" (with the highest significance of 1) and LowOnly-NoPossess (with the lowest significance of 0.269) were the most and the least significant behaviors in the High Performance groups, respectively. On the other hand, the resulting blocks of "HighOnly-Possess" (with the highest significance of 1) and "NoImpact-Possess" (with the lowest significance of 0.216) were the most and the least significant behaviors in the Low Performance groups, respectively as shown in Figure 18 (right).

Table 12.Comparison of the resulting top-3 frequent itemsets based on Context 1

Frequent Item Sets Mining ***(Apriori Algorithm)***	**High Performance Groups** **- Num of Groups: 13 -**	**Low Performance Groups** **- Num of Groups: 7-**
Context 1 ***(Top Three Item Sets)***	1. {Open-M}, {Add-C (**Another)**}, {Add-A (**Same**)}, {Edit-A (**Another**)} *Number of Process Instances (i.e., HP Groups) satisfying this Frequent Items Set : 8	1. {IdleLong}, {Add-C (**Same**)}, {IdleShort}, {Add-A (**Same**)} *Number of Process Instances (i.e., LP Groups) satisfying this Frequent Items Set : 6
	2. {Open-M}, {IdleLong}, {Edit-C (**Simultaneous**)}, {Close-M (**Another**)} *Number of Process Instances (i.e., HP Groups) satisfying this Frequent Items Set : 8	2. {IdleLong}, {Add-C (**Same**)}, {Edit-A (**Same**)}, {Shift-C (**Same**)} *Number of Process Instances (i.e., LP Groups) satisfying this Frequent Items Set : 6
	3. {Open-M}, {Add-C (**Another**)}, {Add-A (**Same**)}, {Edit-C (**Simultaneous**)} *Number of Process Instances (i.e., HP Groups) satisfying this Frequent Items Set : 8	3. {Open-M}, {IdleLong}, {Add-C (**Same**)}, {IdleShort}, {Edit-A (**Same**)}, {Shift-C (**Same**)} *Number of Process Instances (i.e., LP Groups) satisfying this Frequent Items Set : 6

4.2 Distinguished Patterns of Participation and Involvement

4.2.1 Participation Dynamics. A process mining Frequent Item Sets Mining technique based on the Apriori algorithm was used in order to analyze the collected collaborative interaction data with respect to Context 1 (i.e., participation dynamics) of the study. A total of 164 different patterns and clusters of Frequent Itemsets was identified for both of the High Performance groups (with 85 patterns) and Low Performance groups (with 79 patterns). By only focusing on the resulting top-3 patterns of Context 1 in the High Performance groups, we realized that the occurrence of actions performed simultaneously (i.e., containing the keyword Simultaneous) and alternatively by different fellow group members (i.e., containing the keyword Another) was very high and included majority of the observable actions in the top-3frequent itemsets as shown in Table 12 (left). This indicates that group members in the High Performance groups mostly participated in performing the actions together at the same time or they executed the activities alternatively by different fellow group members.Alternatively, it was realized that in the Low Performance groups the occurrence of actions performed by only one person (i.e., containing the keyword Same) was very high and included almost all of the observable actions in the top-3frequent itemsets as shown in Table 12 (right). In other words, group members in the Low Performance groups mostly participated in performing the actions alone without any contribution from other peer members. Accordingly, the keywords Simultaneous and Another appeared in 31.27% (frequency: 131) and 18.86 % (frequency: 79) of the entire dataset for the High Performance groups, respectively, as shown in Figure 19 (up). The same keywords appeared in only 4.49% (frequency: 16) and 11.23% (frequency: 45) of the entire dataset for the Low Performance groups, respectively, as shown in Figure 19 (down). As a result, overall the extent of participation dynamics with respect to both Simultaneous and Another keywords was almost 3.5 times greater (i.e., 3.443 times) in the High Performance groups compared with the Low Performance groups. However, by taking to account the number of groups participating in the activity (i.e., 13 HP groups and 7 LP groups), the average number of times the keyword Simultaneous and Another appeared in the High Performance groups was almost double (i.e., 1.854 times more) compared with the Low Performance groups.

These results were completely compatible with the findings of Martinez-Maldonado et al. (2013b) who used multi-user tabletops in their research. Similarly, the results were consistent with previous work done by Premchaiswadi and Porouhan (2015a) who applied concept mapping in an online collaborative learning environment. Moreover, several studies (Henri 1992; Garavalia and Gredler2002 ; Wang and Wu 2008) have also suggested that students' involvement is important for learning in computer-mediated communication, and groups of students who have higher level of involvement have better performance as well. The results of these studies, even though they did not focus on using interactive Table Computers as a computer-mediated tool, are completely compatible with our findings.

Table 13. Distribution of the number of active students in terms of blocks of activity

	1u	2u	+u
High Performance groups	10.02%	0%	89.98%
Low Performance groups	26.69%	25.28%	48.03%

(Adopted from: Section 6.2, "Process mining results", Martinez-Maldonado et al. 2013b ; Section 8.7.4, "Process Mining Results", Page 184, Martinez-Maldonado 2014 ; Premchaiswadi and Porouhan 2015a)

4.2.2 Participation Rate. The rationale for the analysis of the participation rate was to investigate the differences among the total numbers of individuals (students) who actively participated in the concept map construction during Activity #2 of the M-ITCL classroom. By exploring the values of the High Performance groups, we discovered that out of the total of 52 students; (i) 47 students actively engaged in the tutorial sessions, while (ii) 5 students did not engage in any activity (i.e., playing absolutely an idle role). Therefore, the total participation rate in the High Performance groups was 90.39%.

On the other hand, out of a total of 30 students in the Low Performance groups; (i) 17 students actively engaged in the tutorial sessions, while (ii) 13 students did not engage in any activity during Activity #2. Thus, the total participation rate in the Low Performance groups was only 56.70%.

Table 14.Comparison of the resulting top-3 frequent itemsets based on Context 2

Frequent Item Sets Mining ***(Apriori Algorithm)***	**High Performance Groups** - Num of Groups: 13 -	**Low Performance Groups** - Num of Groups: 7-
Context 2 ***(Top Three Item Sets)***	1. {Add-C (Possess)}, {Edit-A (**NoPossess**)}, {Edit-C (**NoPossess**)}, {Close-M (**NoPossess**)} *Number of Process Instances (i.e., HP Groups) satisfying this Frequent Items Set : 12	1. {IdleLong}, {IdleShort}, {Add-A (**Possess**)}, {Edit-C (**Possess**)} *Number of Process Instances (i.e., LP Groups) satisfying this Frequent Items Set : 7
	2. {Add-A (**NoPossess**)}, {Edit-A (**NoPossess**)}, {Edit-C (**NoPossess**)}, {Close-M (**NoPossess**)} *Number of Process Instances (i.e., HP Groups) satisfying this Frequent Items Set : 12	2.{Add-C (**Possess**)}, {IdleShort}, {Add-A (**Possess**)}, {Edit-C (**Possess**)} *Number of Process Instances (i.e., LP Groups) satisfying this Frequent Items Set : 7
	3. {Open-M (Possess)}, {Add-C (Possess)}, {Edit-A (**NoPossess**)}, {Edit-C (**NoPossess**)}, {Close-M (**NoPossess**)} *Number of Process Instances (i.e., HP Groups) satisfying this Frequent Items Set : 12	3.{Open-M (**Possess**)}, {IdleShort}, {Add-A (**Possess**)}, {Edit-C (**Possess**)} *Number of Process Instances (i.e., LP Groups) satisfying this Frequent Items Set : 7

4.2.3 Participation Density. The rationale for an analysis of participation density was to examine the entire blocks of activity with respect to 1u (i.e., when only 1 group member participated in all the activities), 2u (i.e., when only 2 group members participated in all the activities), and, +u (i.e., when more than 2 group members participated in all the activities). As shown in Table 13 in the High Performance groups almost 90% of the activities were executed by more than 2 group members (i.e., +u). However, in the Low Performance groups, only 48.03% of the actions were performed by more than 2 group members (i.e., +u) which was almost 2 times less than the High Performance groups. But, 10.02% (10.02 + 0) and 51.97% (26.69 + 25.28) of the actions were executed by 1 and 2 group members (i.e., 1u and 2u) in the High and Low Performance groups in total, respectively. This means that the total number of activities performed by only 1 or 2 group members was over 5 times more in the Low Performance groups. These results were consistent with other studies done by Hooper (2003), Kutnick et al. (2008), Martinez-Maldonado (2014), Premchaiswadi and Porouhan (2015a), and Stamovlasis et al. (2006) who suggested that students who participated more in group processes have better academic achievement and better performance.

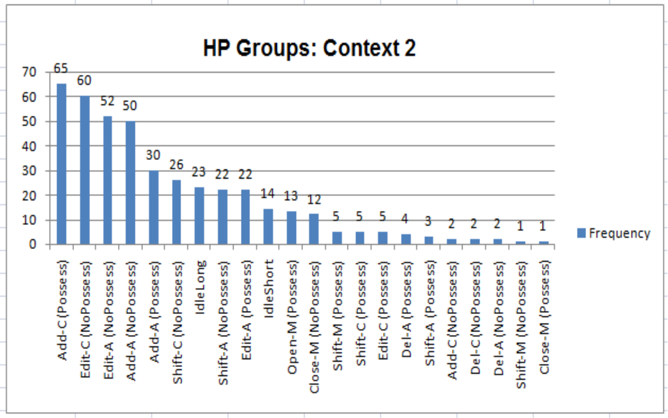
4.3 Distinguished Patterns of Interaction and Handover of Task

4.3.1 Interaction Density. A process mining Frequent Item Sets Mining technique based on the Apriori algorithm was used in order to analyze the collected collaborative interaction data with respect to Context 2 (i.e., interaction density) of the study. A total of 130 different patterns and clusters of Frequent Itemsets was identified for both the High Performance groups (with 67 patterns) and Low Performance groups (with 63 patterns). By only focusing on the resulting top-3 patterns of Context 2 in the High Performance groups, we realized that the occurrence of actions containing the keyword NoPossess was very high and included a majority of the observable actions in the top-3frequent itemsets as shown in Table 14 (left). This means that each member of the High Performance group had a tendency to interact with objects previously created by other fellow group members. Quite differently, all of the observable actions in the top-3frequent itemsets in the Low Performance groups' dataset contained the keyword Possess instead of NoPossess as shown in Table 14 (right). In other words, each member of the Low Performance group had a tendency to interact with objects previously created by himself/herself.

In general, the keywords Possess and NoPossess appeared in 36.50% (frequency: 153) and 54.66% (frequency: 229) of the entire dataset for the High Performance groups, while the same keywords appeared in 72.70% (frequency: 259) and 13.48% (frequency: 48) of the entire dataset for the Low Performance groups, respectively, as shown in Figure 20.

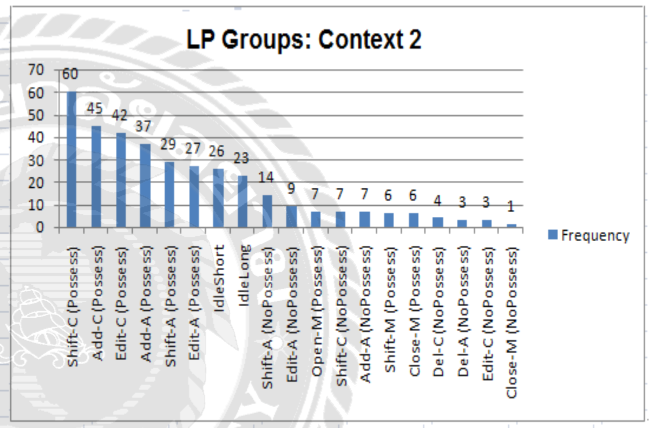
Therefore, overall the keyword NoPossess appeared about 4 times more often (i.e., 4.05 times) in the High Performance groups compared with the Low Performance groups. However, by taking into account the number of groups participating in the activity (i.e., 13 HP groups and 7 LP groups), the average number of times the keyword NoPossess appeared in the High Performance groups was about 2 times more (i.e., 2.18 times) compared with the Low Performance groups. Consequently, the extent of interaction density was much higher in the High Performance groups. These results were compatible with the findings of Dillenbourg (1998), Dillenbourg and Evans (2011), Do-Lenh et al. (2009), Martinez-Maldonado (2014), and Premchaiswadi and Porouhan (2015a) who studied the extent of interaction in multi-tabletop environments. In addition, several studies (Hooper 2003 ;Ke 2013 ; Jung et al. 2002 ; Puntambekar 2006 ; Van Drie et al. 2005) have also suggested that interaction plays a significant role in Computer-Supported Collaborative Learning (CSCL) situations, and groups of students who have higher levels of interaction have better performance. The results of the latter studies, even though they did not focus on using interactive Table Computers as a computer-mediated tool, are completely compatible with our findings.

Activity	Frequency	Relative frequency
Add-C (Possess)	65	15.51%
Edit-C (NoPossess)	60	14.32%
Edit-A (NoPossess)	52	12.41%
Add-A (NoPossess)	50	11.93%
Add-A (Possess)	30	7.16%
Shift-C (NoPossess)	26	6.21%
IdleLong	23	5.49%
Shift-A (NoPossess)	22	5.25%
Edit-A (Possess)	22	5.25%
IdleShort	14	3.34%
Open-M (Possess)	13	3.10%
Close-M (NoPossess)	12	2.86%
Shift-M (Possess)	5	1.19%
Shift-C (Possess)	5	1.19%
Edit-C (Possess)	5	1.19%
Del-A (Possess)	4	0.95%
Shift-A (Possess)	3	0.72%
Add-C (NoPossess)	2	0.48%
Del-C (NoPossess)	2	0.48%
Del-A (NoPossess)	2	0.48%
Shift-M (NoPossess)	1	0.24%
Close-M (Possess)	1	0.24%



Overall	Frequency	Relative frequency
Overall (Possess)	**153**	**36.50%**
Overall (NoPossess)	**229**	**54.66%**

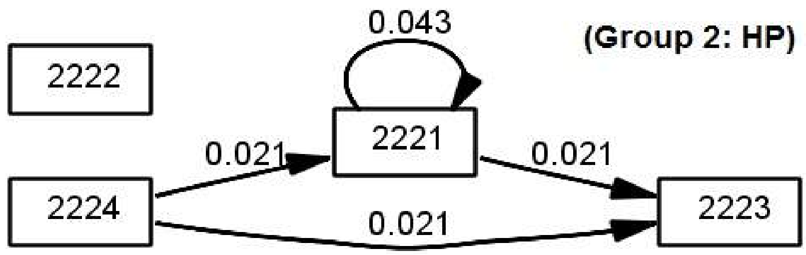
Activity	Frequency	Relative frequency
Shift-C (Possess)	60	16.85%
Add-C (Possess)	45	12.64%
Edit-C (Possess)	42	11.80%
Add-A (Possess)	37	10.39%
Shift-A (Possess)	29	8.15%
Edit-A (Possess)	27	7.58%
IdleShort	26	7.30%
IdleLong	23	6.46%
Shift-A (NoPossess)	14	3.93%
Edit-A (NoPossess)	9	2.53%
Open-M (Possess)	7	1.97%
Shift-C (NoPossess)	7	1.97%
Add-A (NoPossess)	7	1.97%
Shift-M (Possess)	6	1.69%
Close-M (Possess)	6	1.69%
Del-C (NoPossess)	4	1.12%
Del-A (NoPossess)	3	0.84%
Edit-C (NoPossess)	3	0.84%
Close-M (NoPossess)	1	0.28%



Overall	Frequency	Relative frequency
Overall (Possess)	259	72.76%
Overall (NoPossess)	48	13.48%

Figure 20. Comparison of the absolute frequencies of the actions based on Context 2 between the High (up) and Low (down) Performance groups.

4.3.2 Interaction Dynamics. A Process mining visualization Social Network Analysis technique was used in order to further investigate the interaction dynamics or handover of work based on students' traces of interaction with others' objects during Activity #2 in the Multi-Interactive Table Computer classroom. The technique allowed us to visualize the handover of work occurring from Student A to Student B if there were two subsequent activities where the first is completed by Student A and the second by Student B (Jermann et al. 2009 ; Premchaiswadi and Porouhan 2015a,b ; Sundararajan 2010). To better understand the technique, the results of applying the Social Network Miner on Group #2 (consisting of 4 members) of the Multi-Interactive Table Computer Lab (M-ITCL) classroom are shown and interpreted as the following:



	2221	2222	2223	2224
2221	0.0425531...	0.0	0.0212765...	0.0
2222	0.0	0.0	0.0	0.0
2223	0.0	0.0	0.0	0.0
2224	0.0212765...	0.0	0.0212765...	0.0

Student 2221 has executed at least one action on an object previously created by Student 2224.

Student 2223 has executed at least one action on an object previously created by Student 2221.

Student 2221 has executed at least one action on an object previously created by himself (i.e., Student 2221).

Student 2223 has executed at least one action on an object previously created by Student 2224.

Student 2222 has never executed an action on an object previously created by either others or by herself (i.e., Student 2222).

The main idea in the analysis of the handover of work situation (i.e., interaction dynamics) taken placed in Group #2 was to (i) first count the number of times Student 2221 has executed an activity on an object previously created by Student 2224, and (ii) secondly, divide the obtained number by the total number of handovers of works that has taken place in Group#2. And finally, these relationships are illustrated as the above-mentioned graph.

In the same way, the holistic comparisons of the handover of work (i.e., based on the interactions with others' objects) for both High and the Low Performance groups were illustrated in Figure 21 (up) and Figure 21 (down). By comparing the above Social Network Miner graphs, we realized that the High Performance groups were obviously more involved in the production of more collaborative processes while they also showed a more sophisticated and complex handover of tasks (i.e., interaction dynamics) from one student to another student. These results were compatible with other studies previously done by Dillenbourg (1998), Dillenbourg and Evans (2011), Jermann et al. (2009), Sundararajan (2010), Donath (2002), Kay et al. (2006), Bandura (1997, 2000), Myers et al. (2004), Premchaiswadi and Porouhan (2015a), and Stajkovic et al. (2009) who suggested that the interaction dynamics has a significant effect on group functioning, especially on levels of effort, persistence and achievement of students in collaborative environments. The results were also consistent with the findings of Chow (2009), Goddard (2001) and Hooper (2003) who indicated that the handover of work is positively correlated to group performance in schools, universities/colleges, organizations, and sports. The results of these studies, even though they did not focus on using interactive Table Computers as a computer-mediated tool, are completely compatible with our findings.

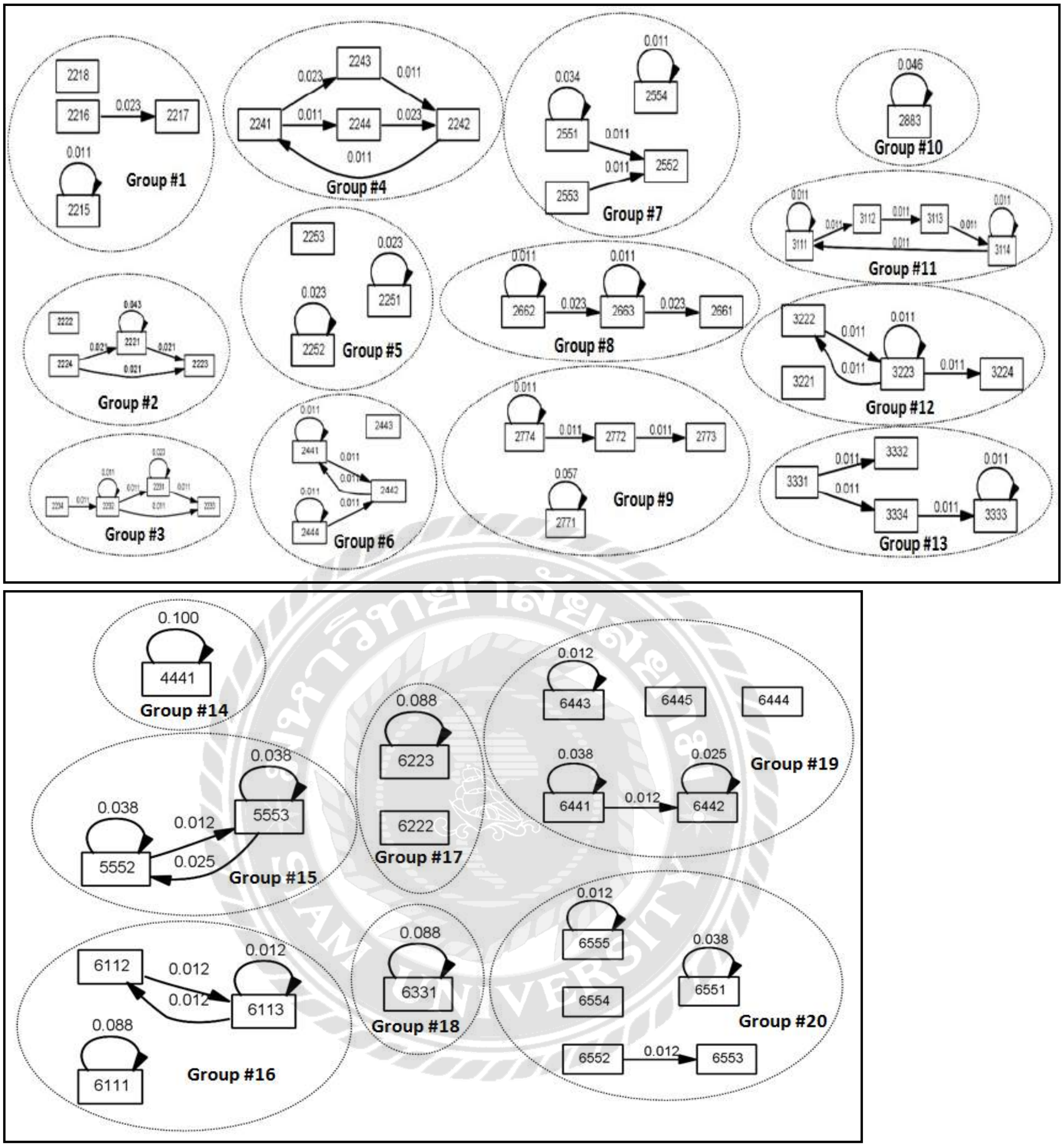


Figure 21.Comparison of the interactions with others' objects within the High (up) and Low (down) Performance groups.

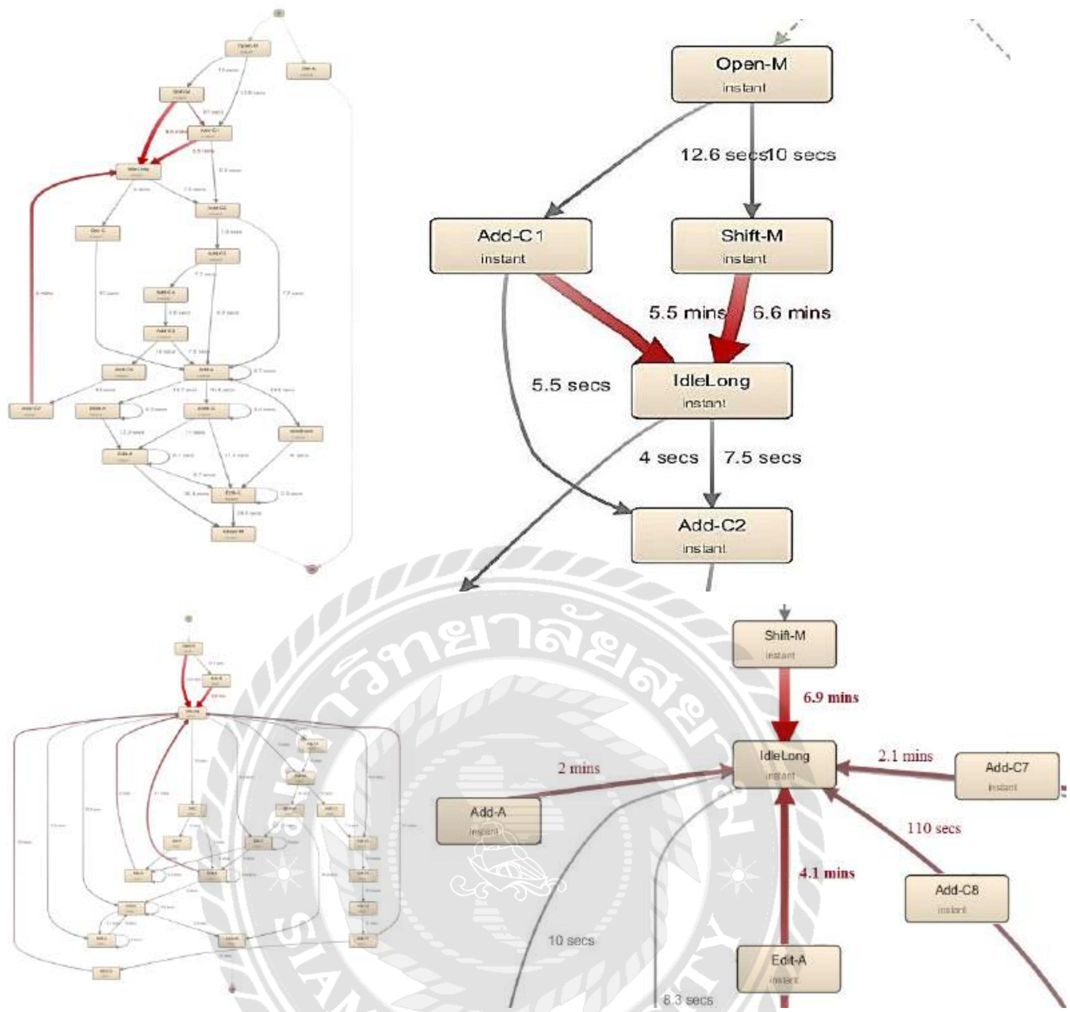


Figure 22.The resulting fuzzy process models based on the average durations (mean) of the long inactive waiting times between the High (up) and Low (down) Performance groups.

4.4 Distinguished Patterns of Time Performance

4.4.1 Time Intervals and long (waiting time) gaps among activities. In addition to the participation and interaction metrics, we also decided to analyze the time intervals and long (waiting time) gaps among the activities as previously mentioned in Section 1.2 and Section 1.4. To do this, the average durations of the activities as well as the inactive (waiting) times among activities were automatically extracted from the timestamps in the dataset and were visually projected onto the process map. Figure

22 (up) and Figure 22 (down) show the mean (average) durations for each activity and the critical paths (i.e., with long waiting times) for the High Performance and Low Performance groups, respectively. Comparing the two maps we realized that both groups spent considerable inactive (waiting) times at the beginning of the Activity #2. To simplify the resulting (time) performance-based fuzzy process model, a threshold of 60% of the paths (with 100% of the activities) was deliberately and purposely applied. Due to the fact that we were interested in the analysis of the long waiting time gaps occurred among the actions/activities, the deduction of the total observable paths did not have any impact on the results of our investigation.

However, the High Performance groups spent long waiting times (i.e., IdleLong) either after instantly scrolling the Main Menu Window (i.e., Shift-M, 5.5 mins on average), or after instantly creating the first component (i.e., Add-C1, 6.6 mins on average). On the other hand, the Low Performance groups only spent long waiting times (i.e., IdleLong) after instantly scrolling the Main Menu Window (i.e., Shift-M, 6.9 mins on average). Additionally, the Low Performance groups exhibited long waiting times dealing with editing arrows (i.e., Edit-A, 4.1 mins on average) or adding arrows (Add-A, 2 mins on average). This may indicate that for the Low Performance groups dealing with the arrows was the most difficult part of the activity. Contrary to this, except at the beginning of the Activity #2, the High Performance groups did not spend extended long waiting times (on average) executing the activities.

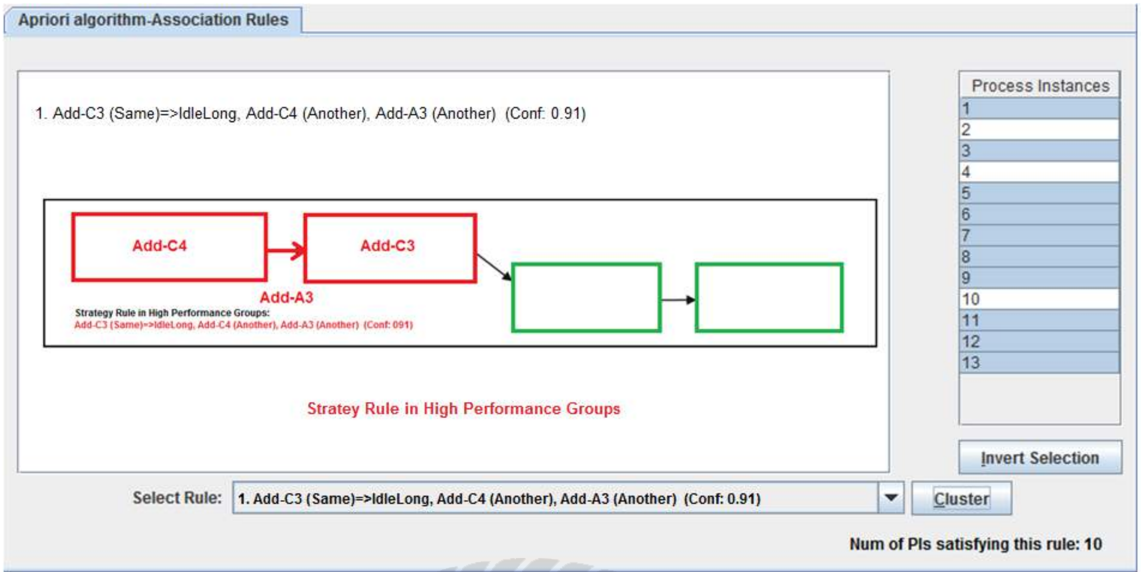


Figure 23.Using association rule mining technique to discover concept map construction strategy in the High Performance groups.

By further investigating the long (waiting time) gaps among the activities and by using process mining Association Rule Mining technique based on the Apriori algorithm; we discovered interesting information about the concept map construction strategy in the High Performance groups as the following:

Strategy Rule in High Performance Groups:

Add-C3 (Same) =>IdleLong, Add-C4 (Another), Add-A3 (Another) [confidence=0.91]

As shown in Figure 23, the above Rule gives the information that:

"91% of students in 10 (out of 13) High Performance groups who created Component #3 of the TRA concept map during the Activity #2; if previous action captured by the M-ITCL system also was done and executed by them, then:

a long pause for over 27 seconds (i.e., IdleLong) has occurred after the creation of Component #3, and after the long pause, Component #4 and Arrow #3 have been created respectively and immediately by another peer group members."

4.4.2 Total inactive (idle) versus active (not idle) batches of time intervals. In total, the Low Performance groups exhibited more periods of idle time (i.e., almost 1.5 times more) in terms of both IdleShort and IdleLong compared with the High Performance groups during Activity #2 in the M-ITCL classroom. Although the total number of occurrences of short periods of idle time (i.e., containing the keyword IdleShort) were almost double in the Low Performance groups; there was no significant difference in the total number of occurrences of long periods of idle time (i.e., containing the keyword IdleLong) between the High and Low Performance groups. However, the total number of occurrences of periods of activity (i.e., containing the keyword NoIdle) was slightly higher in the High Performance groups. These findings were not consistent with the results achieved by Martinez-Maldonado et al. (2013b) since in their work the total frequencies of long periods of waiting time were higher in the Low Achieving groups, and the total frequencies of short periods of waiting time were equal in both of the groups. However, the results were consistent with the findings of Premchaiswadi and Porouhan (2015a).

4.5 Distinguished Patterns of Similarity of Tasks and Division of Labor

4.5.1 Examples of Symmetry of Actions (Similarity of Tasks) and Symmetry of Roles (Low Division of Labor). As mentioned earlier in Section 1.2 and Section 1.4, the Similarity of Task indicator does not take into account how students work together on a shared (common) goal but emphasizes the activities and actions they perform. According to Dillenbourg (1998 ; 1999) and Dillenbourg and Baker (1996), students in CSCL situations tend to perform a similar range of actions, and similarity of task among two individuals is considered as the power of the relationship among them. This means that if two students perform similar types of actions, there is probably a strong relationship among them (Social Network Miner 2009). The main idea in the M-ITCL system is that every group member has a "profile" based on how frequently he/she performs specific tasks (actions). This metric specifies the similarity of two students performing actions considering the similarity of their profile. There are many different approaches to calculate the "distance" between 2 profiles. In this study, the Euclidean distance algorithm was used in order to determine the "ordinary" similarity distance among two individuals (or nodes) through the process mining Social Network Miner (Similar Task) and the Basic Performance Analysis (Task-by-Originator) techniques.

Figure 24 shows a screenshot of the above mentioned techniques applied to the dataset of Group 1 (HP) who participated in the second concept mapping activity in the M-ITCL classroom. Based on the figure, it is clearly obvious that both Student 2216 and Student 2218 performed exactly the same types of activities including: {Add-C, Add-A, Edit-C, Edit-A}. Student 2217 also performed the same types of activities in addition to closing the main menu/window of the task (i.e., Close-M) including: {Add-C, Add-A, Edit-C, Edit-A, Close-M}. Student 2215 performed activities: {Open-M, Shift-M, Add-C, Edit-C, Edit-A, Shift-C, Shift-A}.

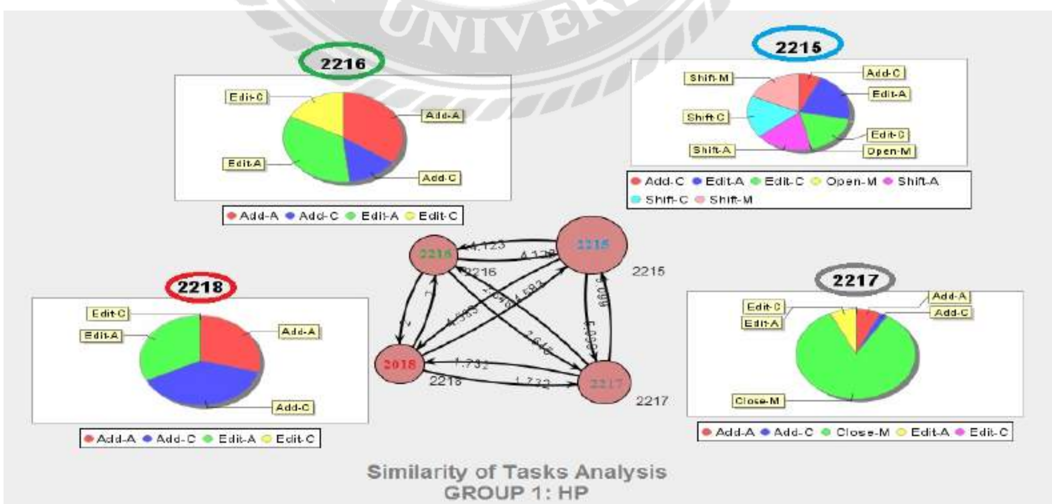


Figure 24.Using social network miner and basic performance analysis techniques to investigate the extent of symmetry of tasksin the HP groups.

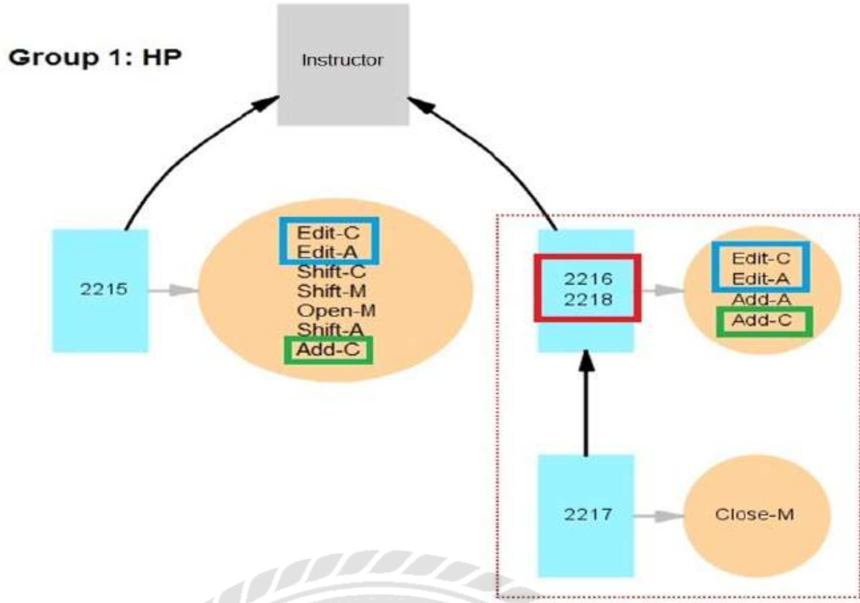


Figure 25.Using role hierarchy miner technique to investigate the extent of symmetry of roles in the High Performance groups.

Therefore, since Student 2216 and Student 2218 and Student 2217 performed almost the same type of actions, they are more similar (to each other) compared with Student 2215 who contained profiles with slightly different types of actions. The more two linked- nodes resemble each other based on their size and shape (i.e., for example, here the Nodes 2216 and 2218 are linked with and are 100% identical in terms of size and shape) the stronger the similarity of task exist among them. If two nodes are not linked with each other, even with the same size and shape, no similarity of task among them exists.

Dillenbourg (1998 ; 1999) also showed that students in cooperative learning situations tend to divide the main task into some sub-tasks while each group member tries to do and accomplish the sub-task individually, and finally these sub-tasks are assembled and presented in form of a final output. However, quite the opposite is true in collaborative learning situations where students tend to perform and accomplish the main task together in an entirely collective and spontaneous manner. By using the process mining Role Hierarchy Miner technique and by investigating the situation illustrated in Figure 25 we realized that the level of division of labor among group members in Group 1 (HP) was very low and they did the work 'together'.

Table 15 shows more details about the division of labor situation in Group 1 (HP) through Originator-by-Task Matrices. As mentioned earlier, there were great similarities between the tasks performed by Student 2216 and Student 2218 and Student 2217.

Table 15. Investigation of the symmetry of rolesthrough originator-by-task matrices based on high-impact actions in the High Performance groups

Group No.	Student Login ID	Task(s) Performed	Impact(s)
1	**2215**	Open-M ; Shift-M ; Shift-C ; Edit-A ; Edit-C ; Add-C ; Shift-A	No-Impact *High-Impact* Low-Impact
	2216	Add-A ; Edit-A ; Edit-C ; Add-C	*High-Impact*
	2217	Close-M ; Add-A ; Edit-A ; Edit-C ; Add-C	*High-Impact* No-Impact
	2218	Add-A ; Edit-A ; Edit-C ; Add-C	*High-Impact*

O/T Matrix	Add-A	Add-C	Shift-C	Shift-M	Close-M	Open-M	Edit-A	Edit-C	Del-C	Shift-A
2215	1	1	2	—	—	1	2	1	—	3
2216	1	1	—	—	—	—	2	2	—	—
2217	3	1	—	—	1	—	1	1	—	—
2218	2	2	—	—	—	—	1	1	—	—

Impact Level Matrix	*High-Impact*	Low-Impact	No-Impact
2215	4	5	2
2216	6	—	—
2217	6	—	1
2218	6	—	—

However, by considering only High-Impact types of actions (i.e., those types of actions that can significantly or substantially change the content or structure of the concept map as mentioned in Section 3.2) we realized that almost all of the group members had equal roles to accomplish the assigned concept mapping task 'together'. Student 2215, Students 2216, Student 2217 and Student 2218 performed 5, 6, 6, and 6 actions with a high level of impact, respectively, during the TRA concept map construction task in the M-ITCL classroom. Accordingly, the level of asymmetry of actions and division of labor in this group were very low, and the tasks and roles were symmetrically distributed.

Figure 26 shows two screenshots of the process mining social network analysis and the role hierarchy miner techniques applied on the dataset of Group 16 (LP) who participated in the second concept mapping activity in the M-ITCL classroom.

Based on the above figure, there was no similarity of tasks among the actions performed by the group members and each student played totally different roles. Moreover, in order to further investigate the division of labor situation in Group 16 (LP) through Originator-by-Task Matrices (as shown in Table 16) and by considering only High-Impact types of actions (i.e., those types of actions that can significantly or substantially change the content or structure of the concept map as mentioned in Section 3.2) we realized that only one member (i.e., Student 6112) played a major role by performing high-impact actions during the assigned task. Each group member worked on different types of actions 'individually'. Student 6111, Student 6112, and Student 6113 performed 8, 20, and 2 actions with high impact while Student 6114 played absolutely an idle role by not contributing in any activity or action at all. Accordingly, the level of asymmetry of actions and division of labor in this group were very high, and the tasks and roles were asymmetrically distributed.

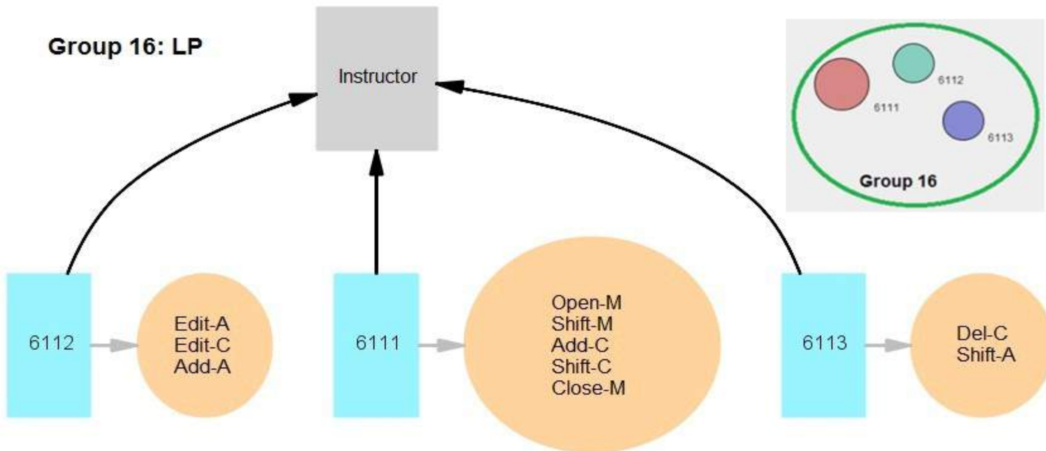


Figure 26.Using social network analysis and the role hierarchy miner techniques to investigate the extents of symmetry of tasks and symmetry of roles in the Low Performance groups.

Table 16.Investigation of the symmetry of roles through originator-by-task matrices based on high-impact actions in the Low Performance groups

Group No.	Student Login ID	Task(s) Performed	Impact(s)
16	6111	Open-M ; Shift-M ; Add-C ; Shift-C ; Close-M	No-Impact *High-Impact* Low-Impact
	6112	Add-A ; Edit-A ; Edit-C	*High-Impact*
	6113	Del-C ; Shift-A	*High-Impact* Low-Impact
	6114	—	—

O/T Matrix	Add-A	Add-C	Shift-C	Shift-M	Close-M	Open-M	Edit-A	Edit-C	Del-C	Shift-A
6111	—	8	26	1	1	1	—	—	—	—
6112	6	—	—	—	—	—	6	8	—	—
6113	—	—	—	—	—	—	—	—	2	12
6114	—	—	—	—	—	—	—	—	—	—

Impact Level Matrix	*High-Impact*	Low-Impact	No-Impact
6111	8	26	3
6112	20	—	
6113	2	12	—
6114	—	—	—

4.5.2 Holistic Comparison of Symmetry of Actions (similarity of tasks) between High Performance (HP) and Low Performance (LP) Groups. By having a holistic view of all of the groups as shown in Figure 27 we found out that, in total, the level of symmetry of actions (or similarity of tasks) was much higher in the High Performance groups (i.e., 13 groups) compared with the Low Performance groups (i.e., 7 groups) during the TRA concept map construction Activity #2 in the M-ITCL classroom. These findings were compatible with previous studies conducted by Dillenbourg (1998 ; 1999), Dillenbourg and Baker (1996), Do-Lenh et al. (2009) and Casillas and Daradoumis (2009).

4.5.3 Holistic Comparison of Symmetry of Roles (low Division of labor) between High Performance (HP) and Low Performance (LP) Groups. By having a holistic view of all of the groups as shown in Figure 28 we found out that, in total, the level of symmetry of role (or low division of labor) was much higher in the High Performance groups (i.e., 13 groups) compared with the Low Performance groups (i.e., 7 groups) during the TRA concept map construction Activity #2 in the M-ITCL classroom. These findings were compatible with the studies of Dillenbourg (1998 ; 1999), Dillenbourg and Baker (1996), Do-Lenh et al. (2009) and Casillas and Daradoumis (2009).

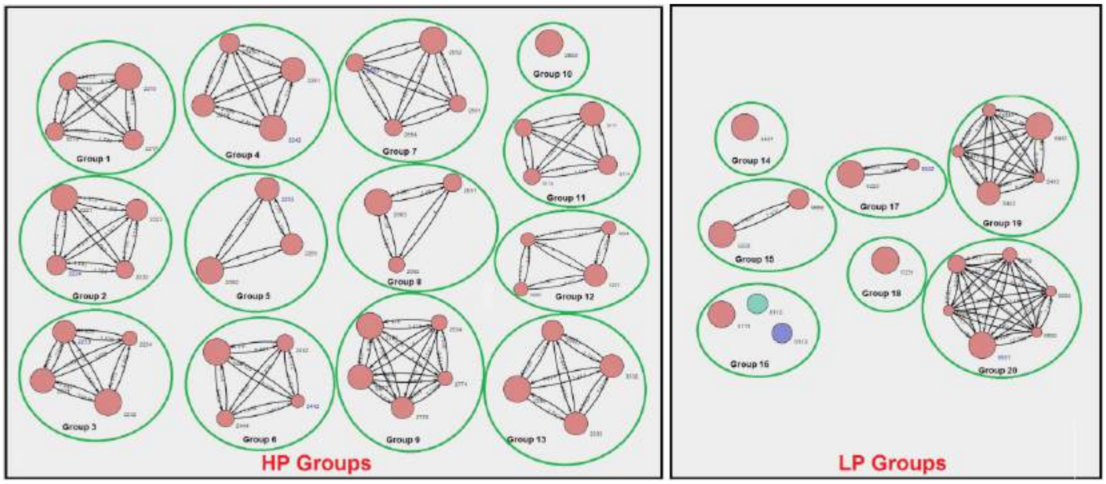


Figure 27. A holistic comparison of the extent of symmetry of actions between the High (left) and Low (right) Performance groups.

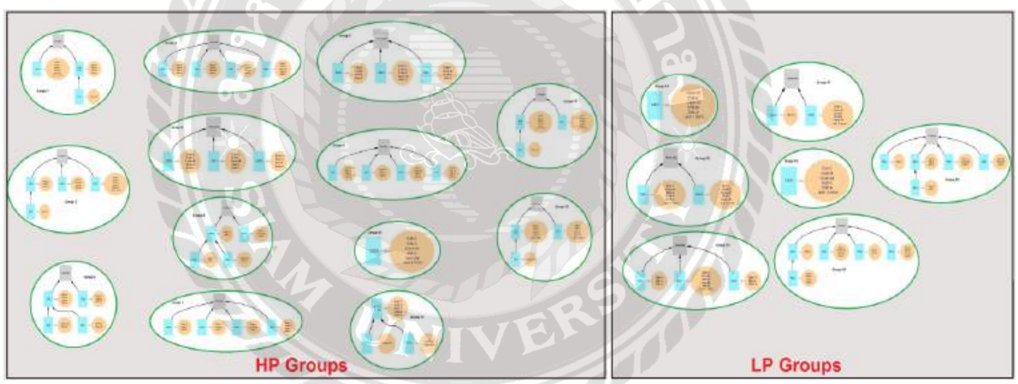


Figure 28.A holistic comparison of the extent of symmetry of roles between the High (left) and Low (right) Performance groups.

5.0 CONCLUSIONS AND DISCUSSIONS

This thesis is founded on the intersection of four areas. The first area is collaborative learning which can significantly increase the thinking skills of students by activating specific learning mechanisms that cannot be acquired via individual learning situations. The second area is interactive Table Computers (or tabletops). This is the provision of symmetry of work space where a group of students attempt to learn something together which is one of the most important features of a collaborative tabletop learning environment. The third area includes the concept mapping as a technique that can help students create visual representations of the structure of their understanding about almost any knowledge domain and provide meaningful learning. And the fourth area contains the educational process mining which is a new field in the educational data mining discipline that is used to discover patterns in educational datasets (event logs) with the purpose of developing methods to better understand and analyze students' learning habits and behaviors as well as the factors affecting their collaborative performance. Therefore, a synergy of "collaborative concept mapping through interactive Table Computers" and "analysis of students' interaction data through process mining tools and techniques" was the main motivation for the study.

Although the intersection of the above-mentioned four areas appears interesting; collaborative relationships do not always automatically, ideally and perfectly occur when students work on a group activity even through state-of-the-art educational facilities such as interactive Table Computers and smart handheld devices. Without the provision of appropriate feedback and self-regulation, students do not always spontaneously collaborate to accomplish the assigned tasks. Therefore, the role of instructors and facilitators in the classroom is important for helping students to be more aware of their group dynamics so as to improve their collaboration and social interaction skills. However, instructors need appropriate tools and resources in order to increase their awareness (knowledge) about students' collaboration process and the flow of knowledge building during small-group learning activities. In real learning situations, instructors mostly care (and are only aware of) the final artifacts (outcomes) created (accomplished) by groups of students instead of the details of the whole collaboration process or dynamics of the groups' progress. Instructors usually have a short time and limited tools to control and monitor all the group activities of students. Moreover, the final artifacts (outcomes) created (accomplished) by groups of students also provide imperfect information about students' collaboration process (and group progress) in detail. Therefore, the study was aimed to analyze and interpret the students' collaborative interaction data —previously captured, collected, and formatted during a concept map construction activity in a networked-based multi-tabletop learning environment so-called M-ITCL through an empirical investigation of the collaboration process using process mining techniques in order to increase the instructor's awareness (knowledge) about the collaborative group's activities. However, being aware of the fact that the term collaboration process in Computer-Supported Collaborative Learning (CSCL) situations is too general and can depend on countless (qualitative and quantitative) variables and factors; a quantitative survey was conducted. After reviewing a wide variety of secondary data related to the "Theories of Groups" (McGrath 1991), "Theories of Groups Performance and Interaction" (McGrath 1984), Theory of Group Cognition, Stahl (2006), and based on the definition of collaboration in CSCL described by Dillenbourg (1998), Dillenbourg and Jermann (2010), Dillenbourg et al. (2011), Dillenbourg and Evans (2011), Martinez-Maldonado (2014), Martinez-Maldonado et al. (2013b), and Roschelle's and Teasley's (1995); 8 independent indicators and 1 dependent indicator were selected for the initial Conceptual Framework of the survey. The results showed that "Extent of Participation", "Extent of Interaction", "Division of Labor and Similarity of Tasks", and "Time Performance", respectively, were the most significant indicators affecting the collaboration process (and collaborative group performance) in CSCL environments. Therefore, this study focused on the analysis of students' collaboration process with respect to specific quantitative indicators and dimensions as the following:

1- General collaboration quality indicators consisted of (i) total time spent to accomplish the concept mapping task, (ii) types of activities performed by the students, (iii) absolute frequencies of the activities, (iv) rate of occurrence of the activities, (v) accuracy or correctness of the activities, and (vi) impact level (or degree of importance) of the activities.

2- Extent of participation indicators consisted of (i) participation density, (ii) participation dynamics, and (iii) participation rate.

3- Extent of interaction indicators consisted of (i) interaction density, and (ii) interaction dynamics.

4- Analysis of time performance consisted of (i) analysis of the time intervals among the activities, and (ii) analysis of the idle versus active time.

5- Extent of symmetry of actions (or similarity of tasks).

6- Level of symmetry of roles (or division of labor).

Accordingly, the main objectives of the study were to analyze and investigate the students' collaboration process by addressing the above-stated issues as the following:

- To discover and compare 'general differences' between the High Performance and Low Performance groups.
- To discover and compare important 'patterns of participation' between the High Performance and Low Performance groups.
- To discover and compare important 'patterns of interaction' between the High Performance and Low Performance groups.
- To discover and compare important 'patterns of time performance' between the High Performance and Low Performance groups.
- To discover and compare important 'patterns of similarity of tasks' (or symmetry of actions) between the High Performance and Low Performance groups.
- To discover and compare important 'patterns of division of labor' (or symmetry of roles)

between the High Performance and Low Performance groups.

A total of 82 students from the same program (i.e., symmetry of status) between the ages of twenty two and twenty five years old (i.e., almost in the same symmetry of age) attended 10 tutorial sessions. 44% of the participants were female while 56% were male (i.e., the level of symmetry of gender is medium). None of the students had any prior experience with regard to a collaborative concept mapping assignment via interactive Table Computers and this was their first MITCL experience (i.e., symmetry of prior experience). To deal with this issue, two types of tutorial sessions were designed. The first activity was only run and practiced as a warm up exercise in order to let the students have a better idea about how different functions and features of the developed Online Concept Mapping Application (OCMA) works (i.e., symmetry of prior knowledge, skills and experience). The second activity was launched and practiced in order to assess and grade the students based on their performance during the tutorial session. In other words, a certain level of success in the first activity was needed (as a pre-requisite) in order to proceed to the second activity. Both activities were set up in the English language. Each tutorial session included 8 to 10 students that were organized in groups of 4 or 5 students. Overall, 18 groups of 4 members and 2 of 5 members participated in the tutorial sessions. The usage of interactive Computer Tables provided equal work space for users, however due to the fact that 2 groups (out of 20 groups) contained 5 members, a little asymmetry in terms of the work space and size of groups may have been occurred and taken placed.The final outcome of the concept mapping activity needed to be a TRA model (i.e., symmetry of task and degree of task difficulty) consisted of six Components and five Arrows in total. At the end of the second activity and after assessment of the final TRA models produced by groups of students, the activity data of all 20 groups were divided into two main categories of (1) High achieving groups, and (2) Low achieving groups. Accordingly, based on the performance (accuracy) of the groups in creating the final TRA models, 13 groups were categorized as groups with high performance while 7 groups were categorized as groups with low performance.

The Instructor Dashboard (equipped with myInvenio, ProM and Disco Fluxicon process mining tools) was designed with the purpose of assisting the instructor for generating real-time reports of the on-task progress of each small group in the M-ITCL's environment. Three Contexts (Context 1, Context 2 and Context 3) were defined and applied in such ways so as to enable the instructor to better investigate and study the "Extent of Participation", "Extent of Interaction" and "degree of Correctness of actions performed by the students" during the online concept map construction activity in the M-ITCL classroom. As a result, all of the learning events and actions were stored, captured and collected in the form of the below format:

{(Activity Type+Object)⟶(Activity Type+Sub.Object)⟶(Context 1)⟶(Context 2)⟶(Context 3)}

In order to analyze the students' actions with respect to the level of influence or impact on the concept mapping assignment; three categories of actions were defined as follows: (1) high-impact actions, (2) low-impact actions, and (3) no-impact actions.

The time intervals of idle time were divided into two main groups as follows: (1) short idle time, and (2) long idle time.

A validation investigation through a confusion matrix for three process mining model discovery algorithms of Alpha, Heuristic Miner and Fuzzy Miner showed that: the "Fuzzy Miner algorithm" could better help the instructor by generating quality process models that can be used to discover, compare and distinguish different patterns of the collaboration process followed by either High Performance or Low Performance. A qualification investigation also showed that the "Fuzzy Miner" algorithm could also differentiate all of the high achieving and low achieving cases correctly with

100% level of replay fitness based on the collaborative interaction data for all of the groups during Activity #2 in the M-ITCL environment.

The findings showed that, out of a maximum 30 minutes of time for Activity #2, it took 13.7 minutes on average for the High Performance groups to finish the TRA concept map creation task. However, for the Low Performance groups, the total average time spent to finish the same task was 24.7 minutes. Therefore, none of the groups consumed the entire 30 minutes allowed to accomplish the task, although the Low Performance groups spent more time (i.e., almost double) to finish the assignment.

In the High Performance groups, the maximum duration of time spent to finish Activity #2 was 20 minutes and 12 seconds whereas the minimum duration of time consumed to finish the same tasks was 7 minutes and 14 seconds. On the other hand, the maximum and minimum numbers of students' total actions (so-called events) were 45 and 31, respectively.
Alternatively, the maximum and minimum duration of time to finish Activity #2 in the Low Performance groups were 29 minutes and 12 seconds and 22 minutes and 5 seconds, respectively. The maximum number of students' total actions during Activity #2 was 81 actions (or events) whereas the minimum number of students' total actions was 48 of the Low Performance groups.

The average number of actions (events) executed in the High Performance groups was 35.62 actions (or 1.87 action per minute) whereas the average number of actions (events) executed in the Low Performance groups was 50.28 (or 1.676 action per minute). This means that the students in the Low Performance groups performed more actions and created more events on average (almost 1.5 times greater) than the High Performance groups in total.

The distribution diagram of the High Performance groups significantly exhibited a very low ratio of actions performed per second a moment just before the end of the tutorial session. On the contrary, the distribution diagram of the Low Performance groups significantly exhibited a very low ratio of actions performed per second a moment just after the beginning of the Activity #2.

Furthermore, in the High Performance groups, the maximum number of the actions per second (ratio) occurred at 10:12:28 o'clock (with 4.15 events per second) while in the Low Performance groups, the maximum number of the actions per second (ratio) occurred at 10:19:32 o'clock (with 2.5 events per second). The usage of the process mining Dotted Chart Analysis technique enabled us to examine the peak times when maximum ratios of actions were performed per second in both of the High and Low Performance groups. The events editing a component and editing an arrow contained the majority of the actions that occurred at the peak area of the High Performance groups. This means that during the peak area in the Activity #2, the majority of the High Performance groups were "adding text objects" to their already created components and arrows. On the contrary, the events shifting a component and shifting an arrow contained the majority of the actions that occurred in the peak area of the Low Performance groups. This means that, during the peak area in the Activity #2, the majority of the Low Performance groups were only "moving" the created components and arrows from one side to another side.

A process mining Frequent Item Sets Mining technique based on the Apriori algorithm was used in order to analyze the collected collaborative interaction data with respect to Context 3 (i.e., correctness) of the study. A total of 638 different patterns and clusters of Frequent Itemsets was identified for both of the High Performance groups (with 127 patterns) and Low Performance groups (with 511 patterns). By only focusing on the resulting top-3 patterns of Context 3, we realized that in the High Performance groups all of the actions in the top-3 most frequent itemsets contain the keyword Correct which means they have been executed correctly. On the other hand, the resulting top-3 patterns in the Low Performance groups included five actions that were performed incorrectly as they contain the keyword False.

In total, the keywords Correct and False (i.e., Context 3) appeared in 89.49% (frequency: 375) and 1.67% (frequency: 7) of the entire dataset for the High Performance groups, while the same keywords appeared in 47.49% (frequency: 169) and 38.76% (frequency: 138) of the entire dataset for the Low Performance groups, respectively. Therefore, overall the keyword False appeared almost 20 times more in the Low Performance groups.

Moreover, a process mining Dotted Chart Analysis technique was used in order to further investigate the extent of groups' correctness in terms of deleting concept map objects such as Components and Arrows during the concept map construction activity. The results showed that, the High Performance groups deleted 6 objects correctly while 2 objects were deleted incorrectly. Therefore, in the High Performance groups, 75% of the deletion/removal actions were performed correctly and were compatible with the instructor's key/master concept map. Quite the opposite was true for the Low Performance groups since only 2 objects were deleted correctly whereas 5 objects where removed incorrectly.

In the High Performance groups only 2 times was (in total) a Component removed or deleted, whereas in the Low Performance groups 4 times (in total) a Component was deleted. In the High Performance groups 6 times (in total) an Arrow was removed or deleted, whereas in the Low Performance groups an Arrow was deleted only 3 times (in total).

Process mining fuzzy discovery models were used in order to study the absolute frequency of actions/events performed in the High and Low Performance groups. By visually comparing the resulting Disco fuzzy graphs, we realized that there were major differences between both groups with respect to the frequency and disposition of the events. Although the total number of the Low Performance groups (i.e., 7 groups) was almost half of the High Performance groups (i.e., 13 groups), the absolute frequencies of the actions moving an arrow and moving a component were almost double in the Low Performance groups, respectively.

Only 46% of the High Performance groups (i.e., 6 groups) navigated through the Main Menu Window, while 86% of the Low Performance groups (i.e., 6 groups) scrolled up and down through the Main Menu Window during the tutorial sessions.

The activities: {Add-A (80 times), Edit-A (74 times), Add-C (67 times), Edit-C (65 times)} were the most frequent actions, respectively, performed by the students in the High Performance groups, whereas in the Low Performance groups the activities: {Shift-C (67 times), Edit-C (45 times), Add-A (44 times), Shift-A (43 times)} were the most frequent actions performed by the students, respectively.

The Disco Fuzzy Miner algorithm was used in order to mine the impact level of actions performed by students in the High and Low Performance groups. By visually comparing the fuzzy graphs we discovered that both groups shared identical core blocks of activity. This was not compatible with the results of Martinez-Maldonado et al. (2013b) as in their work the building blocks of high and low achiever groups was quite different in terms of disposition and layout. Students in the High Performance groups exhibited increased tendencies to execute high-impact actions (such as adding, deleting, or editing a component/arrow/textual object) on the objects created by their other fellow group members. However, students in the Low Performance groups exhibited increased tendencies to execute high-impact actions on the objects created by themselves as shown in Table 66. These findings were compatible with the results obtained earlier through the Sequential Pattern Mining technique by Maldonado et al. (2013b).

Similarly, the Low Performance groups also on average performed more blocks of actions with low-impact (such as shifting or moving an object) compared with the High Performance groups as shown in Table 67. These findings were not consistent with the results achieved by Martinez-Maldonado et al. (2013b) since in their research, high achiever groups performed more no-impact actions.

A process mining Frequent Item Sets Mining technique based on the Apriori algorithm was used in order to analyze the collected collaborative interaction data with respect to participation dynamics (i.e., Context 1) of the study. A total of 164 different patterns and clusters of Frequent Itemsets was identified for both of the High Performance groups (with 85 patterns) and Low Performance groups (with 79 patterns). By only focusing on the resulting top-3 patterns, we realized that the occurrence of actions performed simultaneously (i.e., containing the keyword Simultaneous) and alternatively (i.e., containing the keyword Another) by different fellow group members was very high and included the majority of the observable actions in the top-3frequent itemsets. In other words, group members in the High Performance groups mostly participated in performing the actions together at the same time or they executed the activities alternatively by different fellow group members. Quite the opposite, in the Low Performance groups the occurrence of actions performed by only one person (i.e., containing the keyword Same) was very high and included all of the observable actions in the top-3frequent itemsets. Accordingly, the keywords Simultaneous and Another appeared in 31.27% (frequency: 131) and 18.86 % (frequency: 79) of the entire dataset for the High Performance groups, respectively. The same keywords appeared in only 4.49% (frequency: 16) and 11.23% (frequency: 45) of the entire dataset for the Low Performance groups, respectively.

As a result, overall the extent of participation dynamics with respect to both Simultaneous and Another keywords was almost 3.5 times greater (i.e., 3.443 times) in the High Performance groups compared with the Low Performance groups. These results were completely compatible with the findings of Martinez-Maldonado et al. (2013b) who used multi-user tabletops in their research. Similarly, the results were consistent with previous work done by Premchaiswadi and Porouhan (2015a) who applied concept mapping in an online collaborative learning environment. Moreover, several studies (Henri 1992; Garavalia and Gredler2002 ; Wang and Wu 2008) have also suggested that groups of students who have higher level of involvement have better performance as well.

The rationale for the analysis of the participation rate was to investigate the differences among the total number of individuals (students) who actively participated in the concept map construction during Activity #2 of the M-ITCL classroom. By exploring the values in the High Performance groups (i.e., including 13 groups with 4 members), overall 47 students actively engaged in the tutorial sessions, while (ii) 5 students did not engage in any activity (i.e., playing absolutely an idle role). Therefore, the total participation rate in the High Performance groups was 90.39%. On the other hand, out of a total of 30 students in the Low Performance groups; (i) 17 students actively engaged in the tutorial sessions, while (ii) 13 students did not engage in any activity during the task. Thus, the total participation rate in the Low Performance groups was only 56.70%.

The rationale for the analysis of the participation density was to the entire blocks of activity with respect to 1u (i.e., when only 1 group member participated in all the activities), 2u (i.e., when only 2 group members participated in all the activities), and, +u (i.e., when more than 2 group members participated in all the activities). In the High Performance groups almost 90% of the activities were executed by more than 2 group members. However, in the Low Performance groups, only 48.03% of the actions were performed by more than 2 group members which was almost 2 times less than the High Performance groups. But, 10.02% and 51.97% of the actions were executed by 1 and 2 group members in the High and Low Performance groups in total, respectively. This means that the total number of activities performed by only 1 or 2 group members was over 5 times more in the Low Performance groups. These results were consistent with other studies done by Hooper (2003), Kutnick et al. (2008), Martinez-Maldonado (2014), Premchaiswadi and Porouhan (2015a), and

Stamovlasis et al. (2006) who suggested that students who participated more in group processes have better academic achievement and better performance.Accordingly, by considering all of the 3 different metrics (i.e., participation dynamics, participation rate, and participation density) of the participation indicator; it is clear that the extent of the total participation and involvement was much greater (i.e., almost 2 times more) in the High Performance groups compared with the Low Performance groups as shown in Table 17.

A process mining Frequent Item Sets Mining technique based on the Apriori algorithm was used in order to analyze the collected collaborative interaction data with respect to interaction density (i.e., Context 2) of the study. A total of 130 different patterns and clusters of Frequent Itemsets was identified for both of the High Performance groups (with 67 patterns) and Low Performance groups (with 63 patterns). By only focusing on the resulting top-3 patterns, we realized that the occurrence of actions containing the keyword NoPossess was very high and included the majority of the observable actions in the top-3frequent itemsets. This means that each member of the High Performance group had a tendency to interact with objects previously created by other fellow group members.

Table 17.Comparison of the total participation level between the HP and LP groups

	Participation Dynamics (Simultaneous+Another)	Participation Rate	Participation Density (u +)	Total Participation
HP Groups	☐ Medium : 50.13%	✓ High : 90.39%	✓ High :89.98%	✓ High : 76.84% (mean)
LP Groups	✗ Low : 15.72%	☐ Medium : 56.70%	☐ Medium : 48.03%	☐ Medium : 40.15% (mean)

Quite differently, all of the observable actions in the top-3frequent itemsets in the Low Performance groups' dataset contained the keyword Possess instead of NoPossess. In other words, each member of the Low Performance group had a tendency to interact with objects previously created by himself/herself (i.e., the same person).

In general, the keywords Possess and NoPossess appeared in 36.50% (frequency: 153) and 54.66% (frequency: 229) of the entire dataset for the High Performance groups, while the same keywords appeared in 72.70% (frequency: 259) and 13.48% (frequency: 48) of the entire dataset for the Low Performance groups, respectively.

Therefore, overall the extent of interaction density was 4 times greater in the High Performance groups compared with the Low Performance groups. These results were compatible with the findings of Dillenbourg (1998), Dillenbourg and Evans (2011), Do-Lenh et al. (2009), Martinez-Maldonado (2014), and Premchaiswadi and Porouhan (2015a) who studied the extent of interaction in multi-tabletop environments. In addition, these findings are compatible with several studies (Hooper 2003 ;Ke 2013 ; Jung et al. 2002 ; Puntambekar 2006 ; Van Drie et al. 2005) that proposed interaction plays a significant role in CSCL situations leading to better performance.

A Process mining visualization Social Network Analysis technique was used in order to further investigate the interaction dynamics or handover of work based on students' traces of interaction with others students' objects during Activity #2 in the M-ITCL classroom. This technique allowed us to visualize the handover of work that occurred from Student A to Student B if there were two subsequent activities where the first is completed by Student A and the second by Student. By comparing all of the resulting graphs for all of the groups, we realized that the High Performance groups were obviously more involved in the production of more collaborative processes while they showed a more sophisticated handover of tasks (i.e., interaction dynamics) from one student to another student. The degree of interaction dynamics was high in 61.5% of the High Performance groups. Quite the opposite, the degree of interaction dynamics was high only in 14% of the Low Performance groups. These results were compatible with other studies previously done by Dillenbourg (1998), Dillenbourg and Evans (2011), Jermann et al. (2009), Sundararajan (2010), Donath (2002), Kay et al. (2006), Bandura (1997, 2000), Myers et al. (2004), Premchaiswadi and Porouhan (2015a), and Stajkovic et al. (2009) who suggested that the interaction dynamics has a significant effect on group functioning, especially on levels of effort, persistence and achievement of students in collaborative environments. The results were also consistent with the findings of Chow (2009), Goddard (2001), and Hooper (2003) who indicated that the handover of work is positively correlated to group performance in schools, universities/colleges, organizations, and sports.Therefore, by considering both interaction metrics (i.e., interaction density and interaction dynamics); it is clear that the extent of the total interaction and handover of work was much greater (i.e., about 4 times more) in the High Performance groups compared with the Low Performance groups as shown in Table 18.

Table 18.Comparison of the total interaction level between the HP and LP groups

	Interaction Density (NoPossess)	Interaction Dynamics	Total Interaction
HP Groups	☐ Medium : 54.66%	☐ Medium : 61.5%	☐ Medium : 58.08% (mean)
LP Groups	✗ Low : 13.48%	✗ Low : 14%	✗ Low : 13.74% (mean)

In addition to the participation and interaction metrics, the time intervals and long (waiting time) gaps among the activities were also analyzed and investigated. Using performance-based Disco Fuzzy models (i.e., not frequency-based), the average durations of the activities as well as the inactive (waiting) times among activities were automatically extracted from the timestamps in both groups' event logs and were visually projected onto the process map. The resulting graphs showed that both groups spent considerable inactive (waiting) times at the beginning of the Activity #2. However, the High Performance groups spent long waiting times either after instantly scrolling the Main Menu Window, or after instantly creating the first component (i.e., Component #1). On the other hand, the Low Performance groups only spent long waiting times after instantly scrolling the Main Menu Window. Additionally, the Low Performance groups exhibited long waiting times dealing with editing arrows or adding arrows (Add-A, 2 minutes on average). This indicates that for the Low Performance groups dealing with editing arrows and editing components was the most difficult part of the activity. Contrary to this, except at the beginning of the Activity #2, the High Performance groups did not spend extended long waiting times (on average) executing the activities as shown in Table 19.

Table 19.Comparison of the time long waiting gaps between the HP and LP groups

	Long pause at the beginning of the activity	Long pause after scrolling Main Menu	Long pause after creating the first Component	Long pause before editing Arrows	Long pause before adding Arrows
HP Groups	✓ YES	✓ YES OR	✓ YES	✗ NO	✗ NO
LP Groups	✓ YES	✓ YES	✗ NO	✓ YES	✓ YES

By further investigating the long (waiting time) gaps among the activities and by using the process mining Association Rule Mining technique based on the Apriori algorithm; we discovered interesting information about the concept map construction strategy in the High Performance groups as the following:

Strategy Rule in High Performance Groups:

Add-C3 (Same) =>IdleLong, Add-C4 (Another), Add-A3 (Another) [confidence=0.91]

As shown in Figure 23, the above Rule gives the information that:

“91% of students in 10 (out of 13) High Performance groups who created Component #3 of the TRA concept map during the Activity #2; if the previous action captured by the M-ITCL system also was done and executed by them, then:

- a long pause for over 27 seconds (i.e., IdleLong) has occurred after the creation of Component #3,
- and after the long pause, Component #4 and Arrow #3 have been created respectively and immediately by another peer group members.”

In total, the Low Performance groups exhibited more periods of idle time in terms of both short and long idle times compared with the High Performance groups during Activity #2. Although the total number of occurrences of short periods of idle time were almost double in the Low Performance groups; there was no significant difference in the total number of occurrences of long periods of idle time (i.e., based on the frequency) between the High and Low Performance groups. However, the total number of occurrences of periods of activity was slightly higher in the High Performance groups as shown in Table 79. These findings were not consistent with the results achieved by Martinez-Maldonado et al. (2013b) since in their work the total frequencies of long periods of waiting time were higher in the Low Achieving groups, and the total frequencies of short periods of waiting time were equal in both of the groups. However, the results were consistent with the findings of Premchaiswadi and Porouhan (2015a).

In this thesis, the Euclidean distance algorithm was used in order to visualize the degree of Similarity of Tasks (or symmetry of actions) among group members (or nodes) through the process mining Social Network Miner (via Similar Task metric) and the Basic Performance Analysis (via Task-by-

Originator) techniques. In addition, the process mining Role Hierarchy Miner technique was used in order to investigate and visualize the degree of division of labor (or symmetry of roles) among students in both High and Low Performance groups.

Table 20. Comparison of the extent of high symmetry of actions between the HP and LP groups

	Occurrence of high symmetry of actions with regard to visualization social network models	Ratio
HP Groups	✓ High (high symmetry of actions in 77% of groups)	Exhibited significantly higher degree of Similarity of Tasks by performing the same range of actions
LP Groups	✗ Low (high symmetry of actions only in 14% of groups)	

By having a holistic view to the resulting social network models (in terms of similar task metric) for all of the groups, it was clear that, in total, the degree of symmetry of actions (or similarity of tasks) was much higher in the High Performance groups compared with the Low Performance groups during the TRA concept map construction (i.e., Activity #2) in the M-ITCL classroom. In other words, the tasks were more symmetrically done and distributed in the High Performance groups. The degree of symmetry of actions was high in 77% of the High Performance groups. Quite the opposite, the degree of symmetry of actions was high only in 14% of the Low Performance groups as shown in Table 20. These findings were compatible with previous studies conducted by Dillenbourg (1998 ; 1989), Dillenbourg and Baker (1996), Do-Lenh et al. (2009) and Casillas and Daradoumis (2009).

Table 21.Comparison of the extent of high symmetry of roles between the HP and LP groups

	Occurrence of high symmetry of roles with regard to visualization role hierarchy miner	Ratio
HP Groups	✓ High (high symmetry of roles in 70% of groups)	Exhibited significantly lower degree of division of labor by performing the tasks 'together'
LP Groups	✗ Low (high symmetry of roles only in 28.5% of groups)	Exhibited significantly higher degree of division of labor by performing the tasks 'individually'

In the same way, by having a holistic comparison among the resulting social network models (in terms of similar task metric) for all of the groups, it was shown that, in total, the degree of symmetry of roles (or low division of labor) was much higher in the High Performance groups compared with the Low Performance groups. The degree of symmetry of roles was high in 70% of the High Performance groups. Quite the opposite, the degree of symmetry of roles was high only 28.5% of the Low Performance groups as shown in Table 21. To conclude, students in the Low Performance groups exhibited increased tendencies to work on dissimilar range of actions 'individually'. Reversely, students in the High Performance groups showed increased tendencies to work on similar range of actions 'together'.

Moreover, only few group members in the Low Performance groups played major roles by performing high-impact type of actions during the assigned task. Reversely, majority of group members in the High Performance groups played major roles by performing high-impact type of actions during the assigned task as shown in Table 22.

Table 22.Comparison of the extent of high symmetry of roles based on the high-impact actions

	Occurrence of high symmetry of roles with regard to performing high-impact actions only	Ratio
HP Groups	✓ High (high symmetry of roles in 77% of groups)	Most of the group members played major roles in performing high-impact actions
LP Groups	✗ Low (high symmetry of roles only in 28.5% of groups)	Few members played major roles in performing high-impact actions

As a result, by considering both Similarity of Tasks (or symmetry of actions) and Division of Labor (Symmetry of Roles) metrics; it is clear that the extent of the total "similarity of task and similarity of roles" was much greater (i.e., almost 3.5 times more) in the High Performance groups compared with the Low Performance groups as shown in Table 23.

Table 23.A holistic comparison of the symmetry of tasks and symmetry of roles between the HP and LP groups

	Symmetry of Actions (similarity of tasks)	Symmetry of Roles (low division of labor)	Similarity of Tasks and Low Division of Labor
HP Groups	✓ High : 77%	✓ High : 70%	✓ High : 73.5% (mean)
LP Groups	✗ Low : 14%	✗ Low : 28.5%	✗ Low : 21.25% (mean)

Consequently, the analysis and interpretation of the students' collaborative interaction data collected from Activity #2 of the Multi-Interactive Table Computer Lab (M-ITCL) classroom can be used in order to: (1) help the instructor to improve his/her management and coaching style in the class, (2) help the instructor to improve his/her teaching style in the class based on the feedback received regarding the students' performance during the task, (3) enable the instructor to make quickly informed decisions during the class, (4) enable the instructor to improve and transform the traditional grading system which traditionally it was only based on the final outcomes accomplished by students (i.e., only based on the final concept maps created by students), (5) transcend the students' assessment process from a merely final-outcome-based approach to a more collaboration-interaction-based system, (6) provide a more detailed and more effective feedback to the students based on their collaboration activities during the task, (7) provide instructors with meaningful insights on which groups of students might need more support and attention, and which groups can be left to work by themselves, and (8) provide students (and group members) a new source (or tool) for self-regulation and self-awareness about the extent of their participation and interaction during the assigned task.

6.0 LIMITATIONS AND FUTURE WORK

Although the idea of using process mining techniques in order to analyze and investigate students' collaborative interaction data collected from a networked multi-tabletop environment —during (or after the end of) an online concept mapping activity— appears interesting; we acknowledge some limitations of our study. Firstly, we did not investigate the speech and verbal participation of students using an array of microphones situated above or at one of the edges of the interactive Table Computers. Secondly, the main focus of the empirical part of the study was on quantitatively discovering and analyzing the patterns of interaction and collaborative behavior, patterns of time performance, patterns of similarity of tasks and roles, and the strategies that students in the High Performance groups and the Low Performance groups followed during (or after the end of) the concept mapping task. However, quantitative methods usually contain fewer social clues, such as body gestures, eye contacts and facial expressions. Therefore, to better understand students' interaction behaviors and the collaboration process, some qualitative research methods (such as observations, or in-depth interviewing) should also be conducted. Third, different process mining techniques (such as, Alpha, Heuristic Miner, Fuzzy Miner, Genetic Miner, Region-Based graphs and so on) will lead to new process discovery models with different maps and structures. However, the process models generated through process mining Fuzzy Miner in this study could differentiate all of the groups (i.e., either high achieving or low achieving) correctly with 100% level of replay fitness. Fourth, the discovered patterns themselves do not present everything about the processes or behaviors of the groups. Fifthly, the level of difficulty of the concept mapping assignment has a direct and indirect impact on the way students participate in group activities. And lastly, this work currently includes the exploration of the students' collaborative interaction data during (or after the end of) a Theory of Reasoned Action (TRA) concept map construction activity. This research provides groundwork for further studies. In the future, we also plan to analyze students' collaborative interaction behaviors (and group progress) in an online English learning environment. Below, a prospective view of the possible contexts, constructs and activity types for data generation —and analysis of the collaboration process during the English course— is shown.

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APPENDIX 1: FREQUENT ITEMSETS MINING AND ASSOCIATION RULE MINING (VIA APRIORI ALGORITHM)

As mentioned earlier, the purpose of the Frequent Itemsets Mining and Association Rule Mining through Apriori Algorithm —implemented in the Weka library — is to discover the most frequent itemsets as well as the association rules from the event log. The following ARFF file shows all of the actions and contexts performed by all of the groups (i.e., 20 in total including the HP and LP groups) after the end of the concept mapping Activity 2 via Multi-Table Computer Lab classroom. The below ARFF file can be directly loaded in Weka library to experiment with all Weka algorithms. The first line in the file with the tag @relation indicates the name of this file, which is the name of the log used for mining. In the next lines are the tag @attribute. This represents the activities in the log. In this case, we have 71different types of actions/activities (or attributes), such as Open-M (Possess) (Correct), Shift-M (Same) (Possess) (Correct), IdleLong, Add-C (Another) (Possess) (Correct), Add-A (Same) (Possess) (Correct), and so on. We can also see {yes,?} besides the action/activity (attribute) names. This indicates the values these attributes can take. In terms of data mining, the activities are treated as attributes which can have some values.

The most frequent itemsets and association rules are Boolean rules which establish associations and relationships between the presence or absence of the items. So, each action/activity (attribute) has two values of “yes” or “?” based on its presence or absence in a particular process instance. A “yes” indicates that the activity is present in a particular process instance while a “?” indicates that the activity is not present in the process instance.

The next tag is @data. This is the converted mxml log into a log format acceptable by Weka. If we look at the process instances here we see they contain yes or no values. Let us analyze the first process instance (ie., group 1):

1. {yes,?,yes,?,yes,?,yes,?,?,?,?,?,?,?,?,?,?,?,yes,?,yes,?,?,?,yes,?,?,?,?,?,?,yes,?,?,?,?,?,?,?,?,yes,yes,yes,?}

This means this process instance consists of the following attributes:

{attribute 1, attribute 3, attribute 5, attribute 7, attribute 19, attribute 21, attribute 25, attribute 32, attribute 41, attribute 42, attribute 43}

@relation 'ALL GROUPS_ACTIVITY 2_MITCL.mxml'

1. @attribute 'Open-M\\\\Possess\\\\Correct' {yes}
2. @attribute 'Shift-M\\\\Same\\\\Possess\\\\Correct' {yes}
3. @attribute IdleLong {yes}
4. @attribute 'Add-C\\\\Another\\\\Possess\\\\Correct' {yes}
5. @attribute 'Add-A\\\\Same\\\\Possess\\\\Correct' {yes}
6. @attribute 'Add-A\\\\Same\\\\NoPossess\\\\Correct' {yes}
7. @attribute 'Shift-C\\\\Same\\\\Possess\\\\Correct' {yes}
8. @attribute 'Shift-C\\\\Same\\\\NoPossess\\\\Correct' {yes}
9. @attribute 'Shift-A\\\\Same\\\\NoPossess\\\\Correct' {yes}
10. @attribute 'Shift-A\\\\Same\\\\Possess\\\\Correct' {yes}
11. @attribute 'Add-A\\\\Simultaneous\\\\Possess\\\\Correct' {yes}

12. @attribute 'Add-A\\\\Simultaneous\\\\NoPossess\\\\Correct' {yes}
13. @attribute 'Add-C\\\\Simultaneous\\\\NoPossess\\\\Correct' {yes}
14. @attribute 'Edit-A\\\\Another\\\\NoPossess\\\\Correct' {yes}
15. @attribute 'Edit-A\\\\Another\\\\Possess\\\\Correct' {yes}
16. @attribute 'Edit-A\\\\Simultaneous\\\\NoPossess\\\\Correct' {yes}
17. @attribute 'Edit-C\\\\Simultaneous\\\\NoPossess\\\\Correct' {yes}
18. @attribute 'Close-M\\\\Another\\\\NoPossess\\\\Correct' {yes}
19. @attribute 'Add-C\\\\Same\\\\Possess\\\\Correct' {yes}
20. @attribute 'Add-A\\\\Another\\\\NoPossess\\\\Correct' {yes}
21. @attribute IdleShort {yes}
22. @attribute 'Shift-A\\\\Another\\\\NoPossess\\\\Correct' {yes}
23. @attribute 'Edit-C\\\\Same\\\\NoPossess\\\\Correct' {yes}
24. @attribute 'Edit-A\\\\Same\\\\NoPossess\\\\Correct' {yes}
25. @attribute 'Edit-A\\\\Same\\\\Possess\\\\Correct' {yes}
26. @attribute 'Add-A\\\\Another\\\\Possess\\\\Correct' {yes}
27. @attribute 'Shift-M\\\\Another\\\\NoPossess\\\\Correct' {yes}
28. @attribute 'Add-C\\\\Another\\\\NoPossess\\\\Correct' {yes}
29. @attribute 'Shift-C\\\\Another\\\\NoPossess\\\\Correct' {yes}
30. @attribute 'Edit-A\\\\Simultaneous\\\\Possess\\\\Correct' {yes}
31. @attribute 'Add-A\\\\Another\\\\NoPossess\\\\False' {yes}
32. @attribute 'Del-A\\\\Same\\\\Possess\\\\Correct' {yes}
33. @attribute 'Close-M\\\\Same\\\\NoPossess\\\\Correct' {yes}
34. @attribute 'Add-C\\\\Same\\\\Possess\\\\False' {yes}
35. @attribute 'Del-C\\\\Another\\\\NoPossess\\\\Correct' {yes}
36. @attribute 'Del-C\\\\Same\\\\NoPossess\\\\Correct' {yes}
37. @attribute 'Add-A\\\\Same\\\\NoPossess\\\\False' {yes}

38. @attribute 'Del-A\\\\Another\\\\NoPossess\\\\Correct' {yes}
39. @attribute 'Del-A\\\\Same\\\\NoPossess\\\\Correct' {yes}
40. @attribute 'Shift-A\\\\Another\\\\Possess\\\\Correct' {yes}
41. @attribute 'Add-A\\\\Same\\\\Possess\\\\False' {yes}
42. @attribute 'Edit-C\\\\Same\\\\Possess\\\\Correct' {yes}
43. @attribute 'Close-M\\\\Same\\\\Possess\\\\Correct' {yes}
44. @attribute 'Add-C\\\\Simultaneous\\\\Possess\\\\Correct' {yes}
45. @attribute 'Shift-C\\\\Simultaneous\\\\NoPossess\\\\Correct' {yes}
46. @attribute 'Shift-A\\\\Simultaneous\\\\NoPossess\\\\Correct' {yes}
47. @attribute 'Edit-C\\\\Same\\\\Possess\\\\False' {yes}
48. @attribute 'Shift-M\\\\Another\\\\Possess\\\\Correct' {yes}
49. @attribute 'Edit-A\\\\Same\\\\Possess\\\\False' {yes}
50. @attribute 'Shift-A\\\\Same\\\\Possess\\\\False' {yes}
51. @attribute 'Shift-C\\\\Same\\\\Possess\\\\False' {yes}
52. @attribute 'Edit-C\\\\Another\\\\Possess\\\\Correct' {yes}
53. @attribute 'Edit-C\\\\Another\\\\Possess\\\\False' {yes}
54. @attribute 'Add-A\\\\Another\\\\Possess\\\\False' {yes}
55. @attribute 'Add-A\\\\Simultaneous\\\\Possess\\\\False' {yes}
56. @attribute 'Shift-A\\\\Same\\\\NoPossess\\\\False' {yes}
57. @attribute 'Shift-C\\\\Same\\\\NoPossess\\\\False' {yes}
58. @attribute 'Shift-C\\\\Simultaneous\\\\NoPossess\\\\False' {yes}
59. @attribute 'Del-C\\\\Simultaneous\\\\NoPossess\\\\Correct' {yes}
60. @attribute 'Shift-C\\\\Another\\\\Possess\\\\Correct' {yes}
61. @attribute 'Edit-C\\\\Simultaneous\\\\Possess\\\\False' {yes}
62. @attribute 'Edit-A\\\\Same\\\\NoPossess\\\\False' {yes}
63. @attribute 'Edit-C\\\\Simultaneous\\\\Possess\\\\Correct' {yes}

64. @attribute 'Edit-A\\\\Another\\\\Possess\\\\False' {yes}

65. @attribute 'Edit-A\\\\Simultaneous\\\\Possess\\\\False' {yes}

66. @attribute 'Edit-C\\\\Another\\\\NoPossess\\\\False' {yes}

67. @attribute 'Shift-A\\\\Another\\\\NoPossess\\\\False' {yes}

68. @attribute 'Shift-C\\\\Another\\\\Possess\\\\False' {yes}

69. @attribute 'Close-M\\\\Another\\\\Possess\\\\Correct' {yes}

70. @attribute 'Del-C\\\\Another\\\\NoPossess\\\\False' {yes}

71. @attribute 'Edit-C\\\\Simultaneous\\\\NoPossess\\\\False' {yes}

@data

1. yes,?,yes,?,yes,?,yes,?,?,?,?,?,?,?,?,?,?,?,yes,?,yes,?,?,?,yes,?,?,?,?,?,?,yes,?,?,?,?,?,?,?,?,yes,yes,yes,?
2. yes,?,yes,yes,yes,yes,?,?,?,?,?,?,?,?,?,?,yes,yes,yes,yes,yes,?,?,yes,yes,?
3. yes,yes,yes,yes,yes,yes,yes,yes,yes,yes,yes,yes,yes,yes,yes,yes,yes,yes,?
4. yes,yes,yes,yes,yes,?,?,yes,?,?,?,?,?,yes,yes,?,?,yes,yes,yes,yes,yes,yes,yes,yes,?
5. yes,?,?,yes,yes,yes,?,?,yes,?,?,?,?,?,yes,yes,yes,yes,?,yes,yes,?,?,yes,?,?,yes,yes,yes,yes,?
6. yes,?,yes,yes,yes,yes,?,?,?,?,?,?,?,yes,yes,?,yes,yes,yes,?,yes,yes,?,yes,?,?,?,?,?,?,yes,yes,?
7. yes,?,yes,yes,yes,yes,?,yes,?,?,?,?,?,yes,?,?,yes,?,yes,yes,?,?,?,yes,yes,?,?,?,yes,?,?,?,yes,?
8. yes,yes,yes,yes,yes,yes,?,yes,?,yes,?,?,?,yes,?,?,yes,yes,yes,yes,yes,yes,?,?,?,yes,?

9. yes,?,yes,?,yes,?,yes,?,?,?,?,?,?,yes,?,yes,?,?,yes,?,yes,?,?,?,?,?,?,?,?,?,?,?,?,yes,?,?,?,?,?,?,yes,yes,yes,?,?,?,yes,?,?,yes,?,?,?,?,?,?,?,?,?,yes,yes,yes,?,?,?,?,?,?,?,?,?

10. yes,yes,yes,?,?,?,?,?,?,?,?,yes,?,yes,?,yes,yes,?,?,?,yes,?,?,?,?,?,?,?,?,?,?,?,yes,?,?,?,?,?,?,?,?,?,?,yes,yes,?

11. yes,?,yes,yes,yes,yes,?,yes,?,?,?,?,?,yes,?,?,yes,yes,yes,yes,yes,yes,?,yes,yes,?,?,?,yes,?

12. yes,?,yes,yes,?,yes,?,?,yes,?,?,?,?,yes,yes,?,yes,yes,yes,yes,yes,?,?,yes,?,?,?,?,?,?,?,?,?,yes,yes,yes,yes,yes,yes,yes,?

13. yes,?,yes,?,?,?,?,?,?,?,?,yes,?,?,?,yes,yes,yes,yes,?,yes,?,yes,yes,yes,?

14. yes,yes,yes,?,?,?,?,?,?,?,?,yes,?,?,?,yes,yes,yes,?,yes,yes,yes,?

15. yes,yes,yes,yes,?,yes,yes,?,?,?,?,?,?,?,?,?,?,yes,yes,yes,yes,?,yes,yes,yes,?,?,?,?,?,yes,?,?,?,?,?,?,yes,yes,?,yes,yes,?,?,?,?,?,?,?,?,yes,yes,?,yes,?,?,?,?,?,yes,?,?,yes,yes,?,?,?,?,?,yes,yes

16. yes,?,yes,yes,yes,?,yes,?,?,yes,?,?,?,?,?,?,?,?,yes,?,yes,?,?,?,yes,?,?,?,?,?,?,?,?,yes,?,?,?,?,?,?,yes,yes,yes,?,?,?,yes,yes,yes,yes,yes,?

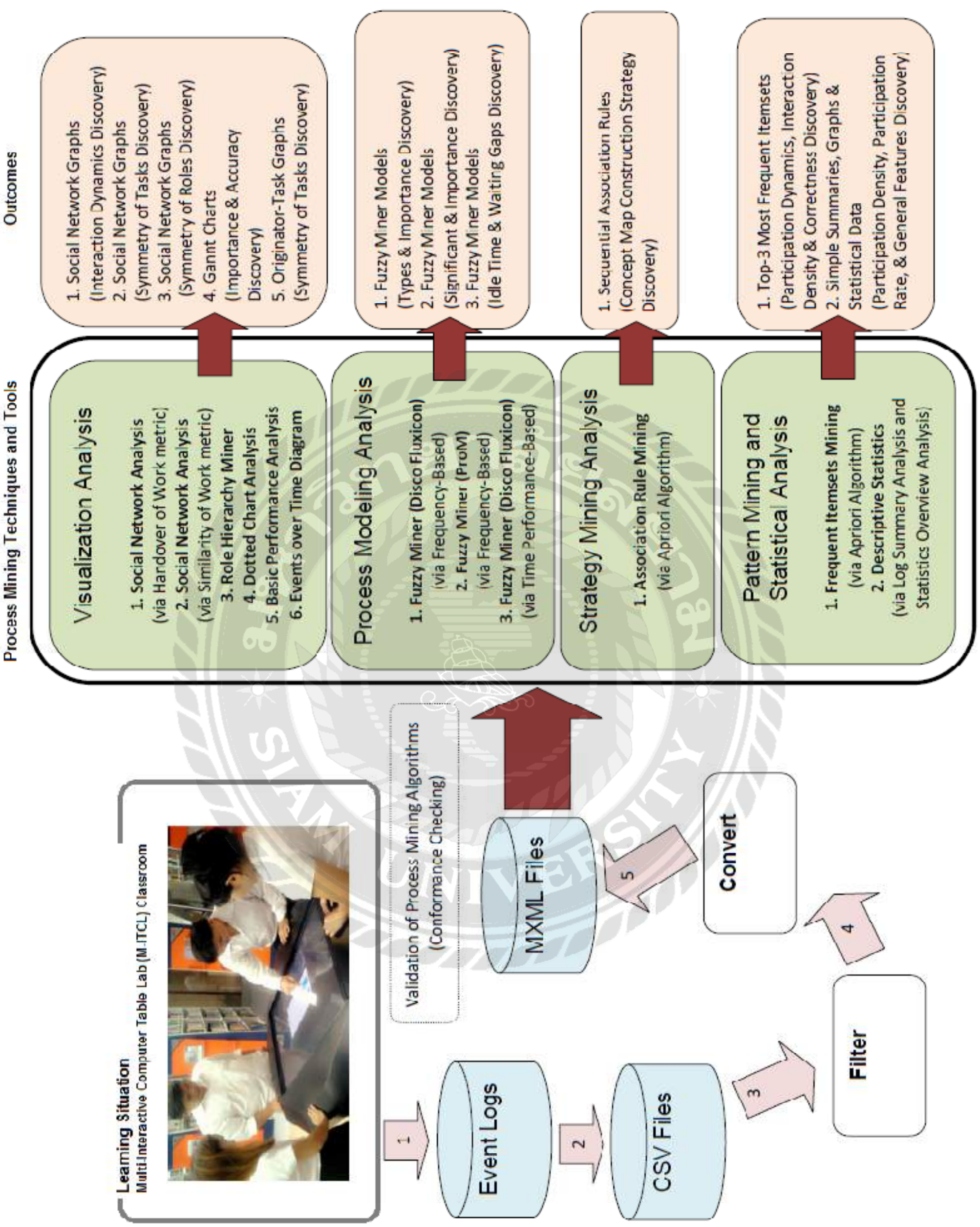
17. yes,yes,yes,?,?,?,yes,?,yes,yes,?,?,?,?,?,?,?,?,yes,?,yes,yes,?,?,yes,yes,?,?,?,?,?,?,?,yes,yes,?,?,?,?,?,?,?,yes,?,?,yes,?,?,yes,?,yes,yes,yes,yes,yes,yes,yes,yes,yes,yes,?,?,?,?,?,?,?,?,?,?,?

18. yes,yes,yes,?,yes,?,yes,?,?,yes,?,?,?,?,?,?,?,?,yes,?,yes,?,?,?,yes,?,?,?,?,?,?,?,?,yes,?,?,?,?,?,?,yes,yes,yes,?,?,?,yes,?,yes,yes,yes,?

19. yes,?,yes,yes,yes,?,yes,?,?,yes,?,?,?,?,yes,?,?,?,yes,?,yes,?,?,?,yes,yes,?,?,?,yes,?,?,?,yes,yes,?,yes,?,yes,?,?,?,?,yes,?,?,?,?,?,yes,yes,yes,?,?,?,yes,?,?,?,?,yes,yes,yes,yes,yes,yes,yes,yes,yes,?,?

20. yes,yes,yes,?,yes,?,?,?,?,?,?,?,?,?,?,?,?,?,?,yes,?,yes,?,?,?,?,?,?,?,?,?,?,?,?,?,yes,?,?,?,?,?,?,yes,yes,yes,?,?,?,yes,?

APPENDIX 2: OVERVIEW FROM DATA CAPTURE TO PROCESS DISCOVERY



APPENDIX 3: OVERVIEW OF THE APPROACHES, TECHNIQUES, OUTCOMES, BENEFITS, AND CONTRIBUTIONS OF THIS THESIS

Approach	Used Technique	Outcome(s)	Benefit(s)	Contribution
Collaboration Indicators Analysis	Pearson Correlation Coefficient (2-tailed)	Provision of a measure of the linear dependence (correlation) between 8 independent variables (i.e., interaction, participation, gender, age, prior experience, time performance, symmetry of tasks, symmetry of roles" and 1 dependent variable "collaborative performance process in CSCL".	Acceptance or rejection of the hypotheses in the initial conceptual framework model. Accordingly, 4 variables of "participation", "interaction", "time performance", "symmetry of tasks", and "symmetry of roles" were supported.	Through an inductive and deductive approach, versatile quantitative indicators selected and investigated in order to identify the most significant factors affecting the collaborative performance of groups in an online collaborative multi-tabletop environment.
Visualization Analysis	Social Network Analysis (via handover of work and similarity of work metrics)	Generation of Social Network graphs based on the extent of handover of work and similarity of work metrics.	Applying social network graphs (via handover and similarity of work of work metrics) enabled us to investigate interaction dynamics and symmetry of tasks performed between HP & LP group members in M-ITCL.	Social network models in terms of handover of work and similarity of work metrics (through ProM process mining tool) were used to investigate the extent of interaction dynamics and symmetry of tasks in an online collaborative multi-tabletop learning environment.

Visualization Analysis	Role Hierarchy Miner	Generation of Social Network graphs based on the hierarchy of roles and tasks performed by peer members in each group.	Applying social network graphs in terms of role hierarchy models enabled us to investigate the symmetry of roles and duties (through an organizational structure view) between HP & LP peer group members in M-ITCL.	In this thesis role hierarchy mining techniques (via ProM) were applied on a data collected from an online collaborative multi-tabletop learning environment.
	Dotted Chart Analysis	Generation of straightforward charts similar to Gannt charts which indicated the spread of events of the collaborative interaction data (collected from M-ITCL environment) over time.	Applying dotted chart analysis charts helped us to better investigate and compare: “the accuracy of the deletions executed on concept maps during the assigned task”, “the types of actions”, “the spread of importance of actions over time” between HP & LP groups.	In this thesis dotted chart analysis techniques (supported by ProM process mining tool) were used in order to investigate the accuracy of actions, the importance of actions, and the types of actions performed in an online collaborative multi-tabletop learning environment.

Visualization Analysis	Basic Performance Analysis	Generation of visualization graphs with calculation of performance measures such as working time (activeness), waiting time (idleness), etc., from collaborative interaction data collected from M-ITCL environment.	Applying Basic Performance Analysis techniques enabled us to better illustrate and simulate the extent of similarity of tasks performed by peer group members in M-ITCL environment.	In this thesis the Basic Performance analysis technique (via ProM process mining tool) was used in order to visualize and illustrate the types of tasks performed by originators (and vice versa) in an online collaborative multi-tabletop learning environment.
	Events Over Time Diagram	Generation of diagrams illustrating the number of students' actions performed per second in the groups based on the collaborative interaction data collected from M-ITCL environment.	Applying Events Over Time Diagram Distribution technique enabled us to better visualize and compare the number of students' actions performed per second among HP & LP groups in M-ITCL environment.	In this thesis the Events Over Time Diagram technique (via Disco Fluxicon process mining tool) was used in order to investigate the rates of actions performed (per second) during the assigned concept map construction activity in an online collaborative multi-tabletop learning environment.

Process Modeling Analysis	Fuzzy Miner (Frequency-Based via Disco Fluxicon)	Generation of Fuzzy Miner models based the frequency (or number of times) specific types of actions are performed in M-ITCL environment.	Applying Fuzzy Miner (Disco, Frequency-Based) techniques enabled us to better simulate, visualize and compare: "the level of importance of the actions performed by the group peer members", "the activities and the paths based on the absolute frequency of actions/ events" among HP & LP groups in M-ITCL environment.	In this thesis fuzzy process models based on the frequency of occurrence of the actions (generated by Disco Fluxicon) were used in order to further study the types and importance of actions based on a data collected from an online collaborative multi-tabletop learning environment.
	Fuzzy Miner (Frequency-Based via ProM)	Generation of Fuzzy Miner models based the frequency or number of times specific actions rooted in two significance and correlation metrics based on the event logs collected from M-ITCL environment.	Applying fuzzy process models (ProM, Frequency-Based) enabled us to better simulate, visualize and compare: "the most significant blocks of activity" among HP & LP groups in M-ITCL environment.	In this thesis the "significance" metric of ProM Fuzzy Miner technique was used in order to identify and compare the most significant blocks of activity between groups of students in an online collaborative multi-tabletop learning environment.

Process Modeling Analysis	Fuzzy Miner (Time Performance-Based via Disco Fluxicon)	Generation of Fuzzy Miner models based the average durations (mean) of the long inactive waiting times among the activities based on the event logs collected from M-ITCL environment.	Applying Fuzzy Miner (time performance-based) models enabled us to better discover and compare: “distinguished patterns of time performance (i.e., analysis of the long waiting times between the activities” among HP & LP groups in M-ITCL environment.	In this thesis for the first the time-based Fuzzy Miner models (via Disco Fluxicon process mining tool) were used in order to analyze, compare and study the mean/total durations of long waiting time (idle time) between groups of students in an online collaborative multi-tabletop learning environment.
Strategy Mining Analytics	Association Rule Mining (via Apriori Algorithm)	Generation of sequential Association Rules and strong relationships between components of data collected from M-ITCL environment and by using Apriori measures of the most frequently repeated actions.	Applying sequential Association Rule Mining technique (via Apriori algorithm) enabled us to discover the concept map construction strategy in the High Performance (HP) groups during the assigned activity in M-ITCL environment.	In this thesis the Association Rule Mining technique (supported by ProM process mining tool) was used in order to discover and investigate the concept map construction strategy of groups in an online collaborative multi-tabletop environment.

Pattern Mining and Statistical Analysis	Frequent Itemsets Mining (via Apriori Algorithm)	Discovery of the top-3 most frequently occurred itemsets (i.e., in this thesis pre-defined contexts) in terms of sequential patterns and based on the event logs collected from M-ITCL environment.	Applying Frequent Itemsets Mining (via Apriori Algorithm) helped us to discover the top-3 frequent itemsets in both HP & LP groups with respect to: "Context 1 (participation dynamics), Context 2 (interaction density), and context 3 (correctness of the executed actions), .	In this thesis the Frequent Itemsets Mining technique (supported by ProM process mining tool) was used in order to discover and investigate the top-3 most frequent itemsets occurred within the event logs of groups of students in an online collaborative multi-tabletop environment.
	Descriptive Statistics (Log Summary Analysis + Statistics Overview Analysis)	Generation of straightforward statistical tables and simple graphics based on the collaborative interaction data collected from M-ITCL environment in terms of "participation density", "participation rate", and other "general" differences (i.e., mentioned in Sub-question 1).	Applying versatile Descriptive Statistics techniques helped us to better investigate the extents of participation (and other general features) among the HP & LP performance groups in M-ITCL environment.	In this thesis several Descriptive Statistics techniques (supported by ProM and Disco Fluxicon process mining tools) were used in order to provide simple summaries about the log summaries, measures and simple graphics of groups of students in an online collaborative multi-tabletop environment.

Conformance Checking and Replaying	Conformance Checker	Comparison of the process models (generated by Alpha, Heuristic, and Fuzzy Miner algorithms) with the event logs collected from M-ITCL environment in order to establish a mapping between the logged events.	Applying the Conformance Checker technique enabled us to investigate the extents of “Replay Fitness”, “Precision”, “Recall” and “Simplicity” of Structure of the generated Alpha, Heuristic and Fuzzy Miner algorithms applied on collaborative interaction data collected from M-ITCL environment.	In this thesis the extents of “Replay Fitness”, “Precision”, “Recall” and “Simplicity of Structure” of the generated Alpha, Heuristic and Fuzzy Miner models were assessed through Conformance Checker technique (supported by ProM process mining tool) based on event logs collected from an online collaborative multi-tabletop environment.

BIBLIOGRAPHY

Parham Porouhan is a research assistant in Graduate School of Information Technology at Siam University, which currently is recognised as the 5th largest private university in Thailand. His areas of interest and expertise include but not limited to: artificial intelligence, educational data mining, process mining, data science, human-computer interactions, learning analytics, text mining, business management techniques and business process modelling, and educational communications and technology.